Behavioral Asset Pricing in Chinese Stock Markets

By

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Dedication

This thesis is dedicated to my husband, Dazhi Li and my mother. Thank you for all the unconditional love and support that you have always given me.

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Abstract

This thesis addresses asset pricing in Chinese A-share stock markets using a dataset consisting of all shares listed in Shanghai and Shenzhen stock exchanges from January 1997 to December 2007. The empirical work is carried out based on two theoretical foundations: the efficient market hypothesis and behavioural finance. It examines and compares the validity of two traditional asset pricing models and two behavioural asset pricing models.

The investigation is initially performed within a traditional asset pricing framework. The three-factor Fama-French model is estimated and then augmented by additional macroeconomic and bond market variables. The results suggest that these traditional asset pricing models fail to explain fully the time-variation of stock returns in Chinese stock markets, leaving non-normally distributed and heteroskedastic residuals, calling for further explanatory variables and suggesting the existence of a structure break. Indeed, the macroeconomic and bond market factors provide little help to the asset pricing model.

Using the Fama-French model as the benchmark, further research is done by investigating investor sentiment as the third dimension beside returns and risks. Investor sentiment helps explain the mis-pricing component of returns in the Fama-French model and the time-variation in the factors themselves. Incorporating investor sentiment into the asset pricing model improves the model performance, lessening the importance of the Fama-French factors, and suggesting that in China, sentiment affects both the way in which investors judge risks as well as portfolio returns directly. The sentiment effect on asset pricing is also examined under a nonlinear Markov-switching framework. The stochastic regime-dependent model reveals that stock returns in China are driven by fundamental factors in bear and low volatility markets but are prone to sentiment and become uncoupled from fundamental risks in bull and high volatility markets.

Keywords: Asset Pricing, Portfolio Returns, Investor Sentiment, Beta-Pricing Model, Conditional Model, Markov-Switching Model.

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Abbreviations

EMH: Efficient Market Hypothesis

CAPM: Capital Asset Pricing Model

Fama-French or FF: Fama-French three factor model (1993, 1995, 1996)

ICAPM: Intertemporal Capital Asset Pricing Model

BSV: Barberis, Shleifer, and Vishny (1998)

DHS: Daniel, Hirshleifer and Subrahmanyam (1998)

SOEs: State-owned Enterprises

CRR: Chen, Roll and Ross (1986)

TAR: Threshold Autoregression (Tong, 1990)

MS: Markov-Switching (Hamilton, 1989)

Chapter 1 INTRODUCTION

1.1 Background and Motivation

No other country's economy can match Chinese potential. The economy of this most populous nation has grown rapidly for thirty years since the economic reforms launched in 1978. China is becoming an economic superpower and still shows few signs of stopping. Understandably, Chinese citizens want to benefit from the fast growing Chinese economy and many foreign investors also want a share of this exciting market, probably via stock market investments.

China has launched two stock markets, Shanghai and Shenzhen. From 1991 when the two stock exchanges were established, many efforts have been made to improve stock market performance, such as deepening market openness, strengthening the legal and regulatory framework and expansion of domestic and foreign institutional participant, and so on. Yet the Chinese stock markets still lag behind her economy, with less transparent controls, lack of investment instruments, less clear accountability, and being congested by many small, noisy and speculative investors.

Although market capitalisation is comparatively small in relation to the size of the economy, the stock market nevertheless plays a more essential role than in many other countries. With the transformation from a plan-oriented to a market-oriented economy, the social welfare system faces pressure. Factors such as job placement, housing, health care and elderly care tend to break the "iron rice bowl". Wages and salaries are often not adequate to finance these needs. In China, the stock market is commonly regarded a potentially important supplementary source of income: more than 130 million trading accounts were open by the end of 1997， which means almost 10% of China's total population[1] trade in stock markets. The stock market also facilitates

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[1] Source from: China Securities Depository and Clearing Corporation Limited, www.chinaclear.cn

listed firms access to long-term capital to fund their rapidly-growing businesses and equally importantly, provides a route to privatize state-owned companies.

Investors should understand the stock market if they are to invest in shares. Understanding security prices lies at the core of this understanding. For many years, the efficient market hypothesis (hereafter, the EMH) has been the central proposition of finance and the mainstream approach for asset pricing. Academics developed powerful theories to discover the relationship between risks and returns. Real financial markets, such as the U.S. bond or stock markets, were regarded to be consistent with the EMH statements for many years until the development of behavioural finance in the 1990s.

More recently, the debate between the EMH and behavioural finance has become one of the central issues in asset pricing. Behavioural finance provides an alternative explanation of asset pricing to the EMH. Unlike the EMH, it emphasises investor psychology, and arguably uses more realistic assumptions about individual behaviour than the EMH. However，behavioural finance so far cannot so easily account for time, risk and psychology. No unique conclusive story has been provided for asset prices, even when dealing with the 100+ year experience of the mature markets in developed countries, such as the U.S. and U.K. Thus, asset pricing remains an ongoing topic of debate.

Previous empirical research, especially on behavioural asset pricing, has been mainly applied to developed countries. The rapid growth of the Chinese economy and financial markets have attracted domestic and foreign investors, but the extent academic research on these markets falls far short of investors' needs. The Chinese market has not been greatly studied either for its conformity with traditional asset pricing theory or for sentiment effects[2]. Stock markets in China are not fully developed

[2] For an exception, see Burdekin and Redfern (2009). However, their dataset begins only in 2003.

and are likely to be inefficient than more developed countries. This would suggest that the pricing of Chinese stocks may be even more problematic than the developed markets, and therefore that asset pricing results from developed countries may not be relevant for China. Empirical research on Chinese stock market data is relatively limited in scope. Thus, asset pricing issues in China deserve more attention. All these considerations and the literature gap bring the initial motivation for this research.

1.2 Thesis Overview and Aims

1.2.1. Questions to be Answered

Pricing equities is the core task for investors and the central issue for finance. Asset pricing theory tells why prices or returns are what they are, what they "should" be, and provides practical application for guiding investment decision-making. This research is based on the simple issue: how to value stocks in Chinese stock markets. This basic issue is investigated in three sets of questions based on the development of asset pricing theory:

(1) What according to a traditional EMH-based asset pricing model are the fundamental determinants of Chinese stock returns? Do asset pricing models which incorporate the fundamental determinants explain the true variation in Chinese stock returns?

(2) Alternatively, does investor sentiment explain the variation of stock returns, given the failure of a traditional asset pricing model? And if yes, how does investor sentiment affect stock returns?

(3) What is the appropriate specification for the asset pricing model incorporating investor sentiment? In particular, are sentiment effects on stock returns constant or time-varying? If sentiment effects on stock returns are not constant, can we find the pattern of regime shifts in fundamental-driven returns and sentiment-driven returns?

The first two considerations are triggered from the debate between the efficient market hypothesis (EMH) and behavioural finance. Fama (1970) defined an efficient market as one in which security prices should fully reflect all available information. The information updating process is governed by investors' unbiased cognitive evaluation and maximization of expected utility, and leaves no role for investor sentiment. Although the power of the EMH and traditional asset pricing models has become weaker in recent years (Shiller, 2002), they remain an important departure point to study asset pricing. The first set of questions stems from the mainstream approach of theoretical asset pricing under the EMH. The Fama-French (hereafter, FF; Fama-French, 1996) three factor model, which is widely agreed to be a useful description of stock returns (Grauer, 2003), is used and tested as a starting point. Given the failure of the Fama-French model that I encounter, I next investigate whether this failure is due to missing fundamental risk factors by testing a multi-beta pricing model with further risk factors that capture changes in investment opportunities from macroeconomic and bond market circumstances.

Shleifer (2000b) set out the theoretical and empirical challenges to the EMH and the basis for behavioural finance. Behavioural finance states that the irrationality of investors and limited arbitrage opportunities prevent stock prices from moving towards their fundamental values, resulting in persistent deviations. These descriptions are likely to be partially true for Chinese stock markets where features such as lack of investment instruments, less transparent controls and accountability, and the large amount of small investors, appear. Given the lesser development of the Chinese stock market system and possibly less efficiency of the market performance, the behavioural approach to asset pricing is possible to be a more effectual model that fits Chinese stock market data. Therefore, the second question aims to discover whether investor sentiment helps to explain stock returns in China given the failure of the theoretical asset pricing models that I in fact observe. In particular, I investigate the role of sentiment as an irrational risk factor, and the impacts of sentiment on the Fama-French factors.

The background to the third question in that the behavioural approach to asset pricing has been discussed and understood, but only up to a point. Empirical evidence has been found to support behavioural finance[3], however, behavioural approach to asset pricing remains less clear[4].The existing parsimonious models provide mechanisms of behavioural approach to asset pricing, however, do not tell the real stories in financial markets. Baker and Wurgler (2006, 2007) develop an empirical approach to studying the impact of investor sentiment on asset prices by taking sentiment as a conditioning variable for the characteristic factors. Therefore to answer the third question, I first augment the Baker and Wurgler conditional characteristics model by individual symmetric and positive sentiment proxies. Second, I further investigate the time-variant relations between returns, risks and sentiment in a nonlinear framework. The Markov Switching framework is adopted so that the return distributions are allowed to have regime-dependent sensitivities to the fundamental factors and investor sentiment.

1.2.2. Sample Selection

This research is based on 11 years monthly data for Chinese A-share stock markets (Shanghai and Shenzhen), from January 1997 to December 2007. The data period is shorter than much research on developed country markets, but longer than for previous research on Chinese stocks. The beginning of the period is fixed at January 1997 for two reasons. First, Chinese stock markets were established in 1991 and can be assumed to have reached relative maturity by 1997. The smallest test portfolios average about

[3] See the overreaction and underreaction (De Bondt and Thaler, 1985, 1987; Hirshleifer, 2001; Barberis and Thaler, 2003) and Asymmetric volatility (McQueen and Vorkink, 2004; Verman and Verman, 2007).

[4] See Barberis, Shleifer, and Vishny, (1998) for the pricing model with consideration of investor sentiment, Daniel, Hirshleifer, and Subrahmanyam, (1998) for the model with heterogeneous investors of which a part of investors are noise traders, and Barberis, Huang and Santos, (2001) for asset pricing under prospect utility theory.

18 shares at the start of the period. This should be adequate to avoid idiosyncratic fluctuations, but it is difficult to extend the data further back in time as the number of shares would drop sharply. Second, on 16th December 1996 the Shanghai and Shenzhen stock exchanges adopted the Price Limit Regime, which restricts daily changes in stock prices to be +/- 10%. This restriction mechanism is likely to affect the movement of stock prices significantly. Therefore the January 1997 start date eliminates any possible effects arising from this change in market microstructure.

The sample set includes all stocks traded in Chinese A-Share markets that have been listed for at least one year. The number of stocks in the sample increases from 459 in 1997 to 1354 in 2007. The test assets are 25 portfolios simultaneously sorted by size and book-to-market ratio. This elaborate portfolio grouping both reduces the noise generated from individual stocks and minimizes the error-in-variables (EIV) problem (Fama and MacBeth, 1973). It also keeps in line with and makes it comparable to key previous studies, such as Fama and French (1993, 1996).

1.3 Contribution to Knowledge

Overall, this thesis contributes to literature in the following ways. First and foremost, this study fills the literature gap in traditional and behavioural asset pricing theory in developing Chinese stock markets. It provides some new and important evidence that challenges the traditional asset pricing theory over a longer test period than the few existing studies using Chinese data. To improve asset pricing models in Chinese market, this thesis is among the first that brings investor sentiment as the third dimension beside risk and return, and develops a conditional asset pricing model and a non-linear regime-shifting model to govern the time-invariant and regime dependent relations between returns, risks, and investor sentiment, respectively.

Second, the thesis investigates the free float issue in asset pricing: whether the total market capitalisation or the float-adjusted market capitalisation (listed market values) should be used when weighting stocks in portfolio. The empirical findings are compared over four sub-samples, which are differentiated by (i) whether the special treatment firms[5], negative book equity firms, and financial firms are included or not, and (2) either the market capitalisation weights are measured using total market value or free float market value. This comparison helps to understand the Chinese stock markets where listed firms have a large proportion of non-tradable shares. The findings suggest that the Fama-French model fits the data better when the test portfolios and distress premia (return on high book-to-market ratio stocks minus return on low book-to-market equity stocks) are weighted by listed (the free float) market value, but the size risk is more likely to be captured by firms' total market value.

Third, this thesis departs from most previous researchers who have used a composite index of sentiment. Instead, individual sentiment proxies are tested directly: first to reveal differences in sentiment effects, depending on how sentiment is measured; and second, to avoid the problem of replication over time that tends to be an issue when principal components are used to estimate a composite index. I distinguish between normal and positive sentiment in the conditional asset pricing model. In the regime-dependent model, sentiment proxies are tested individually. The findings suggest that the regime performance of sentiment proxies differs each other and has different impacts upon stock returns.

Finally, using the cognitive-based theoretical asset pricing model (Fama-French) as benchmark enables us to examine how far sentiment can contribute to asset pricing theory. In particular, I investigate both the direct effect of sentiment as an irrational risk factor and the indirect effect through the impact of sentiment on the cognitive Fama-French risk factors. The findings support sentiment as pricing factors as well as the reason for the biased cognitive factors. Thereupon, sentiment is used as the

[5] Companies marked as ST are listed companies with more than two years of operating losses, while companies marked as S have not yet started their shareholding system reform. In both cases, the daily prices of these companies are restricted to variation within 5% limits.

condition of the cognitive Fama-French factors in the conditional asset pricing model. Sentiment is also used to orthogonalise the Fama-French factors in the regime-shifting pricing model to decompose the fundamental size and distress premium from the sentiment-driven characteristics.

1.4 Structure of the Thesis

The remainder of the thesis consists of 6 chapters organised as follows.

Chapter 2 reviews the relevant literature on asset pricing theory, organized according to the debates between the EMH and behavioural finance. The review starts with the brief introduction to the EMH, its problems, and the behavioural finance critique. Then, theoretical asset pricing models and their empirical evidence are summarised, followed by a more detailed description of behavioural finance. Finally the behavioural approach to asset pricing is reviewed in both theoretical and empirical aspects.

Chapter 3 introduces background knowledge about Chinese financial markets. This chapter provides an overview of the Chinese economy, its bond markets and stock markets and points out the history of reform and regulation.

Chapter 4 studies traditional asset pricing models in Chinese A-share stock markets. The Fama-French three factor model is used and tested first. In response to the failure of the Fama-French model, additional risk factors are specified into the model. However, the empirical results reveal that missing fundamental risk factors is not the reason for the failure of the Fama-French model.

Chapter 5 incorporates investor sentiment as an alternative explanation for the Fama-French failure. This chapter tests sentiment effects on both the mis-pricing components of returns in the Fama-French model and the cognitive Fama-French factors. Based on these preliminary results, a sentiment-based conditional asset pricing model is introduced extending Baker and Wurgler (2006).

Chapter 6 further studies the regime-dependent dynamics of investor sentiment and extends the time-invariant sentiment-based asset pricing model to a non-linear, regime-dependent model, which is used to investigate regime-shifting relations between stock portfolio returns, fundamental risks, and investor sentiment.

Chapter 7 provides an overall conclusion to the thesis and suggests further possible research directions implied its findings.

Chapter 2 LITERATURE REVIEW

2.1 Introduction

Asset pricing theories work to identify the expected prices or returns on securities with future cash flows in financial markets. Theories of the pricing of ordinary stocks frequently boil down to one simple concept: prices equal expected discounted future payoffs. From here risk factor (beta) pricing models are introduced to be testable empirically and, more importantly, to have practical value and to guide investment decisions. Well-known asset pricing theories, such as dividend discount models, the Capital Asset Pricing Model (CAPM), and the Fama-French three-factor model, differ in the way they measure future payoffs and risk factors, but build on the same assumption of the *efficient markets hypothesis* (EMH). However, financial markets show many anomalies that cannot be explained by the EMH. To explain these anomalies, researchers have suggested numerous theories, including: investor irrationality, arbitrage limitation and noise trading. Pricing theories that relax the assumptions of the EMH and study the influence on asset pricing of investor behaviour under more general assumptions than the EMH constitute the field of *behavioural finance*.

It should be noted that in this literature review and the entire thesis, the efficient market theory is discussed and tested in the context of the Fama-French model and the multi-beta pricing model with more fundamental risk factors. In other words, I focus not on testing the efficient market theory but on the asset pricing models under the EMH in Chinese stock markets. The beta pricing models, rather than the discount pricing models (such as the dividend discount model), are focused on because they are more flexible for augmentation with behavioural finance variables.

This literature review is concerned particularly with the debate about the EMH and behavioural finance. In this section the theoretical foundations of asset pricing theories are discussed, beginning with the EMH and its applications. Some empirical puzzles that are commonly used as arguments against the EMH in the finance literature are mentioned with a brief introduction to new explanations from behavioural finance. Section 2 focuses on those theoretical pricing models that have their foundations in the EMH. Empirical evidence provides incompatible conclusions with respect to these theoretical pricing models. To address these problems, the detailed concepts of behavioural finance and its empirical applications in financial markets are summarised in Section 3. Section 4 reviews some existing asset pricing models which incorporate behavioural considerations. The final section concludes the literature review.

2.2 Theoretical Foundations: Efficient Market Hypothesis vs. Behavioural Finance

2.2.1. Efficient Markets Hypothesis

To build up a framework for studying asset pricing and financial markets, researchers need to assess a set of assumptions about investor preferences, human judgment and decision making in financial markets. Theoretically, the dominant neoclassical assumption of many asset pricing theories is the Efficient Markets Hypothesis, defined by Fama in the 1960s. The EMH states that in an efficient market, security prices are equal to the mathematical expectation of the present value of the future payoffs of the security, reflecting all the information available at the time.

The EMH describes a paradigm of financial markets where equilibrium exists, in line with the law of one price and an absence of arbitrage opportunities, where investors are rational and markets are complete. It asserts that market participants on the whole form rational expectations when making investment decisions. Their actions drive security prices towards their fundamental values. To the extent that some investors are not rational, they trade randomly so as to be cancelled out by each other. To the extent that investors are irrational in a similar way, they are cancelled by the arbitrageurs. These ensure that the homogeneous investor equilibrium condition is satisfied.

The EMH was widely adopted in asset pricing theories and proved successful both theoretically and empirically in the first decade after its introduction, and many asset pricing theories were developed within this framework. Asset pricing models that are consistent with the EMH and emphasise the fundamental value of securities are called *theoretical* or *traditional* asset pricing models. The early pricing model of Gordon (1962) that applies dividends as a measure of fundamental value is an example. The CAPM, the first and most popular equilibrium model introduced by Sharpe (1964), Lintner (1965), and Mossin (1966), stems from the mean-variance frontier and states that the rate of return on any security is related only to systematic risk (beta). The Fama French three-factor model (Fama and French, 1992, 1996) develops the CAPM by introducing size and book-to-market betas to capture some anomalies that are related to firm characteristics, including firm size, book-to-market ratio and earnings-to-price ratio. Today, the EMH is still the dominant theory in finance.

2.2.2. Problems of the EMH

However, empirical evidence suggests that there are many market anomalies that cannot be explained by efficient market theories, including excess volatility, winner-loser effects, the closed-end fund puzzle and calendar effects. Although researchers argue that such anomalies can be eliminated by improving the explanatory parameters, the basic support for the entire efficient market theory is called into question.

1) Excess volatility

Within these anomalies the most important is the excess volatility of realized stock returns. If the EMH holds, variation in stock returns should be commensurate with changes in fundamental variables. However, episodes often occur when stock prices rise or fall in the absence of news about fundamentals. Excess volatility describes the empirical phenomenon that stock returns are far more volatile than can be explained by their fundamental values (LeRoy and Porter, 1981; Shiller, 1981, 2002). Moreover, it is well known that the unconditional distribution of return series is positively autocorrelated and excessively leptokurtic (Hamao, Masulis and Ng, 1990). These empirical findings suggest that changes in price may occur for no fundamental reason at all.

2) Winner loser effect

In violation of EHM statement that past performance has been priced thus has no effect on the future, financial markets show some correlations of security returns over time. Jegadeesh and Titman (1993) find that over a short period (3 to 12 months) past winners will continue to outperform past losers. De Bondt and Thaler (1985) report that portfolios of past losers experience much higher returns than past winners for as long as five years after portfolio formation. The winner-loser effect casts doubt on the EMH which asserts that investors cannot make excess return according to the past return performance, since all the relative information should be immediately and fully reflected in contemporaneous stock returns.

3) Closed-end fund puzzle

Closed-end funds are mutual funds that issue a fixed number of shares, trading in exchange at their market prices rather than their net value per share (NAV). The fundamental value of closed-end funds is easy to observe: it is just the weighted average values of assets that the funds hold. If the market is efficient and investors are rational, the trading prices of closed-end funds should be equal or very close to their NAVs. However, empirical findings suggest that closed-end funds are initially traded at a premium (10%), move to a discount (10%-25%) during their life time and move to a narrow discount at termination (Zweig, 1973). Although some research attributes the closed end fund puzzle to the result of agency costs, illiquidity of assets and/or capital gains tax liabilities, Shleifer (2000a) suggests that the discounts and premiums on closed end funds reflect the expectations of individual investors in respect of their sentiment about future returns.

4) Calendar effects

Calendar effects describe anomalies in which stock returns are above or below average on certain days, months or times of year. The most common calendar anomalies are the January effect and the day-of-the-week effect. The January effect indicates that stock returns in January tend to be higher than the average returns of the year (Keim, 1983). Day-of-the-week effects indicate that stock return movements are not random within the week. For example, a large literature suggests that the mean return on Friday is higher than average while the mean return on Monday is much lower than average (Siegel 2002, Gao and Kling 2005). Calendar effects show that market returns follow seasonal patterns and can therefore call into question the randomness of stock price movements implied by the EMH.

2.2.3. The Behavioural Finance Approach

In response to the difficulties in the EMH, in the 1990s behavioural finance provided a new approach to explain financial market phenomena by relaxing the assumptions of the EMH. In general, behavioural finance argues that some market phenomena can be better understood by considering that investors are not fully rational and that human fallibility influences the pricing of assets. The behavioural approach to asset pricing is built on two micro foundations: *Limits of Arbitrage* and *Investor Irrationality*. The former considers that real world arbitrage is costly and risky, and therefore limited. The latter analyses how investors actually form their beliefs, valuations, and demands.

1. Limits of Arbitrage

As a fundamental concept in traditional finance, arbitrage plays a critical role in the theoretical field to ensure the existence of equilibrium prices. Sharpe and Alexander

(1990) define arbitrage as “the simultaneous purchase and sale of the same, or essentially similar, securities in two different markets for advantageously different prices”. As long as prices get out of fundamental value, arbitrageurs buy the underpriced securities and sell the overpriced securities to earn costless riskless return will occur, pushing prices back to the equilibrium level of one price. However, in real markets where transaction and information are not free, unlimited arbitrage is harder than it looks (Shleifer and Vishny, 1997; Shleifer, 2000b; Brealey, Myers and Allen, 2008).

Arbitrage is not risk-free. *Fundamental risks* arise when arbitrage is not perfect. In practice it is hard to find a perfect substitute for an asset. By purchasing stock A and selling stock B as substitute may not remove all fundamental risks, possibly resulting in an arbitrage loss. *Implementation risks* are also involved because of costly trading, especially when short sales are involved (Shiller, 2002). Shiller states that arbitrageurs (‘smart money’) can easily purchase securities if the price is below fundamental value. However, arbitrageurs face difficulties in selling if they no longer own the securities. Even if short sales are not constrained, implementation risks still exist. For instance, arbitrageurs borrow to purchase low and may have to wait to sell high, meaning that it is possible for the interest on borrowing to be greater than the increase in asset prices. The existence of the risks may stop arbitrageurs acting even if prices are not in equilibrium.

Performance-based arbitrage is limited due to agency risks and noise trading (De Long, Shleifer and Summers, 1990; Shleifer and Vishny, 1997). In the real world, brains and resources are separated by an agency relationship. The few professional, highly specialised ‘arbitrageurs’ combine their knowledge with resources from other ‘investors’. The less educated and less specialised investors judge the ability of the arbitrageurs, such as their fund managers, according to their short-term performance. When prices deviate from their equilibrium level, and there is an expectation in the short term that prices will continue to increase or decrease, arbitrageurs may act to worsen mis-pricing in short run rather than push prices towards the fundamentals. This is because arbitrageurs who suffer from short-term losses may be forced to sell their assets because the investors withdraw their funding, even if they know that over the long run they will gain. Consequently, performance-based arbitrage reduces arbitrageurs' incentive to trade against mis-pricing when they should hold for a longer period compared with the short horizon of resource holder's response.

2. Investor Irrationality

A crucial basis for any asset pricing theory is to specify agents' expectations. The Efficient Markets Hypothesis assumes that investors can rationally form unbiased expectations about the future and the risks involved, but behavioural finance questions the applicability of these assumptions and discusses the possibility that investors form erroneous beliefs and/or behavioural bias about the future distribution of returns on risky assets. In the real world, agents may neither update in response to risks nor form judgements in accordance with Bayesian principles. Instead, they may use other preferences when evaluating information to make investment decisions.

Applying some psychological theories, behavioural finance indicates that investors cannot update their beliefs or make judgements and decisions under risky situations as correctly as suggested by the EMH. Instead they could be biased in collecting, receiving, and updating information, and in drawing conclusions. For example, investors may form their beliefs using 'rules of thumb', in other words, some simplified procedures (Slovic, 1972; Tversky and Kahneman, 1974). A detailed discussion of psychological foundations and application to asset pricing will be given in section 3.

2.2.4. Summary

In short, the theoretical foundation of asset pricing models stem from two contrary statements – the efficient market hypothesis and behavioural finance. The EMH describes an efficient market where arbitrage is unlimited and investors are rational as a whole. Prices of securities in such markets are the mathematical expectation of the present value of the future payoffs, reflecting all the information available at the time. However, there are some phenomena observed from financial markets that cannot be explained under the EMH framework. They are called the anomalies.

To deal with the anomalies that cannot be explained by efficient market theories, behavioural finance relaxes the assumption of the EMH and suggests implications arising from limited arbitrage and irrational investors. In real financial markets arbitrage is limited because of the existence of various risks. Arbitrageurs lose their power to drive prices towards fundamental value in a market where arbitrage is costly and risky. Performance-based arbitrage may even push stock prices away from their theoretical values as arbitrageurs maximise short-term rather than long-term profit. On the other hand, investors in financial markets, even the so-called arbitrageurs, may not be as rational as expected by the EMH but may instead show bias in decision-making.

2.3 Survey of Traditional Asset Pricing Models

To justify a more detailed analysis of behavioural finance it is important to provide evidence for the rejection of efficient market theories, or at least to demonstrate that the EMH may be an unsound basis for asset pricing. The EMH asserts that in an efficient market, prices (and returns) of securities should be equal or close to their expected fundamental values. Therefore my survey of theoretical asset pricing models begins with a summary of the determinants of the fundamental values of securities. I then provide a summary of existing traditional asset pricing models, followed by a discussion of testing methodologies. Finally, empirical results and open issues are discussed.

2.3.1. Explanatory Factors for Fundamental Valuations

The theoretical literature on the determinants of fundamental values can be catalogued into two major aspects: firm-level and market-level observations. Firm-level variables involve dividend payments, earning-price ratios and other financial variables such as firm size, sales, revenue or total assets, that are information from company accounts. Market-level measurements calculate fundamental values taking into account market reactions to firms' information and characteristics. Researchers also think that stock markets cannot be isolated from the economy as a whole. Therefore macroeconomic factors, such as exchange rate, interest rates, and inflations, may also influence stock pricing.

2.3.1.1 Firm-level measurements

According to the EMH, stock prices should be equal to the expected future cash flows they provide. Thus a natural way to value stock prices is to observe the performance of companies as presented in their financial reports. The basic firm-level variables include dividends (Miller and Modigliani, 1961; Gordon, 1962), earnings (Campbell and Shiller, 1988b), and other variables that have a stable long-run relationship with the fundamental value of firms (Kamstra, 2001).

1. Dividend Payments

Investors' actual benefits are generated from capital gains or losses, and from dividend payments. Over infinite time, the discounted capital gain tends to be zero[6], and the

[6] $p_t = E_t\left[\sum_{k=1}^{n}\left[\frac{D_{t+k}}{(1+r)^k}\right]+\frac{p_{t+k}}{(1+r)^k}\right]$, where p_t is price at time t, D_{t+k} is the K-period expected dividend payment

only source of future cash flow is from dividends. Thus a natural way of thinking about the fundamental value of a stock is the current value of future dividend cash flows discounted at the appropriate discount factor.

Early work using dividends to model stock prices is traced to Gordon (1962), where stock prices are purely the discounted dividends assuming a constant dividend growth rate. Pettit (1972) indicates that the announcements of changes in dividend payments have significant impact on the values of securities. Campbell and Shiller (1988a) provide a dividend discount model using dividend yields to explain fluctuations in stock prices: they relate the dividend- price ratio to the forecasted future returns and future dividend growth rate. Fama and French (1988) also use the dividend-price ratio to forecast stock returns. They indicate that dividend yields explain only a very small fraction of the variation of returns in the short term, say a few months, but the that the explanatory power increases over the longer term of 2 to 4 years.

2. Earnings

Accounting earnings are widely thought to be a powerful variable for representing the fundamentals of stocks because they are direct indicators of company performance. Earnings may contain information about dividend changes and earnings are a good predictor of future dividends (Pettit, 1972; Watts, 1973; Aharony and Swary, 1980). Campbell and Shiller (1988b) employ historical averages of real earnings to predict the present values of future dividends and report that the optimal forecast of the present value of future real dividends is roughly weighted average of 2/3-3/4 of moving average earnings and 1/3-1/4 of the current real price.

To estimate the prices of stocks with zero dividend payments and to achieve better

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from time *t* and *n* is the time to maturity. $\lim_{k\to\infty}\left(\frac{p_{t+k}}{(1+r)^k}\right)=0$, so $p_t=\sum_{k=1}^{\infty}E_t\left[\frac{D_{t+k}}{(1+r)^k}\right]$.

estimation, earnings can be used directly to evaluate the fundamental worth of companies. Like dividend yields, earnings yields (E/P, the inverse of the price/earnings ratio) have power to explain stock returns, although the impact is less important than dividend yield (Shiller, 1984; Fama and French, 1988). Lament (1998) combines the dividend yield and earning yield ratios to the dividend payout ratio (D/E) as a good measure of current business conditions of companies. More commonly, earnings per share (EPS) and its growth rates are discovered to be important explanatory factors in stock returns (Patell, 1976; Bakshi and Chen, 2005). Bagella, Becchetti and Adriani (2005) show that earnings-price ratios of high-tech companies are driven by fundamentals in both US and European financial markets.

3. Other Financial Yield ratios

Other financial variables that may explain the cross-section variation of stock returns include firm leverage (book-to-equity ratio), book-to-market equity ratios, cash flow to price ratios and past sales growth (Cook and Rozeff, 1984; Fama and French, 1992). Kamstra (2001) considers fundamental valuations of firms that may have no history of cash payments to their shareholders and states that firm values can be based on any variable that has a stable long-run relationship with fundamental value, such as firm sales, revenues and total assets. When pricing using financial yield ratios such as earnings, sales, revenues, shareholder equity and total assets, forecasts can be based on past values of these variables and/or knowledge of these variables from similar firms. The general model for all firm level variables is simply the sum of the expected future payoffs discounted at an appropriated discount rate.

2.3.1.2 Market-level measurements

Miller and Modigliani (M&M, 1961) suggest that payment streams from trading or dividend payments are equivalent. In other words, instead of holding stocks and waiting for dividends, investors can sell at a premium and receive capital gains. If the

EMH holds, markets will value firms accounting for all information including their performance and the valuations will be reflected in prices. Consequently, instead of using firm-level variables, valuations can be calculated by considering observations from financial markets.

The principal market-level risk factor is the market (excess) return that is the basis of the CAPM. Fama and French (1993, 1996) develop a fundamental three-factor valuation model in which the three factors are thought to be closely related to firm-level 'anomaly' variables, such as size, book-to-market ratio, earnings-price ratio, cash flow to price ratio and past sales growth. These factors are (1) the excess return on a broad market portfolio (R_m-R_f); (2) the difference between returns on small stocks and returns on large stocks (Small-Minus-Big, or SMB); and (3) the difference between returns on high-book-to-market stocks and return on low-book-to-market stocks (High-Minus-Low, or HML).

Fama and French argue that the excess market return captures the sensitivities of individual stocks or portfolios to non-diversified systematic risks, that SMB is a proxy for the market valuation of size risk, shedding light on the fact that small stock portfolios usually outperform big stock portfolios, and that HML captures the distress risk in portfolio returns. If the EMH holds, investors require higher returns for firms with higher systematic risks. Small stocks and high book-to-market stocks tend to have higher returns than big stocks and low book-to-market stocks as the size risk and distress risk are considered by investors and the premiums are required.

2.3.2. Methodology Review of Theoretical Asset Pricing Models

Prices equal expected discounted future payoffs. Theoretical asset pricing models are derived from the classic pricing equation of the first-order condition of maximising utility under risk. It comes from the statement that the marginal utility loss of consuming less today and buying more assets should equal the marginal utility gain of consuming the asset payoffs in the future. This is in accord with the theory of expected utility and the classical consumption-based asset pricing approach (Cochrane, 2001).

2.3.2.1 Discount approach

From the above, one can derive the theory that an asset's price should be equal to the expected discounted value of its future payoff. This is widely adopted in dividend discount models.

The Gordon dividend Growth model (Gordon, 1962) is probably the first well-known pricing model under the discount approach. Gordon's model specifies that stock prices equal discounted future dividend payments, using the difference between the rate of interest and the constant dividend growth rate as the discount factor. However, Gordon's growth model is strictly limited by its assumption of a constant dividend growth rate and is sensitive to the measurement of interest and dividend growth rates[7].

To allow for greater flexibility, Campbell and Shiller (1988a) provide a dynamic version of the Gordon model by employing one-period discount and growth rates of dividends over succeeding periods. The Campbell and Shiller dynamic Gordon model begins from

$$h_{1t} \approx \log(\exp\left(\delta_t - \delta_{t+1}\right) + \exp\left(\delta_t\right)) + \Delta d_t$$

Here h_{1t} is the one-period return, δ_t is the log dividend-price ratio and Δd_t is the dividend growth rate. To linearize the model, take a first-order Taylor expansion

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[7] The Gordon Growth Model of infinite series is $P^G = D\left[\frac{1+g}{r-g}\right]$, where r is the discount rate and g is the constant dividend growth rate. If the interest rate r is close to g, the estimated price will be unreasonably large in valuation. If r < g, the theoretical price becomes negative. Thus Gordon's model is inapplicable for the cases of r≈g or r < g.

around the point $\delta_{t+1} = \delta_t = \delta$, as the log dividend-price ratios follow a stationary stochastic process. Also define the interest rate as $r = g + \ln(1 + \exp(\delta))$, where g is the mean of the dividend growth rate. The approximated log one-period return is

$$\xi_{1t} \equiv (1-\rho)d_t + \rho p_{t+1} - p_t + k$$

where $\rho = 1/\left(1 + \exp\left(\overline{d-p}\right)\right) = \exp(g - R)$. R is the sample mean stock return and g is the sample mean dividend growth rate. This equation can be extended to a multi-period model of returns by taking the discounted sum of approximate one-period returns. Therefore, the discounted model specifies the log return on stock as a linear function of log dividend-price ratio and dividend growth rate.

2.3.2.2 Factor pricing approach

Beta pricing models are the particular example of factor pricing approach. Cochrane (2001) shows that consumption-based discount models and factor (beta) pricing models are connected in the sense that one representation can generate the other. For example, the Capital Asset Pricing Model (CAPM) introduced by Sharpe, Linter and Mossin in the 1960s is derived from the mean-variance frontier and represented in the form of beta pricing framework. The factor pricing framework is widely adopted in modern financial fields. It states that the expected return on an asset is the linear combination of the expected risk premiums on associated risks, and the risks are represented by the factor loading betas. Factor pricing models are relatively easy to implement so they are widely applied in practice, helping in the calculation of the cost of capital, risk management and investment decisions, which are all key issues in practical finance.

The CAPM beta depends only on the covariance and variance of individual asset returns and the excess market returns. The literature suggests that the single beta pricing model is too simple to fully explain asset returns. Merton (1973) challenged the CAPM and developed the Intertemporal Capital Asset Pricing Model (ICAPM) that also takes into account of the effects of uncertain changes in future investment opportunities. Fama and French (1992, 1993, 1995 and 1996) argue that realised anomalies with respect to firm size, earnings-price, cash flow-price, book-to-market, and past sales, *etc*., are interrelated. They develop a multi-beta pricing model which adds two further explanatory risk factors to the CAPM. Fama and French state that their three-factor model can capture most of the anomalies. The model is specified as

$$E(R_i) - R_f = \beta_{r_M i}\left\lfloor E(R_M) - R_f \right\rfloor + \beta_{SMBi} E(SMB) + \beta_{HMLi} E(HML) \tag{2.1}$$

Here $E(R_M) - R_f$, $E(SMB)$ and $E(HML)$ are expected premiums. β_{r_M} (the factor loading on the excess market returns) measures the sensitivities of individual stocks to the non-diversified systematic risk. If the EMH holds, investors require higher returns for firms with higher systematic risk. Thus excess returns of stocks are expected to be positively correlated with the excess market return. Similarly, β_{SMB} and β_{HML} are factor sensitivities on SMB and HML, respectively. Fama and French (1995) indicate that slopes on book-to-market equity and HML proxy for *distress* risks, where weak firms with high BE/ME are more likely to be in distress (positive slopes on HML). Similarly, SMB is used to capture the covariance in small stock returns and smaller stocks tend to have higher returns, which is called the *size* effect.

2.3.2.3 Testing of the factor (Beta) pricing models

1. The Two-Pass Procedures

Factor pricing models are widely used to capture cross-sectional variation in asset returns. The basic procedure involved in testing factor pricing models has been the two-step approach: in the first step the factor loading betas are estimated in time-series regressions while in the second step the expected risk premiums are estimated by cross-sectional regression. To test a multifactor pricing model with *K* risk factors, the two-pass approach can be shown as follows:

Step 1: Time-series Regression

$$R_{i,t} = \alpha_i + \beta_{i1} F_{1,t} + \ldots + \beta_{iK} F_{K,t} + \varepsilon_{i,t}, \; i = 1,\ldots N, t = 1,\ldots,T \tag{2.2}$$

Here *N* is the number of assets and *T* is the number of time-series observations. $R_{i,t}$ is the return on asset *i* at time *t*, $F_{j,t}$ is the *j*th risk factor at time *t* ($(1 \le j \le K)$, and $\varepsilon_{i,t}$ is the disturbance or residual for asset *i* at time *t*. The disturbances are assumed to be independent and jointly distributed with zero mean and finite variance. $\beta_{i,j}$ is the estimated coefficient in regressions. It captures the asset returns' sensitivity to the risk factor *F* so that beta is called the factor loading on the relative risk *j*.

Step 2: Cross-sectional Regression

$$\bar{R}_i = \gamma_0 1_N + \gamma_1 \beta_{i1} + \ldots + \gamma_k \beta_{iK} \tag{2.3}$$

Here $\bar{R}_i$ is the average return of asset *i* and $\beta_{i,j}$ is the factor loading for asset *i* on the *j*th risk factor, estimated in the time-series regression. $\gamma_j, (1 \le \mathrm{j} \le \mathrm{K})$ is the risk premium for risk factor *j*, measuring the expected returns per unit of risk.

2. Tests and Estimates

A key empirical issue is the estimation of the factor loading betas. For example, Sharpe (1964) and Linter (1965) estimate these using separate regressions for each asset and then regress the average return of each asset on the estimated betas. Alternatively, Fama and MacBeth (1973) adopt a *rolling beta* technique by running cross-sectional regression of returns on betas in each period, using time-series beta estimates obtained from several years of data prior to the cross-sectional regression. Jensen, Black and

Scholes (1972) and Fama and MacBeth (1973) also group stocks into portfolios, rather than using individual stocks. This reduces the measurement error associated with estimating beta for individual assets and thus relieves a potential bias in the estimated coefficients of the second-pass cross-sectional regression that arises when the independent variables (the estimated betas) are measured with error. This elaborate portfolio grouping procedure is adopted by Fama and French (1993) and in much subsequent research.

Shanken and Zhou (2007) provide an excellent comparison of estimating techniques in the two-pass regression approach. They conduct a simulation analysis to compare estimator performance from ordinary least squares (OLS), weighted least squares (WLS), generalised least squares (GLS), maximum likelihood (ML) and generalised method of moments (GMM) for the second-pass cross-sectional regression. Their analysis shows that none of the estimation methods dominates in all respects: the GLS estimators are more precise, but more biased than the OLS and WLS estimators. The ML risk premium estimators are unbiased and perform well in term of precision, but are less reliable than the OLS estimators when applied to real data, since they tend to overstate precision and reject true null hypotheses, while GMM estimation performance is very similar to ML. Shanken and Zhou therefore conclude that the OLS/WLS estimations are reliable and preferred in all scenarios.

It should be mentioned that the γ risk premiums are usually measured under the assumption that the factor loading betas are constant over time. Risk premiums are not easily justified in pricing models with time-varying betas (Velu and Zhou, 1999), such as conditional nonlinear asset pricing models. In such cases, one can only estimate the factor loading parameters to analyse the exposure of asset returns to certain risks in model (2.2).

2.3.3. Previous Results and Open Issues: Deviations from Fundamentals

2.3.3.1 Firm-level Information and Stock Prices

Many efforts have been made to test the relationship between dividends and stock returns. Despite the early successful evidence discussed in section 2.3.1, much research finds that stock prices can diverge significantly from the present value of dividends. Taking the dividend discount model described in section 2.3.2.1 as a benchmark for the theoretical value of stock returns, Campbell and Shiller (1988b) test the dynamic relationship between the log dividend-price ratio, the lagged dividend growth rate, the log earnings-price ratios based on moving average of past earnings (i.e. one-period lagged earnings, ten-year and thirty-year moving average of log real earnings), and the theoretical value in a Vector-Autoregressive (VAR) framework. Using 1871-1987 annual US market data, they report that the dividend-price ratio is unrelated to its theoretical value implied by the Gordon growth model, although it helps to forecast short-run dividend changes.

The literature also suggests the existence of a structural break in the relationship between dividends and stock prices. Koustas and Serletis (2005) indicated that the dividend-price ratio behaves differently before and after the 1990s. Before a break point in 1996 there seems to be co-movement between stock returns and dividends, but this disappears after the break point. This result is consistent with empirical findings suggested by behavioural finance that the EMH does not explain market behaviour very well after the late 1980s.

There are also contradictory conclusions concerning the relation between earnings and stock prices. Patell (1976) supported the significant power of EPS (earnings per share) to explain stock returns. A positive relation between earnings and returns was also supported by Gennotte and Truemann (1996). However, Lamont (1998) indicated that dividends and earnings contribute substantial explanatory power to predict stock returns only for short horizons. Su (2003) tests the cointegration relationship between earnings announcements and stock prices in markets for Chinese A and B shares and reports the absence of co-movement between EPS and stock prices, suggesting that Chinese domestic investors cannot quickly adjust to new earnings information.

2.3.3.2 Market-level Risk Factors and Stock Returns

The Fama-French three factor model is very successful and has been regarded as a benchmark of theoretical asset pricing, stimulating much subsequent research and leading to many empirical results that support the explanatory power of the betas on the aggregate market, size, and book-to-market effects (Fama and French, 1996; Lewellen, 1999; Davis, Fama and French, 2000). Brennan, Wang and Xia (2001) apply Fama-French data and report that HML and SMB strongly predict information about the real interest rate and the optimal risk premiums. Yang and Chen (2003), Yang and Teng (2003) separately test the performance of the Fama-French three factor model in Chinese A-share stock markets, finding significant explanatory power of the three factors in the cross-sectional variation of Chinese stock returns.

On the other hand, He, Kan, Ng and Zhang (1996) apply a conditional multifactor pricing model and show that the size and book-to-market effects cannot be captured by the marketwide factors of the market returns, bond market factors, SMB and HML. Gentry, Jones and Mayer (2004) test the relationship between net asset values (NAV) of real estate and real estate investment trusts (REIT). They apply the Fama-French three-factor model and find that the volatility of REIT returns is too great to be explained by the model. Shum and Tang (2005) test the model in three Asian emerging markets (Hong Kong, Singapore and Taiwan). While market excess return $b_i\lfloor E(R_M) - R_f \rfloor$ contributes strongly to the prediction, size and book-to-market effects are limited. Morelli (2007) finds that size is not significantly priced for UK securities, while book-to-market equity is a significant risk factor. The market beta has no common effect on stock prices, but does have power to discriminate between risk premiums in up-market and down-market conditions.

2.3.4. Summary and Further Discussion

To sum up, theoretical asset pricing models stem from the EMH state that asset prices and/or returns should follow the fundamental values generated by specified theoretical models. Thus one of the key components of theoretical asset pricing is to identify such fundamental values. Literature in this field focuses on both firm-level accounting information and market-level observable risk factors. Based on these fundamental variables the discounted asset pricing models and factor pricing models are introduced to measure the theoretical prices of assets.

However, the theoretical asset pricing models face some difficulties because studies provide conflicting views about the relationship between stock returns and their fundamental values. These contrary results are summarised in Table2.1. Studies in the first row measure fundamental values of stocks by dividends, studies in the second row by earnings and other financial yields, while studies the last row are based on market-level risk measurements.

Table 2.1 Summary of Theoretical Asset Pricing Literature

Predict Factor	Support EMH		Reject EMH	
Dividends	Gordon (1962) Pettit (1972) Fama and French (1988)	U.S. U.S. U.S.	Campbell &Shiller(1988b) Froot & Obstfeld (1991) Craine (1993)	U.S. U.S. U.S.
Earnings	Pettit (1972) Watts (1973) Gennotte & Truemann (1996)	U.S. U.S. U.S.	Lamont (1998) Su (2003)	U.S. China
Market Factors	Stattman (1980) Fama and French (1993, 1995) Davis, Fama & French (2000) Yang and Chen (2003)	U.S. U.S. U.S. China	He *et al.* (1996) Gentry *et al.* (2004) Shum and Tang (2005)	U. S. REITs Asia

It is necessary to explain the fact that empirical evidence suggests that fundamental values measured by the explanatory variables (either firm-specific or market-level) leave random residuals in modelling stock returns. Two possible reasons could be that the explanatory factors are inappropriate or inefficient in capturing risks, or that the risk-return trade-off does not exist. Theoretical asset pricing models work to improve the appropriateness of explanatory factors by 'mending' either the factors or the econometric models, but behavioural finance allows mis-pricing effects to arise from irrational investors and limited arbitrage. In the behavioural finance approach investor sentiment has influence on stock prices, so psychological effects should be considered when pricing securities.

2.4 Explanations of Deviations: "Irrational" Considerations

If empirical evidence suggests that stock returns persistently deviate from fundamentals, whether fundamentals are measured at firm level or market level, and rejects the risk-return relationship, there must be other explanations to describe stock returns. The assumptions based on the EMH may be too restricted to be true in fact. Asset pricing models based on behavioural considerations relax the assumption of rational investors and unlimited arbitrage and therefore introduce some irrationality into the valuation. In this broader approach, expected return is determined by both *risk factors* and *misevaluation*, beta represents fundamental parameters and mispricing is generated by irrational investor sentiment.

This section first discusses the psychological foundations of behavioural finance, in order to identify why investors fail to update their beliefs in risky situations (fail to obey the rationality suggested by the EMH), then describes and explains some observed stock market anomalies in terms of irrational considerations. Further behavioural applications of investor irrationality in stock markets are mentioned so as to provide a linkage with standard asset pricing models.

2.4.1. Psychological Foundations

In order to model irrational behaviour in financial markets and its influence on asset pricing, behavioural finance applies psychological theories of bias in decision-making in conditions of risk. Hirshleifer (2001) identifies five biases: heuristic simplification, self-deception, emotion and self-control, social interactions, and modelling alternatives to expected utility and to Bayesian updating. These biases can be further categorised in two ways. On the one hand, economic agents cannot always make judgements and decisions unconditionally and objectively. On the other hand, emotions, mood and feelings play an important role in making decisions. The former is usually referred to as 'cognitive' bias and the latter as 'affective' bias. This section reviews various effects that are supported by psychological theory and are potentially relevant to financial markets and asset pricing.

2.4.1.1 Cognitive biases

Cognition in psychology, or cognitive processes, refers to an individuals' psychological function in processing information, learning and decision-making. It is argued that people do not use Bayesian information updating processes but are instead bound by cognitive constraints. Cognitive bias may be involved in all judgement and decision-making. For example, limited attention span implies that people focus only on subsets of available information. They may fail to comprehend the content of received information through ignoring relevant and responding to irrelevant information, and instead use heuristics[8] to update their attitudes and decisions. Hirshleifer (2001) provides a survey of judgment and decision biases.

[8] See Tversky and Hahneman, 1973; Hirshleifer, 2001; Stracca, 2004)

An early discussion of human judgment related to security analysis is by Slovic (1972) who provides reasons for applying behavioural psychology to describe the behaviour of security analysts, brokers and investors. Tversky and Kahneman (1974) refer to the heuristics and biases involved when investors try to make perfect decisions by employing imperfect rules.

Following the work of Tversky and Kahneman, the concepts of *representativeness* and *conservatism* play essential roles in the early work on behavioural finance. The representativeness heuristic asserts that when people evaluate the probability of uncertain events, they tend to predict by seeking the closest match in its essential properties to past patterns (Tversky and Kahneman, 1974; Kahneman, Slovic and Tversky, 1982). Conservatism, first discussed by Edwards (1968, 1982), describes the phenomenon that individuals are slow to change their beliefs in the face of new evidence. These two psychological concepts provide a theoretical basis for the well-known market phenomena of over- and under-reaction (De Bondt and Thaler, 1985, 1987), by which investors (i) underweight the base rate in the short-run and over-estimate securities following a series of good announcements, as they attach the wrong probabilities to the underlying independent process and (ii) are conservative in changing their beliefs in face of new information.

2.4.1.2 Affective Biases

Psychological theory asserts that risky decision-making process is not a purely cognitive process. Moods, feelings, emotions, such as affective ‘goodness’ or ‘badness’, are triggered by facing decision situations under uncertainty and influence the decision-making and final actions. The ‘affective bias’ view is proposed by Slovic and colleagues (Slovic, Fischhoff and Lichtenstein, 1980, Slovic, Flynn and Layman, 1991, Slovic, Finucane, Peter and MacGregor, 2007) who argue that affective responses and reactions occur rapidly and automatically and impact peoples’ daily lives.

Ambiguity aversion defines the tendency for people to dislike ambiguous choices, such as an ambiguous probability distribution and unknown structure of risky alternatives. The Ellsberg paradoxes (Ellsberg, 1961) present experimental evidence that known risks are preferred over unknown risks, even if the overall probability distributions of consumption outcomes are the same. Ambiguity aversion is usually linked with uncertainty and therefore risk. Einhorn and Hogarth (1986) state that greater risk aversion can be observed when an event involves ambiguous probabilities and unclear structure of gamble choices.

Another pattern of psychological biases stems from investor *overconfidence* and *biased self-contribution*. These ideas are introduced by Oskamp (1982) who argues that people are overconfident in the accuracy of their judgments. Investor overconfidence describes that people who are overconfident about the precision of private information, therefore overestimating their ability to evaluate securities in financial markets. Biased self-contribution describes the situation when investors increase their confidence after receiving information in agreement with their prediction or private information, but do not decrease their confidence symmetrically after received contradictory information. Overconfidence and biased self-contribution may be linked to the financial market phenomenon of excess volatility, price bubbles and crashes, because they cause asymmetric shifts in investor confidence as a function of their investment outcomes (Griffin and Tversky 1992, Daniel, *et al.* 1998). Investor overconfidence results in incorrect valuation of stocks in response to information announcements, an outcome made worse by biased self-contribution if the initial prediction is confirmed by real market movement in the next period. This pair of psychological biases may work continuously in financial markets, pushing stock prices to increase (decrease) further and further, which increases excess volatility of stock returns and generates stock prices bubbles and crashes.

2.4.2. Empirical Applications

2.4.2.1 Overreaction and Underreaction

Long-term trading patterns in share prices seem to violate the EMH. Studies of overreaction and underreaction play an important role in supporting market inefficiency and investor irrationality. Underreaction states that investors tend to underreact to news announced in the short-run. As a result it can be observed that the average return on stocks in the period following an announcement of good news is higher than the average return in the period following bad news (Shleifer, 2000b). In overreaction, on the other hand, securities that have had a long record of good news tend to become overpriced over longer horizons (3-5) years. Again, overreaction is defined by Shleifer as “the average return following not one but a series of announcements of good news is lower than the average return following a series of bad news announcements” (Shleifer, 2000b: 120).

Empirical findings support the existence of underreaction and overreaction in financial markets, as documented by the work of De Bondt and Thaler (1985, 1987). They identified a pattern suggesting that portfolios of stocks with poor historical returns dramatically outperform portfolios with high historical returns. Based on the notion that many investors are poor Bayesian decision makers, De Bondt and Thaler conjecture that as a consequence of investor overreaction to earnings, stock prices may temporarily depart from underlying fundamental values. They suggest a series of issues such as the ‘winner-loser effect’, the impact of time varying betas, seasonal effect etc. Zarowin (1989), Hirshleifer (2001), and Barberis and Thaler (2003) provide empirical results supporting continuously positive short-term returns and their long-run reverse. De Bondt and Thaler (1985) and Jegadeesh and Titman (1993) observe the phenomena of under- and over-reaction for the cross-section of returns. Cutler, Poterba and Summers (1991) find evidence supporting the existence of under- and overreaction for a variety of markets. Barberis, *et al.* (1998) summarise the statistical evidence of underreaction and overreaction in security returns.

2.4.2.2 Asymmetric Volatility

Empirical evidence suggests some stylized facts about volatility clustering and autocorrelation that cannot be explained by theoretical return patterns. For example, both ‘good’ and ‘bad’ news lead to higher levels of volatility (Engle, 1982); the effects of news on volatility are permanent (Engle and Lee, 1999); returns are negatively correlated with conditional volatility in the following period and bad news tends to increase volatility more than good news (Black, 1976; Nelson, 1991; Bekaert and Wu, 2000). The latter phenomenon, asymmetric volatility, has been widely found in empirical tests. However, the reasons for volatility asymmetry are still to be determined.

1. Empirical Evidence and Prediction Models

Asymmetric volatility refers to the phenomenon that the conditional volatility of stock returns responds asymmetrically to the arrival of unexpected news: negative shocks generate more volatility than positive shocks of the same magnitude. This pattern of asymmetric volatility has been found in many developed and developing financial markets (although it is less clear using developing markets data – see Table 2.2). To predict volatility clustering, econometrics models are specified to capture the volatility of stock returns. Table 2.2 provides some existing literature in asymmetric volatility studies and Table 2.3 presents the popular volatility prediction models.

Table 2.2 Summary of Empirical Literature on Asymmetric Volatility

Study	Market	Volatility Measure	Finding
Tests on Developed Markets			
French, Schwert and Stambaugh (1987)	US Index	Conditional Volatility	Positive relationship
Nelson (1991)	US Index	EGARCH	Asymmetry
Engle and Ng (1993)	Japan Index	EGARCH, GJR (better)	Asymmetry
Bekaert and Wu (2000)	Japan Nikkei 225 (1985-1994)	GARCH-in-Mean	Asymmetry
Li, Yang, Hsiao and Chang (2005)	12 Countries: US, Canada, Japan, Australia, Hong Kong, Singapore, UK, Germany, France, Italy, Netherlands, Switzerland (1980-2001)	AR-EGARCH-M and semiparametric specification	Negative relationship of 6 out of 12 countries, and 7 after 1987 financial market crash when use semiparametric specification
Ferreira, Menezes and Mendes (2007)	Portugal, US, UK, Germany, France, Greece	GJR, EGARCH, TAR, M-TAR	TAR and M-TAR: no GJR and EGARCH: Asymmetry
Verma and Verma (2007)	US, S&P 500	Tri-variable EGARCH	Asymmetry of irrational market
Tests on Emerging Markets			
Lin, Liu and Wu (1999)	Taiwan	GJR and Volatility-switching GARCH model	Asymmetric volatility but direction is changeable: depends on real volatility Vs. expected volatility
Chiang and Doong (2001)	7 Asian countries: Hong Kong, Malaysia, Philippines, Singapore, Thailand, and Taiwan	TAR-GARCH-M	Asymmetric volatility in daily return series but absent for lower frequency data
Lu and Xu (2004)	China (1990-2003) Daily	EGARCH	Positive shock generates more volatility than negative shock
Yan (2004)	China (2000-2004)	EGARCH, EGARCH-M	Volatility with long-term effects and asymmetry
Leeves (2007)	Indonesia (1990-1999)	GJR, NGARCH and AGARCH	Asymmetry during Asian crisis (1997-1999)

Table 2.3 Summary of Volatility Models

Model	Formula	Asymmetry
ARCH(q)	$y_t = \beta_1 + \beta_2 x_{2t} + ... + \beta_k x_{kt} + \mu_t,\ \mu_t \sim N(0, h_t)$ where $h_t = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \alpha_2 \mu_{t-2}^2 + ... + \alpha_q \mu_{t-q}^2$	N/A
GARCH(p,q)	$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \mu_{t-i}^2 + \sum_{j=1}^{p} \beta_p \sigma_{t-p}^2$	N/A
EGARCH(1,1)	$\log(\sigma_t^2) = \omega + \beta \log(\sigma_{t-1}^2) + \gamma \frac{\mu_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{\lvert \mu_{t-1} \rvert}{\sqrt{\sigma_{t-1}^2}} - \frac{2}{\pi} \right]$	$\gamma < 0$
TGARCH (1,1) (GJR)	$\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma \mu_{t-1}^2 I_{t-1}$ where $I_{t-1} = 1$ if $\mu_{t-1} < 0$ and 0 otherwise	$\gamma > 0$
GARCH-M	$y_t = \mu + \delta \sigma_{t-1} + \mu_t,\ \mu_t \sim N(0, \sigma_t^2)$ where $\sigma_t^2 = \alpha_0 + \alpha_1 \mu_{t-1}^2 + \beta_1 \sigma_{t-1}^2$	N/A

From Table2.2 it is obvious that volatility asymmetry exists in both the developed and emerging financial markets. It should be noticed that most of the volatility studies are based on daily data. When weekly or monthly data are used, the asymmetry tends to disappear. Table 2.3 summarises the volatility models and shows whether the model is available to test the asymmetry.

2. Explanations of Asymmetric Volatility

Compared with the widely documented empirical findings, the underlying determinants of asymmetric volatility remain largely unexplained and problematic. Two existing explanations are leverage effects and volatility feedback theory, which both explain the volatility asymmetry through a rational asset pricing theoretical framework. In the former (Black, 1976; Christie, 1982; Schwert, 1989) a negative shock induces a drop in the value of stock, increasing the financial leverage of a firm. This makes the stock riskier and causes the volatility of the equity return to rise. Thus the leverage hypothesis holds the asymmetric nature of volatility to be the result of return shocks.

Volatility feedback theory, introduced by French, *et al.* (1987) and Campbell and Hentschel (1992), asserts that return shocks are caused by changes in conditional volatility. By assuming that volatility is persistent and priced, large pieces of good or bad news increase the expected volatility. If there is a positive relation between the expected components of return and the conditional variance process then required return on equity will increase, consequently producing an immediate decrease in the stock price. To explain the asymmetry, feedback effects ensure that a large piece of bad news not only decreases the stock price directly but also increases the expected volatility and the discount rate so as to decrease the expected returns indirectly. However, a large piece of good news increases the stock return directly, but decreases the return indirectly because of the increased discount rate implied by the increasing expected volatility. This offsets the direct effects and results in asymmetry in conditional volatility of stock returns.

Both the leverage and feedback effect explanations are partially successful. Wu (2001) shows the significance of both effects when using dividend growth and its volatility as shock variables. However, both explanations are problematic: the leverage effect alone cannot account for the magnitude of the negative relationship between return and conditional volatility, and fails to predict lower volatility after good news (Christie, 1982; Schwert, 1989); the volatility feedback effect is restricted by strong implications, such as a positive risk-return correlation, that do not hold in real world (Bekaert and Wu, 2000).

More recent research links asymmetric volatility with behavioural issues by introducing investor sentiment into the explanation. McQueen and Vorkink (2004) state that volatility clustering and asymmetry are endogenously induced because, aside from feedback effects, investors are temporarily more attentive or sensitive to news (time-varying risk aversion) when their portfolios have been perturbed from their customary level of wealth. Given their preferences over financial wealth, the time-varying risk aversion of agents depends on prior investment performance: after unexpected gains (losses), investors are less (more) risk averse and the risk premium required to hold stocks is smaller (larger). Therefore bad news decreases prices through three processes: the bad news itself, the increase in risk aversion, and the increase in sensitivity to news. However, good news only initiates a double process: the good news itself and the reduction in risk-aversion, while the increase in price induces the increase in expected volatility, ensuring that the positive shock has smaller effects on price and volatility than the negative shock.

Verma and Verma (2007) challenge the assumption of agent homogeneity and explain asymmetric volatility as the impact of noise trading. They decompose investor sentiment into fundamental (rational) sentiment and noise (irrational) sentiment, arguing that rational sentiment has greater positive effects on stock returns while irrational sentiment has greater negative effects on volatility. Also, they find empirically asymmetric (symmetric) negative effects of irrational (rational) sentiment during the bull/bear market lifecycle. To conclude, noise trading has greater negative effects on the volatility of stock returns during bullish markets than bearish markets, which is consistent with the asymmetric nature of volatility – positive shocks (in bullish markets) have lower effects on conditional volatility than negative shocks (in bearish markets).

2.4.3. Irrational Investors in Stock Markets

Financial markets show some trading patterns that can also be described within a framework of investor irrationality. More important, these phenomena are tightly linked with behavioural asset pricing models. From this point of view, two more behavioural applications are described here, with their links to asset pricing. One takes account of heterogeneous expectations, in which different types of agents co-exist. The other is a type of representative agent issue where investors herd in trading.

2.4.3.1 Heterogeneous Investors and Noise Trading

The simplifying assumption that all investors have homogeneous beliefs about the future is problematic. Disagreements may arise because people have different ability to access information (Grundy and Kim, 2002; Biais and Bossaerts, 2003). Even if information is equally receivable, people may still differ in their ability to interpret the information in hand (Kandel and Pearson, 1995; Bamber, Barron and Stober, 1999; Boswijk, Hommers and Manzan, 2005). It seems reasonable to suggest that professional institutional investors have more information in hand or greater ability to identify fundamental prices compared to individual investors who may be less educated and spend less resources on information search. Consequently, it is natural to separate investors into two groups: more rational and informed investors (fundamentalists) and less rational individual investors (noise traders or trend followers).

Fundamentalists believe in mean reversion of stock prices toward benchmark fundamental values and their trading drives prices towards these fundamentals. On the other hand, noise traders expect deviations from fundamentals to become trends and may drive asset prices to deviate from fundamentals. Academic work incorporates the interaction between the two. Since arbitrage is limited and even professional investors are subject to some cognitive and affective biases in evaluations, the existence of noise trading cannot be ruled out.

Noise trading is a key component of the behavioural approach to asset pricing. DeLong, *et al.* (1990) develop a theoretical model of how noise traders determine stock prices. Brock and Hommes (1998), Lux (1998), Chiarella and He (2001, 2003), Chiarella, Dieci and He (2007) discuss asset pricing with heterogeneous investors in models containing only one risky and one risk-free asset. They explore the impact of heterogeneous beliefs on market trading mechanisms and how this causes prices to deviate from fundamental value. In financial markets, empirical evidence to support this statement is found by Kandel and Pearson (1995), Bamber *et al.* (1999), Grundy and Kim (2002), Biais and Bossaerts (2003) and Boswijk *et al*. (2005). Some of these papers assume asymmetric investor information and others assume heterogeneity of beliefs, although fundamental value is assumed common knowledge among investors.

Moreover, the heterogeneity of agent structure makes it possible to describe and model market behaviour in different market regimes. Boswijk *et al.* (2005) use heterogeneous agents in their asset pricing model to explain the US stock price run-up of the 90s. Before the 90s trend followers played a less important role in market but in the late 90s they came to dominate the market, driving stock prices away from their fundamentals. Similarly, Coakley and Fuertes (2006) state that investors behave more like irrational noise traders in a bull market, while fundamentalists dominate in bear markets and drive prices towards their fundamental levels. This two-regime approach to asset pricing will be discussed in more detail in the next section.

2.4.3.2 Herd Behaviour

Herd behaviour is another market phenomenon with implications for asset pricing that stems from behavioural finance. Herding can be described as the average tendency of investors to buy (sell) particular stocks simultaneously (contrary to what could be expected from independent trading). Commonly, investors are portrayed as herds when they are positively influenced by the decisions of others without adequate information and this influence is stronger than the influence from their private signals. Therefore, the existence of herding rejects the EMH statement that investors only trade using a diverse set of fundamental information.

Herding can arise from both rational and irrational behaviour. Rational herding may result from imperfect information. As concluded by Bikhchandani and Sharma (2000), people imitate based on information, reputation and compensation: information based herding arises because people think others are better informed; Reputation based herding is triggered when there is uncertainty regarding to the ability of manager to manage the portfolio; compensation based herding takes place because manager compensation depends on their performance compared to others. On the other hand, in irrational herding investors may be simply influenced by feedback from others without further knowledge. Thus people may herd because of intrinsic preferences for conformity or according to positive feedback (De Long *et al.*, 1990; Lux and Marchesi, 1999).

Empirically, herding behaviour is relatively difficult to identify. The main reason is that the private information of investors is unobservable. If investors take the same action it is impossible to tell whether this is imitation or a response to the same information. Herding clearly induces investors to buy (or sell) at the same time, but the converse may not be true. Typically, research work identifies clustering of decisions in certain financial markets without considering the underlying reasons.

The detection of herding can be through investigating the performance of institutional investors (Lakonishok, Shleifer and Vishny, 1992; Wermers, 1999; and Bernhardt, Campello and Kutsoati, 2006) or through observable market performance (Christie and Huang, 1995; Chang, Cheng and Khorana, 2000). The former emphasises the buying-selling imbalance of institutional investors or their forecasts against the common market mood. The latter suggests that when herding is absent, return dispersion among stocks will increase with the absolute value of market returns, because returns on individual assets differ in their sensitivity to the market return. Yuan and Chen (2004) and Xu and Hou (2004) adopt the Lakonishok *et al.*'s and Wermer models on Chinese institutional investors and find strong herd behaviour among the institutional investors in China. Applying the market return dispersion method, Chang *et al.* (2000) investigate markets in the US, Hong Kong, Japan, South Korea, and Taiwan. They report no evidence of herding in the US and Hong Kong markets, and partial evidence of herding in Japan. However, they find strong evidence of herding in South Korea and Taiwan, which may imply that herding is more likely to be prevalent in emerging markets.

Herding leads investors to trade using the same source of information and generates a uniform market mood. Therefore it is not surprising that herding could drive stock prices up and down in line with this common mood, no matter whether this is towards or away from fundamental values. In other words, herding behaviour induces noise trading in stock markets. Since 1997, Sornette and his colleagues (Sornette and Johansen, 1997; Johansen, Sornette and Ledoit, 1999, 2000; Zhou and Sornette, 2005, 2006) have developed an asset pricing model incorporating herding effects and continuously updated the herding proxy in their studies. They show that herding indeed leads to noise in stock prices.

2.4.4. Summary

Behavioural finance provides an alternative way to explain the deviation of stock prices from fundamental value – investors are irrational as a whole and are subject to both cognitive constraints and affective biases. Based on these psychological foundations, investors in financial markets may underreact to new information but overreact to a series of information signals. Their actions result in volatility clustering and asymmetric volatility. Moreover, behavioural finance emphasises investor heterogeneity and allows noise traders to drive stock prices persistently away from fundamental value. Herd behaviour generates noise and has influence on stock prices

2.5 Modelling Asset Prices Incorporating Behavioural Considerations

Based on the argument that realised stock prices or returns seem to defy EMH explanations, behavioural asset pricing models are developed in recent work. Investor sentiment, deriving from psychological biases and behaving in noise trading and herding, has gained the attention of both academic researchers and financial professionals. The question is no longer whether investor sentiment affects stock prices, but how to measure investor psychology and quantify its effects. A good effort has been made by many studies in recent years but the behavioural approach to asset pricing remains still in an early stage and there is a need for further analysis.

The theoretical inference of behavioural asset pricing has been developed based on the irrational consideration. Dealing with biases in judgment and decision-making, the literature sheds light on representative agent issues where investors as a whole are irrational in some ways. Barberis *et al.* (1998) develop a model to show how investors form their beliefs and analyse the implications for prices. Meanwhile, Daniel, *et al.* (1998) construct a model with heterogeneous investor expectations. It is also argued in the literature that a perfect trade-off between risk and return does not exist: utility is derived not only from consumption but also from fluctuations in the value of financial wealth, as in the prospect theory approach of Barberis, *et al.* (2001).

Three other types of model are summarised in this section, which provide the empirical approach for assessing the impact of sentiment on asset pricing. Presented first is the characteristic model, which questions the theoretical foundations of the Fama-French three factors. Sentiment-based asset pricing models are then discussed, with either direct or indirect measures of investor sentiment. Last, a two-regime model that sheds light on the conditions of different market regimes (up or down) is reviewed to give an introduction to regime-dependent asset pricing.

2.5.1. Theoretical Approach to Investor Sentiment in Asset Pricing

Barberis, Shleifer, and Vishny (1998; hereafter BSV) and Daniel, Hirshleifer and Subrahmanyam (1998; hereafter DHS) presented models explain the anomalies of over- and underreaction in the context of individual investor behaviour. Although the two models are generated from different behavioural considerations, they draw similar conclusions: investors show bias in financial markets and this bias drives stock prices away from fundamental value. Moreover, Barberis, Huang and Santos (hereafter BHS) in 2001 argue that investors derive utility not only from consumption but also from gain and loss of financial wealth. Loss aversion helps to explain the excess mean and volatility of stock returns.

2.5.1.1 The BSV Model:

Barberis, *et al.* (1998) present a representative agent model that is motivated by the two important psychological phenomena of *conservatism* and *representativeness*. They argue that conservatism is extremely suggestive of underreaction, where people underweight changing information and fail to update their beliefs, thereby failing to adjust their valuation of shares. On the other hand, when a company has a series of good earnings announcements, investors judge that past performance is representative of potential earnings growth, which consequently induces overreaction bias.

BSV establish a model with a representative risk-neutral investor and one asset. They begin by defining two regimes – *mean reverting* (regime 1) and *mean trending* (regime 2) where the information signals – shocks to earnings (-y for negative shocks and +y for positive shocks) are updated between one another regimes. The two regimes differ in information transition probabilities. The two regimes for information transition are:

Table 2.4 Information Transition Matrices for BSV Model

State 1	$y_{t+1} = y$	$y_{t+1} = -y$	State 2	$y_{t+1} = y$	$y_{t+1} = -y$
$y_t = y$	π_L	$1-\pi_L$	$y_t = y$	π_H	$1-\pi_H$
$y_t = -y$	$1-\pi_L$	π_L	$y_t = -y$	$1-\pi_H$	π_H

Here y_t is an earnings shock at time t and can be either positive (y) or negative ($-y$) while y_{t+1} is the consecutive shock. π denotes the probability that the earnings shock in t+1 has the same sign as in t. State 1 and 2 represent two processes that investors believe to govern the earning shocks. The two regimes are the similar Markov processes except that the probability is low in State 1 (π_L <0.5), and high in State 2 (0.5< π_H <1). State 1 has low staying probability but high transition probability, and is labelled as a mean-reverting state whereas state 2 is a mean-trending state for the analogous reason. It is assumed that the investor knows π_L and π_H. The probabilities that the investor's forecasts switch or stay in the next period follow a Markov process as shown in Table2.5:

Table 2.5 Decision Updating Probabilities for the BSV Model

	$S_{t+1}=1$	$S_{t+1}=2$
$S_t=1$	$1-\lambda_1$	λ_1
$S_t=2$	λ_2	$1-\lambda_2$

Here λ stands for the transition probability between the two states. Both λ_1 and λ_2 are assumed to be small (less than 0.5), which means that investors' forecasting tends to remain in the same state, and λ_1 is smaller than λ_2, as investors are more likely to believe mean-reverting than mean-trending.

Define the time t probability q_t that earnings shock y_t is generated by state 1 (or $y_t|S_t=1$). The investor updates by trying to forecast which regime the future information will stay in, measured by probability (q_{t+1}). This updating process, supposing that in $t+1$ q is also generated by regime 1, follows Bayes' Rule:

$$q_{t+1}=\frac{((1-\lambda_1)q_t+\lambda_2(1-q_t))\Pr(y_{t+1}|S_{t+1}=1,y_t)}{((1-\lambda_1)q_t+\lambda_2(1-q_t))\Pr(y_{t+1}|S_{t+1}=1,y_t)+(\lambda_1 q_t+(1-\lambda_2)(1-q_t))\Pr(y_{t+1}|S_{t+1}=2,y_t)}$$

Here $\Pr(y_{t+1}|S_{t+1}=1,y_t)$ is the probability that y_{t+1} is also generated by state 1 (mean-reverting state) given that y_t is generated by state 1, and $\Pr(y_{t+1}|S_{t+1}=2,y_t)$ the probability that y_{t+1} is generated by state 2 (mean-trending state) given y_t is generated by model 1. Thus q_{t+1} rises if the earnings shock follows an opposite process (staying in mean-reverting regime) and falls if y_t has the same sign with y_{t-1} (staying in mean-trending regime). In other words, investors put more weight on regime 2 if they receive two consecutive shocks of the same sign and more likely to expect mean reversion if they receive two shocks with opposite signals. The BSV model suggests that, based on the regime-switching process, prices satisfy:

$$p_t = \frac{N_t}{\delta} + y_t\left(p_1 - p_2 q_t\right) \tag{2.4}$$

where N_t is earnings at time t, δ is the constant discount rate, p_1 and p_2 are constant and depend on π_L , π_H λ_1 and λ_2 [9]. Therefore, model (2.4) clearly indicates the mechanism for sentiment-driven mis-pricing: The first term, $\frac{N_t}{\delta}$, the discounted earnings, describes the fundamental price if investors use the true random walk process; and the second term $y_t\left(p_1 - p_2 q_t\right)$ is the deviation from fundamentals – it exhibits both underreaction and overreaction to earnings shocks.

2.5.1.2 The DHS Model:

The DHS model (Daniel, *et al*, 1998) allows for heterogeneous agents and the implications for asset prices. In this model informed investors are able to receive 'private' information while uninformed investors value stocks only according to 'public' information. The model emphasizes two psychological phenomena: investor *overconfidence* (in which investors overestimate their abilities) and *biased self-attribution* (in which asymmetric variations in confidence arise when individuals attribute positive events to their own skill but attribute negative events to bad luck).

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[9] Full explanations are from Barberis *et.al* (1998) appendix A.

Daniel *et al.* build a four-period model to describe the sentiment effect on asset pricing: in period 0 all investors are endowed with the same initial information; in period 1 informed investors receive private information; in period 2 information is made public; in period 3 the value of assets is revealed (as shown in Figure 2.1). They suggest that informed investors receive noisy signals and behave overconfidently if the signal is private and that uninformed investors are unbiased. Thus a private signal is received at time 1, becoming a noisy public signal at time 2, with overconfidence and biased self-attribution effects influencing price behaviour in each stage as shown in Figure 2.2.

Figure 2.1 Information Updating Process in the DHS Model

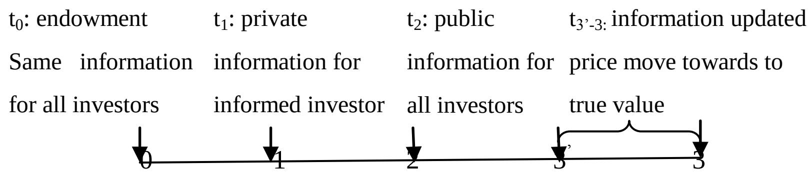
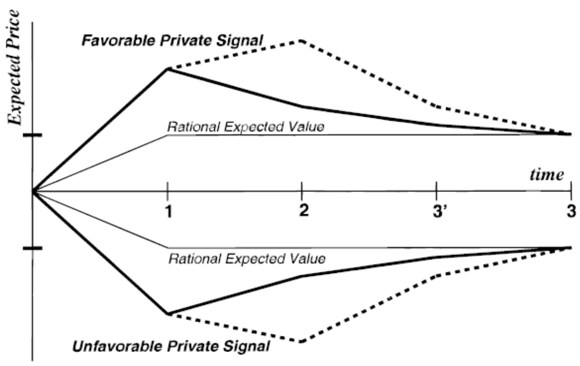


Figure 2.2 Effects of Overconfidence and Biased Self-contribution on Asset Value



Source: Daniel et al., (1998)

The rational expected value in Figure 2.2 implies that a signal received at time 1 should generate no further price adjustments. However, further price changes occur when incorporating overconfidence without self-attribution (solid line) and with self-attribution (dashed line): investors overreact to the shocks because they are overconfident about their private information (over-estimating the precision of asset value) and their confidence rises further because of the biased self-contribution from confirming subsequent information. Thus the DHS model states that security prices overreact to private signals and tend to deviate further if confirming public information continues to arrive. Daniel *et al.* conclude that this finding in consistent with short-term momentum and long-run reversals in stock returns.

2.5.1.3 The BHS Model

Both the discounted dividend and beta pricing approaches are based on the assumption that economic agents derive utility purely from consumption, either today or in the future. An alternative approach stems from prospect theory and states that investor risk aversion seems to be driven not by ultimate consumption but by past stock market movements. The basic idea of (cumulative) prospect theory is first given by Kahneman and Tversky (1979) and later developed by Tversky and Kahneman (1992) and applied to asset prices by Barberis, *et al.* (2001). Forbes (2009) provides a survey of asset pricing under prospect theory.

The BHS model differs from the mainstream of consumption-based approaches in the way of defining risk: investors care about their financial gains and losses. Thus utility comes from not only consumptions but also increases in financial wealth. More specifically, investors are less risk-averse if they experience recent gains in financial wealth and vice versa. Thus the prospect utility function can be expanded from expected utility as:

$$U(c_t) = E\left[\sum_{t=0}^{\infty}\left(\rho^t \frac{C_t^{1-\gamma}}{(1-\gamma)} + b_t \rho^{t+1} \upsilon(X_{t+1}, S_t, z_t)\right)\right] \qquad (2.5)$$

The first term in Equation 2.5 is the same as the consumption-based utility, where ρ is the discount factor corresponding to the discount rate r (ρ = (1/ (1+r)); C_t stands for consumption at time t; and γ is the coefficient of risk aversion. γ is positive, ensuring the concavity of the utility function over consumption.

The effect of asymmetric risk aversion is represented by the second term in Equation 2.5, where X_{t+1} is the gain or loss in financial wealth between time t and t+1; S_t is the value of the investor's current risky asset holdings and z_t is the ratio of prior gains or losses to current holdings. Thus the term $\upsilon\ (X_{t+1}, S_t, z_t)$ allows the dynamic adjustment as prior investment performance is also taken into consideration. b is an exogenous scaling factor to ensure that the second term remains stationary.

Based on the above definition of prospect utility, Barberis *et al.* consider a financial market with two states: economy I and economy II. Economy I is a standard benchmark where asset prices can be modelled using the consumption-based approach. In other words, this state is fundamentals-driven so that the growth of consumption (C) is an identical process to the growth of dividends (D):

$$\log\left(\frac{\bar{C}_{t+1}}{\bar{C}_t}\right) = \log\left(\frac{\bar{D}_{t+1}}{\bar{D}_t}\right) = g_c + \sigma_c \varepsilon_{t+1} \quad \text{where} \quad \varepsilon_t \sim N(0,1).$$

On the other hand, economy II models asset pricing by incorporating different growth rates of dividends and consumption (where divergence may stem from other sources of income besides dividends):

$$\begin{aligned} \log\left(\frac{\bar{C}_{t+1}}{\bar{C}_t}\right) &= g_c + \sigma_c \eta_{t+1} \\ \log\left(\frac{\bar{D}_{t+1}}{\bar{D}_t}\right) &= g_D + \sigma_D \varepsilon_{t+1} \end{aligned} \quad \text{where} \quad \begin{pmatrix} \eta_t \\ \varepsilon_t \end{pmatrix} \sim i.i.d.N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1\,\omega \\ \omega 1 \end{pmatrix}\right).$$

Equilibrium asset pricing in economy I is given by:

$$R_{t+1} = \frac{1 + f(z_{t+1})}{f(z_t)} e^{g_c + \sigma_c \varepsilon_{t+1}} \tag{2.6}$$

Equilibrium asset pricing in economy II can be derived as:

$$R_{t+1} = \frac{1 + f(z_{t+1})}{f(z_t)} e^{g_D + \sigma_D \varepsilon_{t+1}} \tag{2.7}$$

Here *f*(.) stands for the price-dividend ratio, which in models 2.6 and 2.7 are different functions of the state variable z_t[10].

The BHS model is too complicated to be tested empirically. Instead Barberis *et al*. provide a numerical analysis which suggests that the BHS model can help explain anomalies in stock returns such as high mean, excess volatility, and deviation from consumption growth.

2.5.2. Empirical Asset Pricing Models with Investor Sentiment

The empirical behavioural approach to asset pricing remains an undeveloped field. It is relatively easy to see whether stock markets show patterns in line with behavioural explanations but it is relatively difficult to quantify behavioural influences on asset pricing. In this section some important empirical studies that link behavioural finance to asset pricing are discussed. First, the characteristics model challenges the theoretical foundation of the so-called fundamental risk factors. Second, a sentiment-based asset pricing model illustrates how behavioural considerations can be incorporated into asset pricing. Finally, a nonlinear, two-regime framework is surveyed to examine how sentiment effects could differ across different market regimes.

2.5.2.1 The Characteristics Model

Daniel and Titman (1997) introduced a new explanation of cross sectional variation in

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[10] See Barberis *et al.* (2001) proposition 1 and 2 for the detailed discussion of the *f*(.).

stock returns. They develop a characteristic-based model where size and book-to-market ratio are unrelated to the underlying covariance structure. In other words, size and book-to-market appear to explain average stock returns because these factors are correlated with firm characteristics rather than pervasive risks measured by factor loadings. This explanation contrasts strongly with the Fama-French models, which state that these factors are powerful proxies for fundamental risks. Daniel and Titman argue that the factors only reflect individuals' preference towards different features. Instead of factor loadings, the expected returns are a function of the observable, slowly varying firm attribute θ:

$$E\left[\tilde{r}_{i,t}\right] = a + b_1 \tilde{\theta}_{i,t-1} \tag{2.8}$$

To discriminate between the Fama-French and characteristic models, Daniel and Titman test whether the return standard deviation of a portfolio of stocks increases if they all simultaneously become distressed. To do this they separate those high book-to-market firms that do not behave like high book-to-market ones. If the theoretical foundation of the factor pricing model is correct, a high book-to-market (high BE/ME) stock with a low book-to-market factor loading (β_{HML}) should have a low average return. In contrast, if the characteristic model is correct, such a stock should have a high average return regardless of its loading. They sort portfolios in terms of characteristics and factor loadings, and report that characteristics rather than factor loadings determine expected returns.

Further tests of the characteristic model show inconsistent results. Davis *et al.* (2000) reject the characteristic model over a longer period (1929-1997). The model is also rejected using Chinese stock market data (Wu and Xu, 2004). Moreover, empirical implementation of the characteristic model tends to be difficult, limiting its application.

2.5.2.2 Sentiment-Based Conditional Asset Pricing

A direct and easy way to incorporate behavioural considerations into asset pricing is to regard investor sentiment as an irrational risk factor in the pricing model. The model is then consistent with the statement that the expected return is determined in a three-dimensional framework – both rational risks and irrational risks have effects on asset prices. Thus the issues are: first, to identify investor sentiment data in stock markets; second, to specify the pricing model by incorporating investor sentiment.

1. Measuring Investor Sentiment

In recent years, a few studies have emphasized the empirical relationship between investor sentiment and asset prices, with investor sentiment being categorised into two sets: direct sentiment measures and indirect sentiment measures. The direct sentiment measures, applied by Brown and Cliff (2004, 2005), use data from two surveys that are only available for the US markets. One is conducted by the American Association of Individual Investors (AAII) and is targeted towards individual investors so that it is usually viewed as a proxy for individual investor sentiment. The AAII survey began in July 1987 and has weekly responses. The other is conducted by Investor Intelligence (II) and provides the weekly bull-bear spread of approximately 150 market newsletters. Thus the II survey is a proxy of institutional sentiment.

Except in American markets, direct sentiment measure is not common. Instead, the literature reports variables that can be observed in financial markets as indirect proxies of investor sentiment. Brown and Cliff (2004) argue that indirect sentiment measures could include: (i) market performance, such as advancing issues to declining issues, where the advancing (declining) issues are the number of stocks that closed at higher (lower) prices than their opening prices, (ii) trading activity, such as percent change in margin borrowing and the ratio of short sales to total sales, *etc.*, (iii) derivatives variables such as the ratio of option market put trading volume to call trading volume, and (iv) other proxies such as the closed-end fund discount. Baker and Wurgler (2006,

2007) employ other variables such as mutual fund flows, dividend premium, and IPO first-day returns. It is argued that some of these variables proxy for bearish sentiment and others for bullish sentiment. Moreover, instead of using these variables individually, all the above studies construct composite sentiment indices, using either principal component analysis or the Kalman filter to define the component weights. Brown and Cliff (2004) find that Kalman filter estimates are highly correlated with the estimates by the first principal component method.

2. Sentiment Effect on Asset Pricing

Sentiment effects on asset prices are tested in various ways: Brown and Cliff focus on time-series effects whereas Baker and Wurgler consider cross-sectional effects. Brown and Cliff (2004) test the dynamic relations between the component sentiment indices, portfolio returns for large stocks, and that part of small stock returns orthogonal to large stock returns in a Vector Autoregressive framework, where Y_t is the vector of the variables described above:

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + \varepsilon_t \tag{2.9}$$

They suggest that p, the number of lags, is equal to 2 for monthly data and 4 for weekly data, and show that past market returns play an important role in determining future sentiment, although the reverse is not true. Nevertheless, sentiment has strong correlation with contemporaneous stock returns.

Similarly, Brown and Cliff (2005) investigate the long-run relation between sentiment and stock returns. Defining $\boldsymbol{z}_t$ as the vector of fundamental control variables and $\boldsymbol{S}_t$ as the sentiment indices at time t, the long-horizon of sentiment effects on the k-period stock returns is modelled by:

$$\left(r_{t+1} + ... + r_{t+k}\right)/k = \alpha_k + \Theta'_k \mathbf{z}_t + \Phi_k \mathbf{S}_t + \varepsilon_{k,t} \tag{2.10}$$

$\boldsymbol{\Phi}_k$ in Equation (2.10) captures the sensitivity of k-period long-horizon returns to investor sentiment. They show that future returns are negatively related to investor sentiment, since optimism (positive sentiment) drives asset prices above fundamental value in the short-term so that subsequent returns decrease.

Baker and Wurgler (2006, 2007) focus on the sentiment effect in the cross-sectional variation of stock returns. They provide a conditional characteristic model where expected returns are governed by a vector of characteristics $\mathbf{X}_t$ conditioning on investor sentiment S_t and the condition is specified by the interaction between the two variables:

$$E(R_t) = a + \mathbf{b}_X{}'\mathbf{X}_{t-1} + b_s S_{t-1} + \mathbf{c}'\mathbf{X}_{t-1} S_{t-1} \tag{2.11}$$

Here the characteristics vector **X** contains firm size, age, profitability, dividend, asset tangibility and growth opportunity. *S* stands for the component sentiment index. $\mathbf{b}_x$ is a vector of return sensitivities to the characteristic factor, b_s captures the factor loading on sentiment, and **c** is a vector of coefficients on the characteristics conditional on investor sentiment. Therefore non-zero parameters of **c** reveal sentiment-driven mis-pricing. They test the cross-sectional sentiment effects on returns to various short-minus-long portfolios and find that when sentiment is low, the forecasted returns will be high for small, young, high volatility, unprofitable, non-dividend-paying, extreme growth, and distressed stocks. This result is consistent with the hypothesis that such stocks have less information available and are more difficult to value and arbitrage.

It should be noticed that existing sentiment-based asset pricing models remain less developed and require further study. Firstly, direct sentiment measures are limited so that indirect sentiment measures are used instead. The literature so far constructs investor sentiment using certain component index methods, such as the first principal component or the Kalman filter. However, for all the above studies the composite index may face some shortcomings because the correlation matrix of principal components is time-sensitive: the weights could vary over time and the estimated correlation in one testing period may not be appropriate for another period. Thus the estimated sentiment effects may not be reliable. Moreover, if two proxies are both good indicators for investor sentiment it is not necessarily the case that sentiment is captured by the common components of the two proxies. Therefore catching the principal of each proxy may ignore the actual sentiment barometer.

Secondly, the sentiment-based asset pricing literature emphasizes time-series or cross-sectional sentiment effects but pays less attention to the quantitative impact on asset pricing, since the tested portfolios are restricted to short-minus-long portfolios. This is designed to reveal sentiment effects, but does not do so for individual stocks, industry portfolios, or Fama-French size and book-to-market portfolios. Moreover, the literature so far uses only US market data. All these issues suggest further study.

2.5.2.3 Two-Regime Model

If investors do not always use rational judgements, they may predict and interpret stock movements differently in different market environments, so that investor sentiment may vary over different phases of the stock market cycle. Coakley and Fuertes (2006) develop a non-linear, two-regime framework that allows for different behaviour over stock market phases. In this two-regime framework, prolonged price deviations from fundamentals in bull markets are suggested due to the investor sentiment, while in bear markets valuation ratios and prices move towards their fundamental equilibrium levels.

Coakley and Fuertes apply dividends as the proxy of fundamental value and test the performance of the mis-pricing term $E_t\left[\rho^j\left(p_{t+j}-d_{t+j}\right)\right]$, which should be stationary and insignificant if agents are rational and prices are close to fundamentals. They measure the sentimental factor as the speed of adjustment ρ, which differs in bull and bear markets (ρ^c and ρ^r respectively). They state clear hypotheses tests as Table 2.6 present.

Table 2.6 summarizes Coakley and Fuertes' work step by step with the hypotheses and the testing methodologies. Results shown in each step provide a clear evidence to support that the misevaluation occurs in financial market and cannot be eliminated over time in a bull market. This evidence is consistent with the suggestion by the DHS model as Figure 2.3 presented. A natural interpretation is that in bull market, overconfidence, positive feedbacks, and other sentiment behaviour take place and push stock prices further away from the fundamental values, leading further support that investor sentiment plays an important role in the bull markets. The model tests only dividends as the risk factor which may fail to measure fundamentals appropriately. Nevertheless, the two regimes framework indicates that investor psychology and behaviour may be different during different market conditions, which provides an interesting approach to predicting asset prices for further research.

Table 2.6 Test Procedures for Coakley and Fuertes (2006)

Prediction	**Statistics Measurements**	**Results**
1. Valuation ratios behave asymmetrically during bull and bear markets.		
1.A Unit root persistence or mean reversion: H_0: valuation ratios have a unit root. H_1: valuation ratios mean revert (non-) linearly.	ADF tests of unit root with F-Statistics (F_{1A}). The distribution is non-standard and measured by bootstrap.	Rejection. Valuation ratios, mean reverting.
1. B What type of mean-reversion? H_0: valuation ratios mean-revert symmetrically. H_1: valuation ratios mean-revert asymmetrically.	BDS tests and Non-parametric triples statistic with F-statistics (F_{1B}). Rely on the asymptotic chi-square χ^2 distribution.	Rejection. Valuation ratios mean reverting asymmetrically
1. C How do ratios behave during bull and bear markets? H_0: valuation ratios do not mean revert in bull (bear) markets. H_1: valuation ratios do mean revert in bull (bear) markets.	$\rho = \frac{1}{\left[1 + e^{(\overline{d-p})}\right]}$ Should be less than zero (mean-reverse) if EMH holds.	$\rho^c = 0$ $\rho^r < 0$ Valuation ratios mean reverting in bear markets.
2. Shocks to valuation ratios have long-lasting or seemingly permanent effects.		
2. A Is there underreaction-overreaction to news in valuation ratio? H_0: valuation ratios respond fully and immediately to shocks. H_1: valuation ratios follow an underreaction-overreaction time profile.	Generalized Impulse Response (GIR) tests with Monte Carlo simulation approach.	Short-run underreaction(12 month delay to be peak)
2. B Is the adjustment to news rapid or sluggish? H_0: valuation ratios adjust rapidly following innovations. H_1: valuation ratios adjust slowly following innovations.	GIR s	Very sluggish adjustment after 12 months peak taking 20-30 months for reverting.
2. C How pronounced is the impact of shocks during bull and bear markets? H_0: large positive shocks to valuation ratios have similar effects in both bull and bear markets. H_1: large positive shocks to valuation ratios have more marked effects during bull markets.	GIRs	Large positive shocks influence long-lasting and greater in bull than bear market.

2.6 Conclusion

This literature review summarizes the debate between the EMH and behavioural finance: the theoretical asset pricing models based on the EMH and the psychological foundations and empirical applications of behavioural finance. Asset pricing models which incorporate behavioural considerations are also surveyed.

The literature leads to the following conclusions:

- In the debate between the EMH and behavioural finance, the literature provides evidence both to support and to challenge theoretical asset pricing models. There is no clear conclusion about which theory is empirically dominant so further research is required.

- Investors may not be as homogeneous and rational as assumed by the EMH. Psychological factors may lead to biased investor decisions and therefore influence stock prices. Noise trading in markets cannot be completely ruled out. This may affect the behaviour of both mean and volatility of returns, in stock price overreaction and underreaction, and asymmetric volatility.

- Asset pricing models incorporating behavioural biases have been introduced, in both theoretical and empirical work. The theoretical behavioural asset pricing models are easily structured but their empirical applications are relatively undeveloped. Empirical investigations focus on quantifying sentiment effects on asset pricing. However, sentiment-driven asset pricing models need further development.

Chapter 3 EMERGING CHINESE FINANCIAL MARKETS

3.1 Introduction

This research targets the young and ongoing Chinese domestic A-share stock markets. Like most emerging financial markets, the financial markets in China have a relatively short history. Studies of these markets are relatively few. To understand Chinese financial market behaviour it is helpful to provide a description of the markets to give general knowledge about the financial markets in China. This chapter provides an overview of the Chinese economy and financial markets, introducing the history, regulation and essential features of Chinese stock markets.

3.2 An Overview of Chinese Economy

Emerging financial markets have drawn the world's attention because of their rapid economic development and the processes of privatization. Stock market liberalization has provided new opportunities to investors worldwide. The Chinese economy and stock markets are outstanding among them. Since economic reforms began in 1978, which moved China from a planned to a market-oriented economy, GDP growth (1979 to 2004) has averaged 9.6%. Growth was 10.4% in 2005, 11.1% in 2006, and 11.4% in 2007. Even though affected by the global financial crisis of 2007-2010, GDP growth in China was still very high at 9% in 2008 and 8.7% in 2009[11].

The Chinese economy has benefitted from strong government finances and a relatively strong banking system compared with the mature but problematic banking systems in

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[11] Data from: National Bureau of Statistics of China, http://www.stats.gov.cn/

developed countries during the recent crisis. Some of the benefits are due to the less developed and closed financial system that is less vulnerable to the global credit market. Some are supported by high household and corporate savings. Although as a developing and transitional economy China still faces some problems, like the high cost of manufacture, uncertainty of transition, poor social security, *etc.*, the rapid growth of the financial system deserves attention.

3.3 An Overview of Chinese Financial Markets

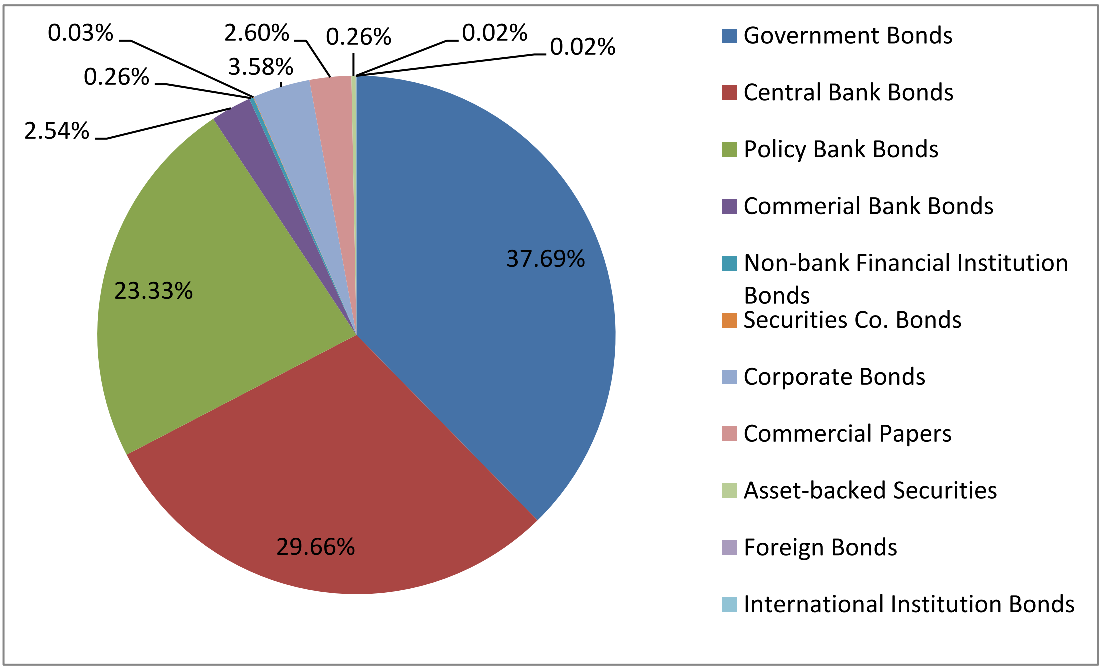
3.3.1. Chinese Bond Markets

After stopping for 30 years, the Chinese government resumed issuing bonds in 1981. Currently, the bond markets in China comprise the interbank market, the OTC market, and the exchange market. The interbank bond market, established in 1997, is a negotiating system between institutional investors, such as banks, securities companies and insurance companies. The OTC market is a commercial bank counter market in which the participants are individual and non-financial institutional investors. The exchange bond market is also a retail market used by individual and non-financial institutions, but pricing is through an electronic matchmaking system rather than the bid-ask quotations of the OTC market.

Not as well-developed as the mature bond markets in developed economies, Chinese bond markets have some imperfect characteristics. The most striking feature is that government bonds, central bank bonds and policy bank bonds dominate the market, whereas corporate bonds have only a small market share. Figure 3.1 presents the market shares of each type of bond at the end of 2007. National issuers comprised over 90% of total bond market capitalisation. The dominant share of government, central bank and policy banks is decreasing as bond markets develop but at the end of 2009, national issuers still took 82.26% of the total bond market depository balance.

Figure 3.1 China Bond Depository Balance at the end of 2007

This figure presents at the end of 2007 the proportion of different types of bonds in terms of the values of bonds.



(Source: China Bond.com.cn)

A second feature is that the bond market remains small. At the end of 2007, total bond market capitalisation was only 47% of GDP. This value is much smaller than in mature bond markets, such as in the US and the UK. The interbank market is the main bond market in China while the OTC market and exchange market remain less-developed. The OTC and exchange bond markets take only a 10% share of the total bond market[12]. As shown in Figure 3.2, exchange traded bonds, including government bonds, corporate bonds and convertible bonds, take only 1.023% of the total value of exchange traded securities[13]. These features strongly imply that Chinese bond markets are largely undeveloped. Corporations lack the ability to raise finance in bond markets

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[12] Source: China Bond. (www.chinabond.com.cn.)

[13] Source: China Securities Depository and Clearing Corporation. (China Clear, http://www.chinaclear.cn)

and the exchange bond market may fail to perform as a good counterparty of stock markets.

3.3.2. Chinese Stock Markets

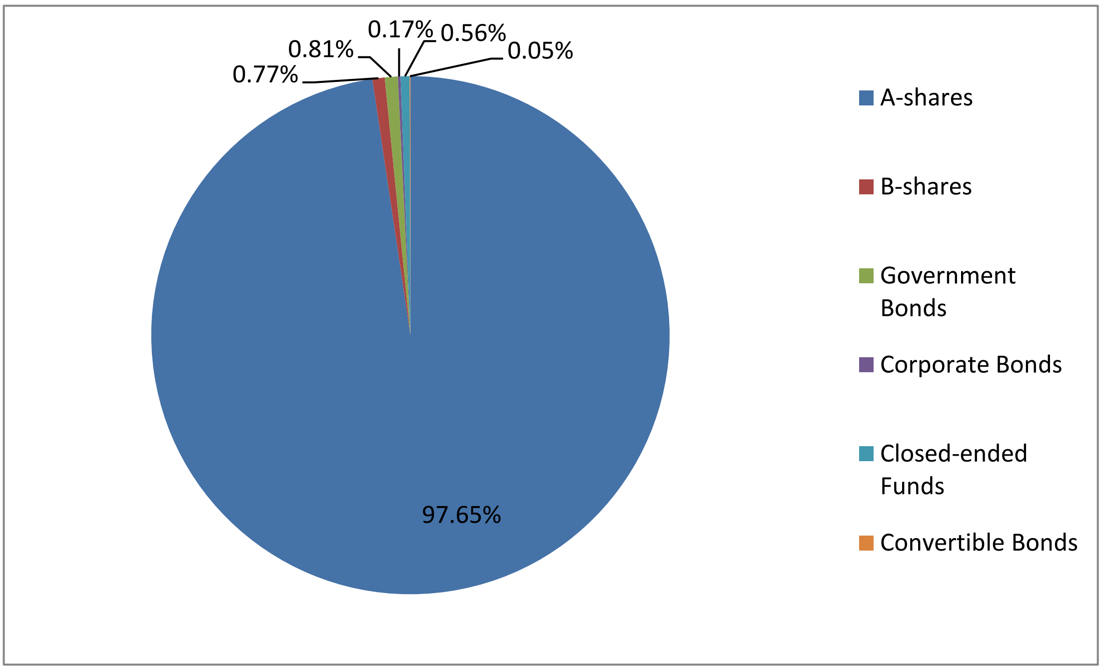
Chinese stock markets are even younger than the bond markets, but are developing more quickly. The two stock exchanges (Shanghai and Shenzhen) were opened in December 1990 and July 1991 respectively. By the end of 2007 there were 1550 listed companies (880 in Shanghai and 670 in Shenzhen), with total market capitalisation of 26.984 tn RMB (US$3696.42 bn) for Shanghai and 2.116 tn RMB (US$289.86 bn) for Shenzhen[14]. On 9th May, 2007, the total turnover in the Chinese exchanges exceeded the rest of Asia combined and was nearly double that of Japan.

Both stock markets are segmented into A-share market and B-share markets. In the A-share markets stocks are priced in Chinese RMB and traded by domestic investors while in the B-share markets shares are quoted in either U.S. dollars or Hong Kong dollars. The B-share market was restricted to foreign investors until January 2001, at which time domestic investors were also allowed to trade. The B-share market is smaller and less active than the A-share market. For example, of the total 29.100 tn RMB market capitalisation of the two stock markets at the end of 2007, 28.936 tn was attributed to A-shares, or over 99%. B-shares generated only 164.225 bn RMB of market value. The total values of A-shares traded in 2007 were 30.196 tn RMB (US$4.136 tn) for the Shanghai stock exchange and 2.925 tn RMB (US$400.671 bn) for Shenzhen. Figure 3.2 shows the listed market value of all securities deposited by China Clear, the official institute for securities depository and clearing. Clearly, A-shares dominate the exchanges while B-shares have only 0.77% of listed market

[14] Source: Shanghai Stock Exchange (http://www.sse.com.cn) and Shenzhen Stock Exchange (http://www.szse.cn)

value.

Figure 3.2 Free-floated Market Values of China' Exchanges by the end of 2007



Source: China Securities Depository and Clearing Corporation (http://www.chinaclear.cn)

Because of the negligible market capitalisation, smaller number of listed shares and smaller number of investors, and also because B-shares traded in US dollars are generally not held by Chinese domestic investors, this research will investigate only the domestic A-share market.

3.4 Reform and Regulation Changes for Chinese Stock Markets

Chinese stock markets exhibit many reform and regulation changes in their short history, including market openness and share privatisations. These historical events are summarised in Table3.1 and Figure 3.3, where the corresponding A-shares market composite index is plotted with the important reforms and regulation changes. Despite their progress, Chinese stock markets still have characteristics that distinguish them from developed financial markets, such as the large number of individual private investors, extreme trading volumes and a lack of financial products.

Figure 3.3 Time Plot of Chinese A-shares Composite Index and Historical Events

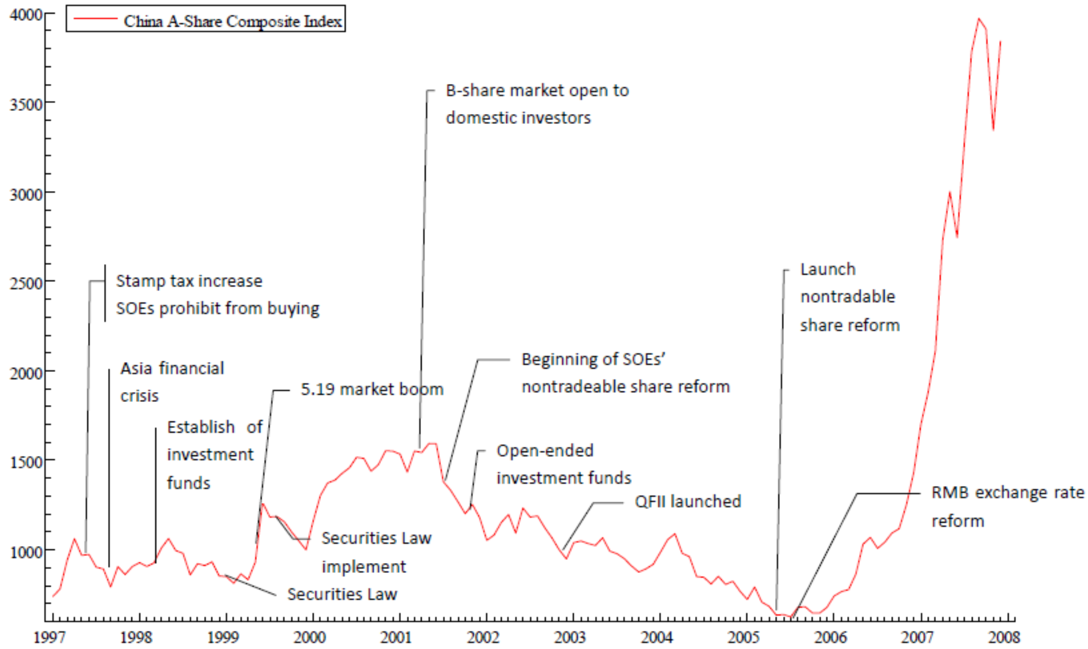


Table 3.1 Historical Events and Regulatory Changes for Chinese Stock Markets during 1997 and 2007

	Time	Events
1	09-05-1997	Stamp tax increases from 3‰to 5‰
2	22-05-1997	Prohibition of SOEs and listed companies from trading in stock markets
3	02-07-1997	The beginning of Asia Financial Crisis
4	23-03-1998	First introduction of investment funds
5	22-04-1998	Implement the Special Treatment (ST) system
6	12-06-1998	Stamp tax decreases from 5‰ to 4‰
7	29-12-1998	Announcement of the Securities Law, to be implemented on 01-07-1999
8	19-05-1999	The "5.19" booming, start-up of high-tech and dot-com bubble
9	08-09-1999	Re-allow SOEs and listed companies to trade in stock markets
10	27-10-1999	Insurance companies enter markets again indirectly via investment funds
11	**19-02-2001**	**Domestic investors are allowed to trade B-Shares**
12	**12-06-2001**	**Beginning of the non-tradable share reform (suspended on 22 Oct, 2001)**
13	04-09-2001	First introduction of Open-ended investment fund
14	16-11-2001	Stamp tax reduces from 4‰ to 2‰
15	08-11-2002	Launch of Qualified Foreign Investment Institutions (QFII) programme
16	08-07-2004	Shanghai Stock Exchange launches ETF
17	18-08-2004	Shenzhen Stock Exchange launches LOF
18	31-08-2004	Suspend IPO process
19	17-01-2005	Resume IPO process
20	24-01-2005	Stamp tax reduces from 2‰ to 1‰
21	05-04-2004	Launch Shanghai and Shenzhen 300 equity index
22	30-04-2005	Beginning of SOEs nontradable share reform
23	25-05-2005	Suspend IPO process
24	21-07-2005	Launch Chinese RMB exchange rate reform
25	22-08-2005	Introduction of warrants into markets

Events 11 and 12 are two of the most important reforms in Chinese stock market history. They have some implications to stock prices and are located in the middle of my sample period. Therefore, these two events are introduced in more details, and will be used as the breaking points to test the structural break of pricing models.

3.4.1. Market Openness

The Chinese stock market is in the process of increasing its openness and financial liberalisation. The A-share market was restricted to domestic investors only. However, in 2002 large foreign institutional investors were allowed to invest in bonds and stocks under the Qualified Foreign Institutional Investor (QFII) programme. By the end of 2007, the 49 QFIIs invested in 10.05 bn U.S. dollars[15]. By March 2010, there are 88 foreign institutional investors and the total allowance of investment increases to 17.07 bn U.S. dollars. However, it should be noticed that compared with the total market capitalisation of the two stock exchanges, QFII investment values remain trivial.

Chinese institutional investors have also tried to enter and learn from foreign mature financial markets. The early effort was in 2004, when Chinese insurance companies were allowed to invest overseas, although the investment was restricted to fixed-income assets. On 25 July 2007 the limit for insurers' overseas investments was raised to 15 per cent of total assets.[16]. The Qualified Domestic Institutional Investor (QDII) scheme was launched in April 2006 and the first QDII (Bank of China) was qualified in July 2006 with an investment limit of 10 billion U.S. dollars. By the end of 2007, 21 banks, 8 fund management companies and 21 insurance companies had joined the QDII programme with a total investment limit of 447.26 billion U.S. dollars. Late in 2008, trust companies also become QDII members. Thus Chinese domestic investors, including individual investors, gained access to foreign financial markets via the above fund management institutions. All these developments show the efforts of Chinese financial markets and investors to open both the markets and their minds.

3.4.2. Non-tradable Shares and the Reform (from 12/06/2001)

Due to historical reasons, listed companies in Chinese stock markets are mainly State-owned Enterprises (SOEs) or their holding companies, with ownership structure segmented into non-tradable shares and tradable shares. Non-tradable shares are held

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[15] Source: State Administration of Foreign Exchange of China (http://www.safe.gov.cn)

[16] JP Morgan Estimate, from FT.com

by the government or state-owned companies, while the tradable shares are listed on stock exchanges and owned by the public. Therefore a peculiarity of Chinese stock markets is that the majority of Chinese listed companies have a mixed ownership structure. More specifically, there are four types of shares for the listed SOEs: state shares, legal person shares, employee shares, and listed shares (A-shares and/or B-shares). The former three types are non-tradable and the first two are usually government owned. Typically, before the non-tradable share reform, only around one-third of shares were legally tradable for listed companies.

This segmentation induces some problems. The most salient comes from the different prices of non-tradable and tradable shares: public investors purchase the tradable shares at market prices but investors in non-tradable shares pay initially only 1 Yuan per share. All shares have the same legal rights but have different costs, which is unfair to public investors who purchase stocks at much higher prices in exchange. This is viewed as a reason for the bear markets between 2001 and 2005, when non-tradable share reform began to be discussed in newsletters, and by professional and individual investors, but was not actually implemented. By then markets were fearful that the cheaper non-tradable shares would enter the markets with the same legal rights as common shares and would drag down the prices of common shares. Also, given that only a small fraction of total shares is tradable, the non-tradable status of some shares restrains the market function in corporate control, such as takeovers, and raises a principal-agent issue since common investors have few management rights and because corporate operations may be less profit-maximisation oriented.

After several false starts, reforms to eliminate non-tradable shares were implemented by the Chinese government in April 2005. This reform was to simplify ownership types and gradually make all shares tradable. One and half years later this process had been completed by almost all listed firms，but the non-tradable shares are not tradable yet. Nevertheless, the reform method for each listed company was negotiated and voted for by both non-tradable shareholders and the tradable shareholders. Since the requirements of common investors were taken into account, investor responses were positive and stock indices subsequently rose dramatically.

3.4.3. Reform in B-share Market

Shares listed in Chinese stock markets have been broadly separated into “A” and “B” share categories. A-shares are traded in Chinese RMB while B-shares are traded in USD in Shanghai and HKD in Shenzhen. The B-share market was restricted to foreign investors only but since 19 Feb, 2001, domestic investors were allowed to trade B-shares. The opening of the B-share market shrinks the price differential between A and B shares by increasing the prices of B-shares immediately. However, as mentioned above, the B-share market is relatively small and less active than the A-share market. Therefore, this reform may affect the price of B-share more than that of A-share.

3.4.4. Other Historical Milestones

In addition to the QFII scheme, there was an increase in the types and powers of institutional investors. The regulation of investment funds was promulgated in October 1997 and soon closed-end funds were introduced to the markets. In September 2001 the first open-ended investment fund was established. By the end of 2007 there were 30 fund management companies, 75 open-ended investment funds and 23 other financial products. The total market capitalisation of these funds took less than half of total market capitalisation[17].

The reform of the RMB exchange rate was launched on 21 July 2005, shifting the

[17] Source: China Clear (http://www.chinaclear.cn)

RMB exchange rate from a U.S. dollar peg to a managed float with reference to a basket of foreign currencies. Since China is a major world manufacturer and there was a large amount of trade surplus, the reform immediately increased the RMB exchange rate from 8.27 per USD to 8.11 per USD[18] in a trading day. Since then the RMB exchange rate has appreciated gradually. However, there is a common argument that the appreciation process is too slow, which not only induces developed countries to threaten the exchange rate but also attracts international hot money to the Chinese domestic market, although the financial sector of the Chinese Balance of Payment is still constrained. The inflow of hot money potentially affects the prices of assets in China, such as stock and property.

3.5 Characteristics of Chinese Stock Markets

Despite regulatory changes and reforms intended to develop and enhance Chinese stock markets, they exhibit characteristics that differ from mature markets, including a large proportion of individual investors, a lack of arbitrage and hedging instruments, and other price patterns such as extreme trading volumes and policy-driven stock prices.

3.5.1. Large Proportion of Individual Investors

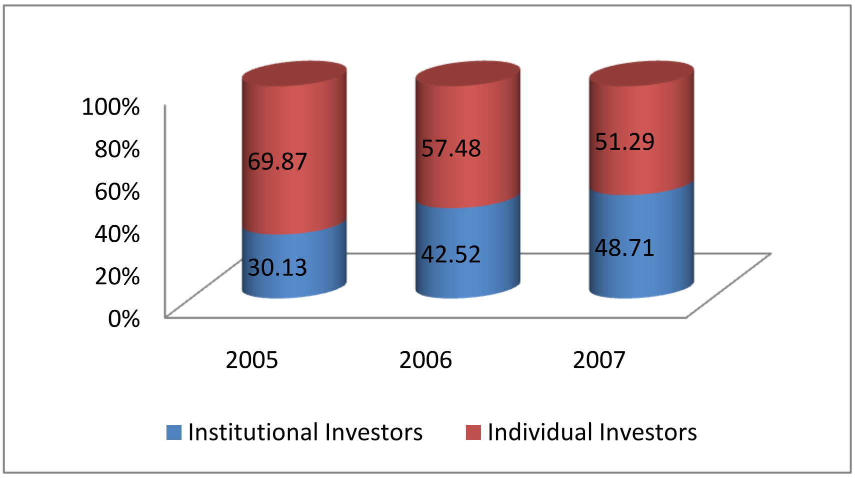
The majority of investors in Chinese stock markets have been individual investors since the two stock exchanges were established and they dominate markets not only in terms of numbers of investors but also in terms of market capitalisation. The China Securities Regulatory Commission (CSRC) has sought to enhance the power of

[18] Source: State Administration of Foreign Exchange of China (http://www.safe.gov.cn)

institutional investors in financial markets by introducing investment funds, QFII, banks and insurance companies into the markets. However, two-thirds of the market value of tradable shares was held by individual investors in 2005. This proportion has decreased over time as institutional investors became more important. Figure 3.4 shows that in 2007, institutional investors increased their market share to 48.71%, although this is still less than half of total market values.

Figure 3.4 Comparison of Individual and Institutional Investors Holding Market Values

This figure shows from 2005 to 2007 the proportion of institutional and individual investors in terms of their holdings of tradable market values in A-share market.



Source: China Securities Depository and Clearing Corporation (http://www.chinaclear.cn)

It is widely argued in the behavioural finance literature that individual investors are more likely to be irrational noise traders since they are less educated, expend fewer resources on information search and have less access to information. They tend to trade following the actions of others and so are called trend followers. Their trading generates noise in markets so they are called noise traders. Given the large amount of small investors in Chinese stock markets, it is reasonable to conjecture that stock prices and returns in Chinese stock markets could more readily deviate from fundamental values and that behavioural finance issues may be more readily observable in Chinese stock markets.

3.5.2. Lack of Investment Instruments

The choice of financial products is quite limited in Chinese stock markets compared to developed markets. For a long time ordinary shares were the only type of financial product, with short sales being strictly prohibited.

The development of financial products was carefully considered and finally implemented after much discussion. Warrants were the first financial derivatives product, introduced to A-share markets on 22 August 2005. However, the warrant market is small, with only 26 warrants on offer at the end of 2007 compared to around 2,000 in Hong Kong[19]. The warrant market has attracted many uninformed individual investors, inflating turnover to US$250 bn in 2006. Stock index future is finally launched in February 2010. The hedging role of the derivatives market does not yet function for the management of ordinary shares. Since investors can gain only from increasing share prices, in Chinese stock markets there is a common desire for increasing prices by all investors no matter whether institutional or individual. This desire may trigger extreme optimism in a bull market and reduce investors' willingness to trade in a bear market and therefore deepen the fluctuation of stock prices.

3.5.3. Inefficient Markets

Despite economic growth and market openness, the behaviour of emerging markets remains ambiguous. Laurence *et al.* (1997) study the empirical evidence and state that Chinese stock markets are efficient in the weak-form sense of the EMH. Girard and Omran (2007) identify the risks involved in investing in Arab stock markets and found

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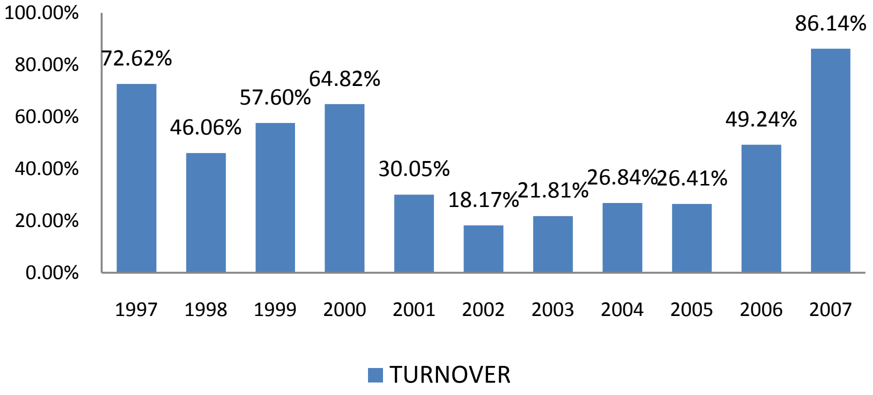
[19] Source: China Securities Depository and Clearing Corporation (http://www.chinaclear.cn)

that firms' fundamentals and country-level risks have significant explanatory power for stock prices. On the other hand, the mainstream literature asserts that emerging markets are characterised by inefficiency and speculative bubbles (Krugman, 1995). The literature tends to explain the inefficiency in terms of a shortage of historical data, barriers to portfolio investment, market segmentation, insider trading, lack of hedging instruments and asymmetric information. As shown above, Chinese stock markets evince some features that may damage market efficiency.

Chinese stock markets show a policy-driven history although policy is now becoming less important. The Chinese government and the China Securities Regulatory Commission (CSRC) always announce regulatory changes and even report official attitudes towards market conditions. For example, the famous '5.19' dramatic rise on 19 May 1999 followed a prolonged bear market of two years during 1997 and 1999. In May 1999 the CSRC announced a series of regulations designed to promote market recovery, such as tempting insurance companies to re-enter the market and reconstructing the stock issue mechanism. The policy-driven market feature is studied by Gao and Kling (2006), who investigated the impact of regulatory changes on A-share market liquidity during 1990 to 2002 and reported that policy changes stimulate immediate but long-run market liquidity.

Another feature that characterises Chinese stock markets as emerging and imperfect is the extreme trading volume. It is commonly viewed that the average trading volume is higher in emerging financial markets than in mature financial markets, and that the trade volume of individual investors is higher. This is reasonable if investors behave like speculators rather than value finders. Moreover, in Chinese stock markets a large proportion of listed firms do not pay dividends and investors seldom take into account dividends when they make investment decisions. Investors earn profits only from capital gains. Thus they tend to purchase and sell in the short-run, which increases trading volume. Figure 3.5 shows clearly that the annual average turnover in Chinese stock markets is high and time-varying. This will be discussed in detail and applied as a proxy of investor sentiment in future chapters.

Figure 3.5 Combined Annual Average Market Turnover of Shanghai and Shenzhen Stock Exchanges



(Resource: Data Stream)

3.6 Conclusion

Chinese financial markets have developed rapidly. However, bond markets are still dominated by government, central bank and policy bank bonds while corporate bonds, commonly viewed as the counterparty of stocks, remain undeveloped.

The Shanghai and Shenzhen exchange markets are dominated by A-shares. Exchange traded bonds account for a very small fraction of market value. For stocks, there are a large proportion of non-tradable shares owned by states and state-owned holding companies, although reform of non-tradable shares have been recently implemented.

Despite the reforms and regulatory changes designed to enhance Chinese market development, the markets exhibit features that challenge market efficiency, in line with behavioural finance considerations: a large proportion of small investors, lack of investment and hedging instruments, policy-driven prices and extreme trading volumes.

Chapter 4 HOW SUCCESSFUL ARE TRADITIONAL ASSET PRICING MODELS?

4.1 Introduction

Since the 1970s, the behaviour of stock markets has been generally thought of as being consistent with the Efficient Market Hypothesis (EMH). In this context, stock returns incorporate the best information about fundamental values while returns change only in response to changes in their fundamentals. The mainstream asset pricing approach under the EMH states that stock returns should be significantly correlated to the specified fundamental risk factors and that the expected returns on assets are linearly related to their loadings on risk factors. A prominent issue has therefore been the specification of the risk factors that capture fundamental value. Some approach this issue from a market-level point of view, as in the famous CAPM model (Sharpe, 1964; Lintner, 1965) and the Fama-French three-factor model (Fama and French, 1993). The literature also shows that economic variables (macroeconomic and money market) influence the determinants of stock returns (Fama, 1981; Chen, Roll and Ross, 1986; Cochrane, 2001; Petkova, 2006). However, failures of cross-sectional asset pricing models have been found empirically and theoretically, raising doubts about the efficiency of markets and stimulating the growth of behavioural finance (Shiller, 2002).

Since mainstream traditional asset pricing models still dominate asset pricing theory, in order to understand the real behaviour of stock returns it is helpful to take the mainstream asset pricing model as a benchmark and to examine whether fundamental risk factors can fully explain stock returns. A successful traditional asset pricing model will support the EMH in Chinese stock markets. To the extent that the model fails, the failure must result from missing fundamental risk variables, in other words, miss-specification of the model, if the EMH holds.

In this chapter the Fama-French three-factor model is used as a benchmark in Chinese stock markets. Given the failure of this model, a multi-beta cross-sectional asset pricing model with more risk factors is tested to see whether the failure of the benchmark model is due to missing fundamental risk factors (a 'rational' reason) or whether other explanations are necessary ('non-rational' reasons).

As noted in Chapter 3, a particularly important feature of the Chinese markets is the size of the non-tradable share issue. In spite of share reform aimed at diminishing the number non-tradable shares, there is still a large proportion of ordinary shares held by SOEs[20] that are not tradable in stock markets. Non-tradable shares lead to the free float issue: whether total market values or listed (float adjusted) market values should be used to weight market-level risk factors and test portfolios, when evaluating stock returns. Research in this chapter contributes to the understanding of asset pricing in Chinese A-share stock markets, with particular investigation into the free float issue.

The rest of the chapter is organized as follows. Section 4.2 discusses the determinants of stock returns in a literature review. Section 4.3 explains the cross-sectional variation of Chinese A-share stock returns using the Fama-French three factors and tests the application of the model. Section 4.4 discusses whether the performance of the Fama-French model could be improved by adding risk factors. Section 4.5 tests the robustness of the results by changing the order of the VAR system. Section 4.6 summarizes and concludes.

4.2 Literature Review: Theoretical Asset Pricing Models

4.2.1. Observable market risk factors and relevant theory

The classic Sharpe-Lintner-Mossin Capital Asset Pricing Model (CAPM) (Sharpe,

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[20] See page 74 for the detailed discussion about State-owned non-tradable shares in Chinese stock markets.

1964; Lintner, 1965; Mossin, 1966) states that average returns to investment opportunities depend only on the interest rate and the slope of the security market line. Fama and French (1993) extended the classic CAPM by adding two other risk factors, in an approach now known as the Fama-French three factor model (henceforward the Fama-French model). The three factors are (i) the excess return on a broad market portfolio (r_M) (ii) the difference between returns on portfolios of small stocks (stock with low market capitalisation, or low market equity ME)and those on portfolios of big stocks (SMB), and (iii) the difference between returns on high book-to-market portfolio (the ratio of book equity (BE) to market equity (ME) and those on low book-to-market portfolios (HML).

Fama and French assert that the three factors capture most of the cross-sectional variation in average stock returns, including differences of returns between portfolios sorted by earning-price ratio (E/P), cash flow-price ratio (C/P), and sales growth. This three factor model works well to explain anomalies that are relevant to firm accounting-level information. They suggest that book-to-market equity and slopes on HML may proxy for the relative health/distress of firms (the distress effect) – firms with low BE/ME and negative slopes on HML tend to be strong firms with persistently high earnings, and vice versa. Similarly, small size firms with low market capitalisation tend to have greater factor loadings on SMB, and the positive excess returns shown by small (low ME) stocks are captured by the slope on SMB. This phenomenon is described as the size effect.

The Fama-French asset pricing model has been widely applied and cited since it was introduced. Various studies provide empirical support for the model (for example, Fama, 1998; Davis, *et al.*, 2000; Wang, 2003). With respect to China in particular, Yang and Chen (2003) find strong support for the Fama-French model in Chinese A-share stock markets using data from 1995 to 2001. Yang and Teng (2003) compare the Fama-French model with the CAPM using Chinese A-share stock markets data and found that the Fama-French model explains more of the cross-sectional variation in stock returns but that the size effect only works for small size stocks listed on the

Shanghai stock exchange. Deng and Ma (2005) tested and rejected the stability of factor loadings on excess market returns, SMB and HML. A weakness of these studies is that the sample periods are rather short and problematic: the longest sample period is used by Deng and Ma from January 1996 through December 2003 and includes 96 months observations. Furthermore, all the papers have sample periods starting before December 1996 and ending after 2000 and are therefore potentially subject to bias arising from a regime change – in December 1996 the two stock exchanges in China adopted daily price limits that subsequently restricted daily price changes to +/–10%. This change implies a structural break that is not considered by the studies cited above.

4.2.2. Economic and other variables as risk factors

In addition to the Fama-French factors, the literature also argues that stock markets cannot be persistently isolated from macroeconomic conditions. The basic argument is that macroeconomic variables are candidate sources of systematic asset risk and that they can be used as proxies for changes in investment opportunities, so that they are called state variables. In general, stock prices in an efficient market should be equal to the discounted sum of expected future earnings. Thus the state variables that forecast changes in future returns should be those that affect either future dividends (or earning abilities) or the discount rate. Chen, *et al.* (1986) (henceforward CRR) suggest that macroeconomic variables affect stock returns by affecting the economy’s pricing factors, influencing dividends and completing the description of the state of nature. Thus economic factors may also influence the cross-sectional variation of asset prices, because firms have different abilities to adjust their operations in response to changes in the economic environment.

CRR used several state variables to describe the economic state and changing circumstances for investment opportunities, including monthly and annual growth rates in U.S. industrial production, changes in expected and unexpected inflation, default spread and term structure. Expected inflation is defined by the difference between the

Treasure-bill rate and the ex post real rate of interest, default spread is defined by the difference between returns on long-term government bonds and low-grade bonds, and term structure is the difference between returns on long-term government bonds and the Treasury-bill rate. Regressing macroeconomic state variables on tested portfolio returns, CCR found a positive relationship between return and the industrial production variables and default spread, and negative relationships between return and the inflation variables and term structure.

It is also argued in the literature that it is not the levels of the macroeconomic variables that influence stock returns but their innovations (shocks). As argued by Sims (1980), the 'best descriptive device' of economic factors is the 'random shocks' to stock markets. Campbell (1996) and Petkova (2006) apply this idea and define innovations as the residual terms from a first-order Vector Autoregressive (VAR) system, which estimate the component of the variables that cannot be forecast from their lagged values. The residuals are that part of the raw variables that have no correlation with their past values or with other variables in the VAR system.

4.2.3. The relationship between the Fama-French Factors and Macroeconomic Variables

Several studies have investigated the nature of size and book-to-market effects by considering whether Fama-French factors are also good proxies for macroeconomic risks. Fama and French (1992, 1993, 1995, 1996) argued that three factors should be able to capture the variation in most macroeconomic factors since economic conditions influence firms' operating profits as represented by firm-level variables. He and Ng (1994) test whether size and book-to-market factors are proxies for the macroeconomic risks defined in the CRR paper and pointed out that size captures the risk exposures associated with the CRR factors, and that the CRR model cannot explain the book-to-market effects.

However, debates exist in the literature. Many empirical tests fail to support the power of the Fama-French factors in explaining macroeconomic variables. Brennan, Chordia and Subrahmanyam (1998) tested whether the portfolio returns were still significantly correlated with the non-risk security characteristics after adjusting for the Fama-French risks and found that the size and book-to-market effects were attenuated but that return momentum and dollar trading volume effects persisted. Black (2006) points out that past values of the conditional variance of the default risk premium contain information that predicts the conditional variances of the value and small stock risk premiums. Moreover, Campbell (1996) and Petkova (2006) test models to explain the cross-section of average stock returns which included shocks to the aggregate dividend yield, term spread, default spread and one-month Treasury-bill yield. When these factors entered the asset pricing model, loadings on HML and SMB lost their explanatory power. Thus they concluded that these factors (dividends, term spread, default spread, Treasury-bill yield) explained the cross section variation of asset returns more powerfully than the Fama-French factors.

4.2.4. Summary

To sum up, theoretical asset pricing models calculate expected stock returns as linear combinations of risk factors and their expected premiums. The literature shows that the significant risks can be aggregate market returns and returns of other portfolios returns. Economic variables that have impact on future earnings and/or discount factors may also have influence on stock returns. There is a debate about whether the economic risks can be captured by the three Fama-French three factors (the return on aggregate market index, the difference in returns between small- and big-size portfolios, and the difference in returns between high- and low-distress risk portfolios).

4.3 Explanation of the Cross-Section of Stock Returns in Chinese Stock Markets: an Application of the Fama-French Model

Since the Fama-French three-factor model has received empirical support in various studies, including studies of Chinese stock markets, the study of asset pricing in Chinese markets reported here begins with an investigation of the Fama-French model applied to A-share data. The aim of this section is to test whether the Fama-French three-factor model can fully explain the cross-sectional variation of asset returns in China. The section also addresses the free float issue by analysing the impact on asset pricing estimation using market capitalisation calculated as first total market value and then listed market value, and by using sample sets with or without financial firms, firms with negative book value, and firms with continuing years of operating losses (flagged as 'special treatments').

4.3.1. The model and testing methodology

The unconditional FF model for expected cross-sectional asset returns is:

$$E(r_i) = \beta_{i,M} E(r_M) + \beta_{i,SMB} E(R_{SMB}) + \beta_{i,HML} E(R_{HML}) + \varepsilon_i \qquad (4.1)$$

Here $E(r_i)$ is the expected excess return on portfolio *i* generated by returns on portfolio *i* minus the risk-free rate of returns R_f. $E(r_M)$, $E(R_{SMB})$ and $E(R_{HML})$ are expected risk premia on the aggregated market index (excess returns) and the SMB and HML portfolios, respectively. ε_i is the estimated error term that should follow an i.i.d. normal distribution with zero mean and finite variance. The model implies that the cross-sectional variation of portfolio returns can be fully explained by beta loadings on the three risk factors.

Empirical tests of beta-pricing models focus on testing three implications: (1) the intercept on the cross-sectional regression is zero when excess returns are employed; (2) the loadings on relative risks (betas) capture the cross-sectional variation of expected excess returns; and (3) risk premiums (gammas) are positive. One of the most widely used methodologies in testing the cross-sectional multi-beta asset pricing model is the two-pass regression approach, known as the Fama-MacBeth procedure, developed by Fama and MacBeth (1973). This approach contains two steps: in the first step the sensitivities (betas) of asset returns to the specified risk factors are estimated for each asset using time series ordinary least squares (OLS) regression; in second step the estimated betas are applied as the observed factor loadings in a cross-sectional regression and the prices of risk (gammas) are estimated.

First Pass: The estimates of the betas are obtained by applying the time-series OLS regression

$$r_{i,t} = \alpha_i + \beta_{M,i} r_{M,t} + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + e_{i,t} \tag{4.2}$$

Here $r_{i,t}$ denotes the excess return of portfolio *i* at time *t*, while $r_{M,t}$, SMB_t, and HML_t are the excess market returns, returns of a portfolio that is long in small firms and short in large firms, and returns of a portfolio that is long in high book-to-market firms and short in low book-to-market firms, respectively. α_i is the intercept return for portfolio *i*. The estimated betas measure the sensitivities of the portfolio returns to the three Fama-French risk factors – in other words, the risk exposures to the aggregate market, firm size, and book-to-market ratio. The estimated error term should be i.i.d. normally distributed if the model specification is fitted to data.

Second Pass: The second-pass is to run a cross-sectional regression of average portfolio returns to estimate risk premiums for the loading factors. A premium generated from this step is the expected price of bearing unit exposure to a given source of risk.

$$\bar{r}_i = \gamma_0 + \gamma_M \hat{\beta}_{M,i} + \gamma_{SMB} \hat{\beta}_{SMB,i} + \gamma_{HML} \hat{\beta}_{HML,i} + \varepsilon_i \tag{4.3}$$

Here $\bar{r}_i$ is the annual average excess returns on asset *i*, while the gammas represent the rewards for bearing the risk. Estimates of $\boldsymbol{\gamma} = (\gamma_0, \gamma_M, \gamma_{SMB}, \gamma_{HML})$ are found from the cross-sectional regression of $\tilde{\mathbf{r}}_{\mathbf{t}} = (\tilde{r}_1, ... \tilde{r}_N)$ on $\hat{\boldsymbol{\beta}} = \left[1_N, \hat{\beta}_M, \hat{\beta}_{SMB}, \hat{\beta}_{HML}\right]$. If asset loadings on the Fama-French risk factors are important determinants of expected average asset returns then $\boldsymbol{\gamma}$ (the risk premiums) should be significantly positive.

The standard two-pass procedure for testing multi-beta asset pricing models is argued to have some shortcomings. The most salient issue is the error-in-variables (EIV) problem involved in the cross-sectional regression that is inherent in two-pass estimation – estimation errors in the first-pass betas will bias the risk premiums estimated in the second pass (Shanken, 1992). One way to deal with this problem is to group securities into portfolios (Fama and MacBeth, 1973; Chen et *al.*, 1986). This grouping helps to minimise measurement error, reduce the noise in individual asset returns and spread portfolio returns over a wide range so as to enhance the discriminatory power of the cross-sectional regression. A widely adopted approach is to sort stocks according to size and book-to-market.

Various estimation methods have been used to deal with the EIV problem. Shanken (1985) provided a solution by using generalized least squares (GLS) estimation in the second pass instead of OLS. Shanken argued that the GLS estimator is asymptotically efficient under residual heteroskedasticity conditions. The maximum likelihood (ML) approach could be an alternative solution to the errors-in-variables problem (Gibbons, 1982) since it estimates the betas, covariance parameters and risk premiums simultaneously.

Shanken and Zhou (2007) compared the performance of Ordinary Least Squares (OLS), Weighted Least Squares (WLS) and Generalised Least Squares (GLS) in two-pass procedures, Maximum Likelihood (ML) and Generalised Method of Moments (GMM) estimation in the second-pass of cross-sectional regression[21]. They concluded that although the estimators are less precise, inference from OLS/WLS is more reliable than from GLS/ML. GMM estimation, unlike least squares and ML, relaxes the assumption that returns are independent and identically distributed over time. Velu and Zhou (1999) indicate that the GMM test allows conditional heteroskedasticity. Similarly, Shanken and Zhou (2007) show that the GMM estimation performs best in terms of root mean square error. Thus, instead of the standard OLS regression, a GMM procedure is employed, with instruments selected to ensure that the regression is unbiased and that factor loadings are orthogonal to the residual term.

4.3.2. Data and summary statistics

4.3.2.1 Data Description

This research uses monthly data from Chinese A-Share stock markets (Shanghai and Shenzhen) over 11 years from January 1997 to December 2007, giving 132 observations for each variable. It is difficult to extend the data further back in time[22].The sample set includes all traded stocks listed for at least one year, divided into two nested data sets. The number of stocks in each data set each year is presented in Appendix 4.1.

Financial companies are usually said to have ‘odd’ betas and may bias the estimation results if introduced into the data set. Special treatment companies (companies marked as ST or S) [23] may also bias the estimation because they are traded at a lower daily

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[21] This study has been surveyed in Chapter 2, see p26, 27.

[22] See page 6 for the reason for the short sample period selection and sample size selection.

[23] Companies marked as ST are listed companies with more than two years of operating losses, while companies marked as S have not yet started their shareholding system reform. In both cases, the daily prices of these companies are restricted to variation within 5% limits.

price variation. Stocks with negative book value equities, which are catalogued into the low book-to-market group and are regarded as having lower distress risk, are actually stocks with high distress risk. Therefore, these three types of stocks (financial, special treatment and negative book value) should be excluded from the sample. However, financial firms and ST firms may have a leading influence on stock markets. In order to test the behaviour of the market as a whole compared to the behaviour of more 'normal' stock markets, in this research the data set is separated into Set A and Set B. Set A includes all firms from the Shanghai and Shenzhen A-share markets, while Set B uses the stocks of Set A with the exception of companies marked ST (special treatment) or S, companies with negative book value of equity, and financial companies.

Chinese markets are unique in that the government holds many shares that cannot be traded. 'Float-adjusted' market value is the percent of total market capitalization where listed market shares are used instead of total shares outstanding. Hence float-adjustment considers only those shares listed in the market and available to investors. However, there are very few reports in the literature that discuss the difference between total market value and float-adjusted market value, since most academic papers are based on US markets where market capitalization of the total stock of shares is used as standard practice. To address this gap in the literature, two subgroups are established in each data set, according to the different definitions of market value: total market value (denoted by TMV) and 'listed' or float-adjusted market value (denoted by LMV). This gives a total of four data sets: Set A (TMV), Set A (LMV), Set B (TMV) and Set B (LMV).

Individual Chinese security returns, book equity (BE) and market equity (MV) are obtained from the Wind Financial Database (hereafter, WindDB)[24], which records the securities in Chinese stock markets and is one of the most popular databases used by

[24] Wind Financial Database: http://www.wind.com.cn/en/home.html, records the securities in China's stock markets and is one of the most popular databases used by the Chinese financial industry. Data are available by subscription.

the Chinese financial industry. BE is defined as the number of shares outstanding times net assets per share from the previous year's financial statement. MV (both total market value and listed market value) is defined as the number of shares outstanding (total or listed) times the stock price.

The market return (R_M) is taken from the S&P/CITIC A-share composite index, which is a value-weighted index that provides a combination of Shanghai and Shenzhen A stocks, measured in natural logarithms.[25]

The 3-month bank deposit rate, taken from the People's Bank of China, is used as the risk free rate of return, in order to calculate excess returns. The reasons for using the 3-month bank deposit rate instead of T-bill rate are as follows:

1. As introduced in Chapter 3, the bond market in China is not well developed and is segmented, therefore bond market data are limited. The Shanghai Exchange total bond index was launched in 2003. The 3-month government bill, usually used as the risk-free asset in developed market studies, was introduced only recently. Moreover, the majority of government bonds are traded in the inter-bank market, which is accessible only to institutional investors. Individual investors can only trade government bonds in the exchange market, where liquidity is quite low. The OTC bonds market is available for new purchases but not for secondary trading. Returns to government bonds differ between the different market segments, with the result that there is no uniform return, so none of the government bond returns can be used to represent a risk-free rate.
2. China has a high level of savings. Traditionally there are few choices open to investors. Households traditionally prefer bank deposits to shield themselves from risk, and investment funds in China have only just been introduced to the majority of individual investors. Individuals cannot trade in the bonds market.

[25] http://www.spcitic.com/

This lack of investment opportunity means that individuals invest over 50% of their savings in bank deposits[26]. Investors regard bank deposits as risk free assets giving the opportunity cost of investment. Thus, it is rational to use the 3-month bank deposit rate as the risk free rate of return.

4.3.2.2 Construction of the Fama-French Factors

In keeping with Fama and French (1996), Davis *et al.* (2000), L'Her *et al.* (2004) and others, the Fama-French factors are constructed to mimic the risk variables related to the aggregate market, company size (size effect) and book-to-market (distress effect). Stocks are first ranked by total Market Equity (lnME) and Book-to-Market (BE/ME) to give 6 portfolios, and returns are then calculated for each portfolio to mimic the risk factors. For each month t from January to December in year y, stocks are ranked by their size ($\ln ME$, the natural logarithm of total market equity) and book-to-market ratio (BE/ME, book equity/market equity) of December year y-1. The construction process is repeated four times, for the four data sets. Firm size is measured by both total market capitalization (TMV) and float-adjusted market capitalization (LMV).

Using the two rank orders of stocks, a 50% breakpoint for size and 30% and 70% breakpoints for book-to-market are calculated. Based on these breakpoints, stocks are sorted into two size groups and three book-to-market groups: stocks above the 50% size breakpoint are assigned to group B (big), while those below the 50% breakpoint are assigned to group S (small). Similarly, stocks above the 70% book-to-market breakpoint are assigned to group H (high) while the middle 40% and last 30% are assigned to groups M (middle) and L (low) respectively. Six value-weighted portfolios are formed from the intersections of the size and book-to-market groups, named S/L, S/M, S/H, B/L, B/M, and B/H. Note that the number of observations varies in each of the portfolios and each of the years. Within each year any company listed for less than

[26] Data from CTR market research.

one year is excluded (no data are available from accounting reports for year $y-1$). The data, their sources and definitions are summarised in Table 4.1.

Table 4.1 Glossary and Definition of Variables

Symbol	Variable	Source or Definition
		Basic Series
$R_{i,t}$	Dividend-adjusted Return to stock *i* at time *t*	WindDB
BE	Book equity of individual stocks	WindDB
TME	Total market equity of individual stocks	WindDB, total shares outstanding $\times$ price
LME	Listed market equity of individual stocks	WindDB, listed shares $\times$ price
R_M	Aggregate log market return	S&P/CITIC A-Share Composite Index
R_f	Risk-free rate of return	People's Bank of China, 3-month bank deposit rate
		Derived Series
r_M	Excess return on market index	$R_M - R_f$
R_{SMB}	Returns on small stock portfolio minus returns on big stock portfolio	$\frac{(S/L-B/L)+(S/M-B/M)+(S/H-B/H)}{3}$
$\boldsymbol{R_{HML}}$	Returns on high book-to-market stock portfolio minus returns on low book-to-market stock portfolio	$\frac{(S/H-S/L)+(B/H-B/L)}{2}$

The SMB factor (Small minus Big) is the equally-weighted average of the difference between the returns on small size stock portfolios and returns on the big size stock portfolios, balanced so as to be neutral with respect to BE. An SMB observation is therefore a size premium:

$$SMB = \frac{(S/L-B/L)+(S/M-B/M)+(S/H-B/H)}{3} \tag{4.4}$$

Similarly, the HML factor (High minus Low) is the equally-weighted average of the difference between the returns on the high book-to-market stock portfolios minus the returns on the low book-to-market stock portfolios, balanced so as to be neutral with respect to size. An HML observation is therefore a book-to-market premium:

$$HML = \frac{(S/H - S/L) + (B/H - B/L)}{2} \tag{4.5}$$

4.3.2.3 Construction of the 25 Test Portfolios

Instead of individual stock returns, the test assets are 25 portfolios simultaneously sorted by size and book-to-market ratio (size-BE/ME). This portfolio grouping both reduces the noise generated from individual stocks and helps to generate normally distributed portfolio returns. Following Cochrane (2001), test assets should have stationary returns, which is more likely for portfolios than for stocks because individual stocks change character over time. Fama and MacBeth (1973) sort and pool portfolios so as to the minimize error-in-variables problem of measuring betas while maintaining considerable cross-sectional variation of betas. In addition, since the Fama-French size-BE/ME portfolios have become a benchmark in tests of asset pricing models, using 25 size-BE/ME portfolios makes it easier to compare results of this study with others.

The 25 portfolios are constructed following Fama and French (1993, 1996). In each year, stocks are sorted into five size and five book-to-market groups respectively, using data from the previous year. The 25 portfolios are constructed by finding the intersection between each size and book-to-market group – the intersection of the smallest size (S1) and lowest book-to-market (B1) is identified as the S1B1 portfolio, and so on. The returns for the 25 portfolios are calculated using the weighted sum of month-end dividend-adjusted returns for (i) all companies (total market capitalisation or float-adjusted market capitalisation) and (ii) all companies excluding financial firms and special treatment firms (total market capitalisation or float-adjusted market capitalisation) quoted on the Shanghai and Shenzhen Stock Exchanges. The tested asset return is the 25 size-BE/ME sorted portfolio return minus the risk-free rate measured by the 3-month bank deposit rate.

4.3.2.4 Summary Statistics of the Fama-French Factors

Summary statistics on the distribution of the risk factors are presented in this section. The results are compared with those reported in the literature for the USA, Asia and China. Panel A in Table 4.2 presents summary statistics for the Fama-French factors obtained in the Chinese stock markets, using both A (TMV and LMV) and B (TMV and LMV) datasets, and compares them to statistics obtained for the US. Statistics for the data used in this research are presented in boldface. Total market value and listed market value are used not only in sorting stocks for constructing the size portfolios, but also in calculating the portfolio value-weights for SMB and HML.

The average monthly market premium is 1.13%, corresponding to 14.48% annually. This is higher than the historical premium observed in the United States and reflects the rapid growth of the Chinese economy. The 8.04% standard deviation is higher than for the US. This result is reasonable because the Chinese stock market, as an emerging financial market, may be less stable.

Over the 1997-2007 periods, the average monthly returns are positive for both SMB and HML, which is consistent with the suggestions of both a size effect and a book-to-market (distress) effect. The size effect is evidently greater for total market equity. In both Sets A and B, SMB returns are smaller when measured by listed market capitalization than when measured by total market capitalization. Standard deviations do not differ very much between the sets. SMB premiums are higher in Set A than in Set B. Because Set A includes stocks with ST and S marks, negative book equity, and stocks in financial industries, this result suggests that investors require a higher premium on small stocks of ‘abnormal’ companies (companies with special treatment and negative book equity are possibly those with higher distress risk).

Table 4.2 Summary Statistics of the Fama-French Factor Returns, 1997-2007

r_M are monthly excess market returns obtained from the value-weighted S&P/CITIC market index return minus the monthly return on a risk-free asset obtained from the 3-month bank deposit rate. SMB is the difference between monthly returns on small size stocks and big size stocks. HML is the difference between monthly returns on high book-to-market and low book-to-market portfolios. The *t*-statistic (mean) is the mean of the monthly returns (mean) divided by its standard error. Set A includes data from all listed firms except those with less than one year of listing. Set B excludes data with special treatment firms, negative book value firms and financial firms. TMV in each set denotes measurement of market capitalization by total market equity, and LMV in each set denotes measurement of market capitalization by float-adjusted market equity.

Panel A	**Market**	**Period**	r_M	**SMB**	**HML**
Set A(TMV)	**China**	**1997-2007**			
Mean			**1.133**	**0.648**	**0.496**
S.D			**8.045**	**4.636**	**4.217**
t(mean)			**1.618**	**1.606**	**1.351**
Set A(LMV)	**China**	**1997-2007**			
Mean			**1.133**	**0.582**	**0.559**
S.D			**8.045**	**4.685**	**4.009**
t(mean)			**1.618**	**1.428**	**1.601**
Set B(TMV)	**China**	**1997-2007**			
Mean			**1.133**	**0.421**	**0.419**
S.D			**8.045**	**3.778**	**4.452**
t(mean)			**1.618**	**1.281**	**1.082**
Set B(LMV)	**China**	**1997-2007**			
Mean			**1.133**	**0.158**	**0.667**
S.D			**8.045**	**4.269**	**4.596**
t(mean)			**1.618**	**0.424**	**1.669**
Yu (2001)	China	1995-2000			
Mean			1.629	1.200	1.144
S.D			9.633	3.268	5.091
Deng and Ma (2005)	China	2000-2003			
Mean			0.794	0.373	0.603
S.D.			10.327	4.417	4.296
Fama-French (1996)	USA	1964-1993			
Mean			0.495	0.41	0.528
S.D			4.714	4.457	3.785
Davis *et al.* (2000)	USA	1929-1997			
Mean			0.67	0.20	0.46
S.D			5.75	3.26	3.11

The book-to-market premiums seem to be less affected by sample selection and the measurement of market capitalization. HML is higher when market capitalization is measured by listed values (LMV) in both sets. The HML premium is the biggest in Set B (LMV), when negative BE firms are excluded. Again, the standard deviations and *t*-statistics (mean)[27] do not differ very much between data sets. These patterns of SMB and HML across sample sets provide an initial sign that size premium is better measured in Set A and total market value, while distress premium is better measured in Set B and listed market value.

The results found here may be more reliable than other published results for the Chinese stock market, because Yu (2001) used data from 1995, before the price limit regime was adopted, while Deng and Ma (2005) employed only four years of data (2000-2003). The results found here are generally consistent with empirical evidence from the US. The annualized size premiums in Chinese equity markets are almost all higher than that found for the US by Fama and French (1996). The annualized book-to-market premium in China is similar to that of the US. The SMB and HML standard deviations are much lower than the market premium standard deviation, suggesting that the SMB and HML factors are less risky than the market index.

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[27] The *t* (mean) statistic is the mean of the monthly returns (mean) divided by its standard error.

Table 4.3 Correlations between the Fama-French Factor Returns, 1999-2007

This table reports correlations between the Fama-French factors. Panel A reports the correlations where Market capitalization is measured by total market value. Panel B is the case that Market capitalization is measured by float-adjusted market value.

		r_M	SMB	HML
Panel A: Total Market Value				
	r_M	1.000		
Set A	**SMB**	0.234^{T**}	1.000	
	HML	0.205^{T*}	0.231^{T**}	1.000
	r_M	1.00		
Set B	**SMB**	0.137^{T}	1.000	
	HML	0.197^{T*}	0.239^{T**}	1.000
Panel B: Listed (free float) Market Value				
	r_M	1.000		
Set A	**SMB**	0.107^{L}	1.000	
	HML	0.178^{L*}	0.397^{L**}	1.000
	r_M	1.00		
Set B	**SMB**	-0.064^{L}	1.000	
	HML	0.197^{L*}	0.204^{L*}	1.000

**Significant at a 99% confidence level;

*Significant at a 95% confidence level.

Table 4.4 Stationary Test of the Fama-French Factor Returns, Jan. 1997-Dec. 2007

This table displays the results of ADF unit root tests of stationarity, with the corresponding probabilities listed on the right side.

	ADF Statistic				Prob.			
	SATMV	SALMV	SBTMV	SBLMV	SATMV	SALMV	SBTMV	SBLMV
r_M	-9.523	-9.523	-9.523	-9.523	0.000	0.000	0.000	0.000
SMB	-8.003	-8.548	-8.170	-8.203	0.000	0.000	0.000	0.000
HML	-11.050	-9.605	-10.023	-10.252	0.000	0.000	0.000	0.000

Table 4.3 presents the correlations between the three factors. SMB and HML show low but significant correlation with the market premium: most of the correlations are significant at the 95% or 99% confidence level. The low correlations between the factors are in line with expectations that they don't have multicollinearity problem, so the three factors can be used together as regressors in the asset pricing model. Table 4.4 presents unit root test results for each factor and shows that none has a unit root. They are therefore all considered to be stationary series, consistent with other published

research.

4.3.3. Regression Results

4.3.3.1 Patterns of Risk Exposures on the Fama-French Factors

This section reports the pattern of the estimated factor loadings from the first-pass time-series regressions on contemporaneous market excess returns and the SMB and HML factors from Equation (4.2)

$$r_{i,t} = \alpha_i + \beta_{M,i} r_{M,t} + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + e_{i,t}$$

This step consists of running 25 time-series regressions of the 25 size and book-to-market sorted portfolio excess returns on the excess market return and the SMB and HML factors, with robust standard errors using the Newey-West method with 4 lags to control for possible serial correlation and heteroskedasticity. The estimated parameters are the alpha and the three betas, which represent the constant term, and sensitivities of the portfolio returns to the market risk, size risk and distress risk.

Table 4.5 presents sensitivities of the 25 size-BE/ME portfolios to the three Fama-French factors for the period January 1997 to December 2007, with the corresponding *t*-statistics in square brackets below the estimators. The estimation is repeated four times with application to the four data sets. Consistent with the literature (Fama and French, 1993; Petkova, 2006), loadings on all three factors are significant. Of these, loadings on excess market returns are the most significant and loadings on HML are the least significant. The results are robust across the four data sets.

Table 4.5 Factor Loadings on the Fama-French Factors.

The table reports the 25 size and book-to-market sorted portfolios returns' sensitivities to the Fama-French three factors (excess market return, small-minus-big, and high BE/ME-minus-low Be/ME). Factor loading beta estimators are computed in the OLS time-series regressions with controlling of possible serial correlation and Heteroskedasticity using Newey-West consistent covariance with 4 lags. The corresponding *t*-statistics are presented in square brackets below the beta coefficients. The table includes four panels. Each part reports the results from same approach but differing in sample set selection: with Set A TMV, Set A LMV, Set B TMV and Set B LMV in panel A, B, C and D, respectively. The adjusted R-squareds and the F-statistics (which test under the hypothesis that all betas are jointly equal to zero) for each regression are presented below the beta estimators.

Panel A: SATMV **Regression:** $r_{i,t} = \alpha_i + \beta_{i,M} r_{M,t} + \beta_{i,SMB} R_{SMB,t} + \beta_{i,HML} R_{HML,t} + \varepsilon_{i,t}$

	Constant					β_M				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	1.975***	1.150***	0.997***	0.750***	1.287***	0.982***	1.030***	1.034***	1.026***	1.168***
	[4.117]	[2.872]	[3.965]	[2.797]	[4.600]	[10.328]	[18.378]	[14.673]	[24.689]	[15.363]
2	1.546***	1.196***	1.470***	1.007***	1.076***	0.958***	1.020***	1.129***	1.064***	1.007***
	[6.184]	[4.960]	[4.683]	[3.937]	[4.205]	[17.441]	[25.067]	[20.154]	[35.595]	[17.563]
3	1.530***	0.969***	0.892***	1.050***	1.041***	1.059***	1.019***	1.006***	1.059***	1.009***
	[6.199]	[4.247]	[3.098]	[4.674]	[3.759]	[22.243]	[34.061]	[24.958]	[23.544]	[21.222]
4	1.432***	1.181***	0.899***	1.541***	1.124***	1.032***	1.040***	1.147***	1.026***	1.009***
	[6.764]	[5.713]	[3.665]	[2.879]	[4.395]	[24.307]	[44.040]	[16.303]	[12.892]	[28.046]
High	1.552***	0.868***	0.697***	0.966***	1.568***	1.059***	1.020***	1.063***	1.049***	1.001***
	[4.728]	[3.538]	[3.154]	[4.267]	[5.498]	[17.014]	[24.485]	[23.099]	[25.353]	[19.498]
	β_{SMB}					β_{HML}				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	1.065***	0.929***	0.576***	0.345***	-0.390***	-0.228	-0.337***	-0.244*	-0.407***	-0.551***
	[7.452]	[12.618]	[6.430]	[5.910]	[-4.265]	[-1.185]	[-3.514]	[-1.903]	[-4.948]	[-5.346]
2	0.946***	0.554***	0.481***	0.175***	-0.594***	-0.064	-0.041	-0.174**	-0.081	-0.410***
	[16.104]	[6.647]	[7.690]	[2.369]	[-9.591]	[-0.500]	[-0.282]	[-2.341]	[-0.978]	[-3.421]
3	1.111***	0.746***	0.466***	0.259***	-0.226*	0.026	0.208***	0.153*	0.062	0.286***
	[11.744]	[17.799]	[4.059]	[4.017]	[-1.895]	[0.242]	[3.109]	[1.693]	[0.743]	[4.117]
4	0.776***	0.650***	0.496***	0.323***	-0.279***	0.219**	0.295***	0.330***	0.360***	0.303***
	[12.114]	[16.665]	[6.873]	[3.130]	[-3.635]	[2.481]	[4.462]	[4.560]	[3.062]	[4.313]
High	0.779***	0.635***	0.427***	0.456***	0.961***	0.358***	0.521***	0.523***	0.530***	0.192*
	[12.722]	[12.621]	[6.668]	[5.906]	[11.758]	[3.457]	[7.499]	[7.716]	[6.495]	[1.894]
	Adj.-R^2					***F-Statistics***				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	0.815	0.882	0.888	0.904	0.893	193.444***	327.771***	346.613***	411.190***	366.505***
2	0.901	0.900	0.896	0.906	0.886	397.558***	395.294***	376.881***	421.370***	339.518***
3	0.915	0.953	0.882	0.910	0.875	468.314***	887.396***	326.771***	444.220***	305.615***
4	0.926	0.964	0.945	0.706	0.900	544.526***	1162.818***	758.258***	105.673***	393.325***
High	0.911	0.949	0.946	0.936	0.904	446.252***	809.226***	766.606***	644.870***	413.946***

Table 4.5 (cont.)

Panel B: SALMV **Regression:** $r_{i,t} = \alpha_i + \beta_{i,M} r_{M,t} + \beta_{i,SMB} R_{SMB,t} + \beta_{i,HML} R_{HML,t} + \varepsilon_{i,t}$

	Constant					$\boldsymbol{\beta_M}$				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	1.752***	0.834**	0.561**	1.021***	1.365***	0.971***	1.095***	0.990***	1.051***	1.194***
	[5.638]	[2.425]	[2.075]	[3.151]	[4.230]	[17.307]	[14.633]	[12.317]	[20.775]	[14.038]
2	0.997***	1.130***	1.524***	1.031***	0.976***	1.043***	1.058***	1.121***	1.083***	0.984***
	[3.375]	[5.437]	[5.274]	[4.516]	[4.143]	[17.002]	[19.817]	[26.213]	[30.530]	[23.299]
3	1.240***	0.807***	0.640**	1.012***	1.003***	1.105***	1.080***	1.041***	1.066***	1.053***
	[5.057]	[3.867]	[2.433]	[4.065]	[3.464]	[19.287]	[18.894]	[26.630]	[22.182]	[21.762]
4	0.981***	1.293***	0.873***	1.028***	1.416***	1.002***	1.092***	1.092***	1.156***	1.034***
	[4.530]	[6.836]	[5.021]	[4.431]	[3.773]	[28.241]	[29.591]	[25.115]	[17.854]	[16.734]
High	1.342***	0.888***	0.941***	0.483**	1.129***	1.074***	1.071***	1.067***	1.042***	0.991***
	[2.845]	[3.771]	[4.716]	[2.286]	[4.684]	[16.094]	[19.007]	[22.449]	[23.829]	[27.255]
	$\boldsymbol{\beta_{SMB}}$					$\boldsymbol{\beta_{HML}}$				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	1.211***	0.860***	0.469***	0.233***	-0.447***	-0.451***	-0.246**	-0.357***	-0.364***	-0.429***
	[16.446]	[7.643]	[4.711]	[3.626]	[-3.779]	[-4.239]	[-2.164]	[-2.928]	[-3.832]	[-3.023]
2	0.999***	0.629***	0.262***	0.163**	-0.504***	-0.282**	-0.091	0.005	-0.197**	-0.393***
	[9.079]	[8.315]	[3.874]	[2.454]	[-7.145]	[-2.064]	[-1.116]	[0.047]	[-2.442]	[-3.895]
3	0.927***	0.715***	0.503***	0.187**	-0.330***	0.169	0.131*	0.086	0.105	0.294***
	[15.422]	[9.460]	[5.560]	[2.450]	[-3.081]	[1.363]	[1.677]	[0.744]	[1.044]	[3.174]
4	0.851***	0.621***	0.440***	0.086	-0.335***	0.274***	0.218***	0.264***	0.339***	0.469***
	[17.715]	[11.281]	[6.094]	[0.746]	[-5.384]	[3.559]	[3.510]	[4.449]	[4.374]	[2.792]
High	1.040***	0.679***	0.408***	0.290***	0.978***	0.225	0.547***	0.654***	0.559***	-0.026
	[5.824]	[11.263]	[5.238]	[3.573]	[18.582]	[1.465]	[7.086]	[9.549]	[7.508]	[-0.321]
	Adj.-R^2					***F-Statistics***				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	0.881	0.849	0.858	0.863	0.866	324.201***	246.288***	264.701***	276.295***	282.874***
2	0.888	0.911	0.891	0.915	0.908	347.298***	446.410***	359.043***	471.982***	432.300***
3	0.907	0.933	0.899	0.899	0.895	427.225***	609.265***	388.418***	387.836***	372.097***
4	0.933	0.948	0.950	0.914	0.786	613.022***	799.854***	836.097***	467.623***	161.499***
High	0.785	0.928	0.944	0.935	0.936	160.838***	562.854***	740.926***	625.747***	636.828***

Table 4.5 (cont.)

Panel C: SBTMV **Regression:** $r_{i,t} = \alpha_i + \beta_{i,M} r_{M,t} + \beta_{i,SMB} R_{SMB,t} + \beta_{i,HML} R_{HML,t} + \varepsilon_{i,t}$

	α					***β***				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	1.585***	1.170***	1.039***	0.856***	1.180***	0.929***	1.013***	1.089***	1.054***	1.188***
	[4.936]	[2.718]	[3.987]	[3.075]	[3.988]	[13.471]	[18.426]	[14.651]	[20.082]	[13.094]
2	1.483***	1.316***	1.294***	0.878***	1.127***	1.004***	1.082***	1.039***	1.125***	1.012***
	[5.380]	[4.544]	[5.199]	[3.024]	[3.736]	[18.807]	[24.724]	[24.428]	[23.876]	[17.474]
3	1.296***	1.111***	1.169***	1.155***	1.368***	1.071***	1.025***	1.019***	1.092***	1.030***
	[4.373]	[4.399]	[3.594]	[4.768]	[4.887]	[18.945]	[23.161]	[31.252]	[26.276]	[21.600]
4	1.582***	1.266***	0.721***	1.756***	1.225***	1.064***	1.044***	1.184***	1.026***	0.984***
	[6.418]	[6.619]	[3.134]	[2.659]	[4.967]	[35.105]	[41.163]	[20.350]	[9.942]	[29.967]
High	1.706***	0.976***	0.771***	1.184***	1.554***	1.123***	1.039***	1.110***	1.055***	0.998***
	[5.479]	[4.232]	[4.142]	[5.141]	[4.247]	[17.352]	[24.206]	[23.286]	[26.970]	[23.559]
	β_{SMB}					β_{HML}				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	1.077***	0.828***	0.459 ***	0.287***	-0.456***	0.033	-0.211	-0.124	-0.287**	-0.575***
	[6.966]	[5.796]	[3.774]	[2.892]	[-4.151]	[0.178]	[-1.604]	[-0.649]	[-2.295]	[-5.396]
2	1.031***	0.598***	0.444***	0.141	-0.532***	0.111	0.045	-0.083	-0.002	-0.232*
	[7.743]	[4.666]	[5.008]	[1.268]	[-6.853]	[0.833]	[0.359]	[-0.753]	[-0.019]	[-1.800]
3	1.106***	0.766***	0.340***	0.291***	-0.410***	0.201*	0.372***	0.135*	0.093	0.218**
	[10.042]	[11.129]	[3.013]	[3.374]	[-3.857]	[1.751]	[4.014]	[1.732]	[0.859]	[2.584]
4	0.892***	0.641***	0.470 ***	0.403**	-0.462***	0.348***	0.362***	0.469***	0.319***	0.264***
	[9.459]	[11.245]	[7.070]	[2.167]	[-6.236]	[5.412]	[7.315]	[6.497]	[2.977]	[3.977]
High	0.738***	0.672***	0.373***	0.361***	0.872***	0.487***	0.664***	0.557***	0.613***	0.276***
	[9.217]	[8.835]	[4.407]	[4.398]	[7.530]	[6.098]	[11.487]	[7.509]	[8.583]	[2.970]
	Adj.-R^2					***F-Statistics***				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	0.811	0.832	0.876	0.868	0.882	188.495***	217.661***	308.752***	287.008***	326.392***
2	0.901	0.905	0.906	0.882	0.876	398.049***	418.345***	420.039***	328.815***	309.875***
3	0.923	0.920	0.875	0.904	0.869	526.110***	504.443***	306.275***	414.337***	291.082***
4	0.929	0.955	0.943	0.596	0.897	570.643***	928.886***	728.575***	65.290***	383.233***
High	0.916	0.952	0.943	0.928	0.880	477.753***	863.231***	727.287***	561.037***	320.638***

Table 4.5 (cont.)

Panel D: SBLMV **Regression:** $r_{i,t} = \alpha_i + \beta_{i,M} r_{M,t} + \beta_{i,SMB} R_{SMB,t} + \beta_{i,HML} R_{HML,t} + \varepsilon_{i,t}$

	α					***β_M***				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	2.081***	2.165***	1.998***	1.986***	1.782***	0.925***	0.977***	1.009***	0.998***	1.079***
	[3.169]	[2.836]	[3.033]	[2.908]	[3.077]	[9.355]	[9.178]	[9.665]	[11.267]	[7.778]
2	1.749***	2.194***	2.329***	1.648***	1.645**	1.001***	1.099***	1.047***	0.977***	0.944***
	[2.938]	[3.482]	[2.952]	[2.886]	[2.605]	[9.461]	[9.647]	[11.153]	[9.697]	[8.548]
3	1.958***	1.935**	2.051***	1.941***	1.908***	1.057***	1.054***	1.089***	1.013***	0.956***
	[3.293]	[2.467]	[3.114]	[2.674]	[3.133]	[10.293]	[12.941]	[11.233]	[9.694]	[10.519]
4	1.617***	2.568***	1.738**	1.784***	2.310***	1.009***	0.970***	0.993***	1.045***	0.893***
	[2.788]	[2.853]	[2.056]	[2.960]	[3.218]	[12.828]	[7.417]	[11.071]	[9.444]	[7.672]
High	1.610**	1.810***	2.125***	1.623***	1.902***	1.069***	1.104***	0.998***	1.010***	0.974***
	[2.502]	[2.850]	[2.796]	[2.687]	[2.989]	[13.892]	[11.665]	[11.066]	[10.349]	[12.324]
	β_SMB					***β_HML***				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	0.905***	0.376**	0.170	0.064	-0.533***	0.120	0.037	-0.139	-0.129	-0.464***
	[4.755]	[2.026]	[1.150]	[0.491]	[-3.727]	[0.586]	[0.275]	[-0.887]	[-1.230]	[-2.985]
2	0.911***	0.524***	0.050	0.067	-0.521***	0.251	0.335**	0.137	0.117	-0.022
	[4.791]	[3.381]	[0.193]	[0.457]	[-3.610]	[1.223]	[2.585]	[1.240]	[0.745]	[-0.103]
3	0.747***	0.456*	0.362**	0.037	-0.412**	0.469***	0.320***	0.252*	0.231	0.228**
	[3.629]	[1.789]	[2.043]	[0.222]	[-2.525]	[3.351]	[2.785]	[1.716]	[1.392]	[2.093]
4	0.798***	0.580***	0.320*	0.033	-0.458**	0.503***	0.370***	0.388***	0.368***	0.502**
	[5.209]	[3.312]	[1.826]	[0.155]	[-2.564]	[5.665]	[3.799]	[3.213]	[2.979]	[2.028]
High	0.705***	0.558***	0.480***	0.234	0.927***	0.544***	0.586***	0.651***	0.553***	0.284
	[3.773]	[3.306]	[2.854]	[1.466]	[4.733]	[4.796]	[7.582]	[5.020]	[4.342]	[1.625]
	Adj.-R^2					***F-Statistics***				
	Small	2	3	4	Large	Small	2	3	4	Large
Low	0.591	0.544	0.636	0.657	0.707	64.058***	53.142***	77.219***	84.618***	106.482***
2	0.670	0.696	0.532	0.644	0.613	89.601***	101.034***	50.723***	79.957***	70.194***
3	0.639	0.584	0.658	0.625	0.685	78.322***	62.359***	84.969***	73.667***	95.864***
4	0.736	0.531	0.646	0.631	0.549	122.853***	50.507***	80.853***	75.551***	54.168***
High	0.717	0.753	0.681	0.715	0.696	111.444***	134.118***	94.046***	110.709***	100.809***

[*] Significant at a 90% confidence level.

[**] Significant at a 95% confidence level.

[***] Significant at a 99% confidence level.

The constant term (alpha) is significantly positive across all portfolios and for the four data sets. The positive alpha is inconsistent with the common expectation of zero alpha restriction but is not surprising, given that the risk-free rate of return used in this study is the three-month bank deposit rate instead of some market rate of return. Although this risk-free asset is selected for good reasons, it has to be acknowledged that the bank deposit rate does not price liquidity and it is therefore possible to conjecture that the zero-beta rate may be higher than the 3-month bank deposit rate, leading to the positive estimated constant term. There is no other systematic pattern for the constant term across the portfolios.

Like Fama-French, all portfolios have slopes close to 1.0 on the excess market returns. For most portfolios, the market risks of greater than 1.0 indicate that returns of the 25 size and book-to-market sorted portfolios are more volatile than the aggregate market returns. There is a striking finding that is true for the four data sets: the portfolios formed by the smallest and lowest book-to-market stocks always report the market risk exposures of smaller than 1, which lead the suggestion that small size stocks and health stocks are less sensitive to the aggregate market.

The slopes on SMB are systematically related to portfolio size, suggesting size effects in the cross-sectional valuation of asset returns. That is to say, for the same level of book-to-market ratio, portfolios with small size stocks are more sensitive to SMB than portfolios with large size stocks, thus producing greater factor loadings. Similarly, the loadings on HML appear to show distress effects since in each size group the HML slopes increase monotonically from negative to positive values. Fama and French suggested that the HML factor captures information about the fundamentals of firms, such as earnings to price ratio (E/P), cash flow to price ratio (C/P), past sales and past returns. Firms with higher book-to-market ratios are those more likely to default, as they have poor records of past sales and returns and low cash flows and earnings. In their 1996 paper Fama and French also consider some irrational reasons for the insignificance of HML. Nevertheless, the factor loadings on

HML are the least significant of the explanatory variables. This may reflect the fact that most listed firms in China are state-owned companies, which have less default and distress probability as they have the government as backer of last resort – therefore the distress risk is of less concern to investors.

4.3.3.2 Diagnostic Checking of the Fama-French Factor Loading Estimations

The adjusted R-squared statistics are quite high and indicate that the Fama-French three factor model is a good fit to Chinese stock market data. The F-statistics are throughout significant at the 99% confident level, which implies a strong rejection of the hypothesis that all betas are jointly equal to zero. Given these regression results, the Fama-French model seems to work well in explaining asset prices in Chinese stock markets. On the other hand, diagnostic tests of the residuals suggest a degree of failure of the standard Fama-French model. The diagnostic tests for residual normality, serial correlation with one lag and heteroskedasticity are reported in Panels A, B and C of Table 4.6. Panel D of Table 4.6 provides results from Ramsey RESET tests.

The normality test is given by the Jarque-Bera (Jarque and Bera, 1987) statistics. As shown in Panel A in each part of Table 4.6, the estimated errors in the Fama-French model time-series regressions strongly reject a hypothesis of normally distributed residuals. This indicates that the standard Fama-French model cannot fully capture the 25 stock portfolio returns and therefore leaves some unexplained components of returns, such as the irregular returns in strong booming or adverse periods. The serial correlation of residuals is tested using the Lagrange multiplier (LM) text (Godfrey, 1978) for second- and first-order autocorrelation. The second-order tests are all insignificant but the first-order tests find some autocorrelation. Consequently, only the first-order LM tests results are reported. However, for most of the portfolios, the residuals are free of serial correlation.

Table 4.6 Diagnostic Checking and Specification of the Factor Loading Estimates of the Fama-French model.

Table 4.6a Diagnostic and Specification Checking for Set A Total Market Value

Panel A: Normality Jarque-Bera Test

	Small	2	3	4	Big
Low	321.697***	433.774***	132.826***	6.492**	106.045***
	[0.000]	[0.000]	[0.000]	[0.039]	[0.000]
2	52.175***	468.381***	1763.699***	13.644***	50.432***
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
3	973.350***	20.959***	251.682***	57.478***	65.013***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
4	19.394***	14.223***	303.332***	33413.880***	23.824***
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]
High	30.852***	58.736***	21.633***	82.626***	157.769***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Panel B: Serial Correlation LM (1) Test

	Small	2	3	4	Big
Low	3.611*	2.548	0.116	3.054*	2.075
	[0.060]	[0.113]	[0.734]	[0.083]	[0.152]
2	10.134***	12.184***	11.225***	0.006	2.102
	[0.002]	[0.001]	[0.001]	[0.937]	[0.150]
3	0.012	1.358	0.024	0.675	0.012
	[0.914]	[0.246]	[0.878]	[0.413]	[0.914]
4	1.400	5.576**	1.679	1.314	3.032*
	[0.239]	[0.020]	[0.197]	[0.254]	[0.084]
High	2.548	7.288***	2.204	2.773*	0.078
	[0.113]	[0.008]	[0.140]	[0.098]	[0.781]

Panel C: White Test of Heteroskedasticity

	Small	2	3	4	Big
Low	16.613***	1.874*	11.117***	5.709***	16.540***
	[0.000]	[0.062]	[0.000]	[0.000]	[0.000]
2	4.674***	4.808***	0.920	3.051***	12.590***
	[0.000]	[0.000]	[0.510]	[0.003]	[0.000]
3	1.357	2.706***	2.656***	3.051***	8.130***
	[0.215]	[0.007]	[0.008]	[0.003]	[0.000]
4	8.070***	2.278**	24.035***	0.668	2.549**
	[0.000]	[0.021]	[0.000]	[0.736]	[0.010]
High	5.709***	3.051***	0.668	3.775***	2.306**
	[0.000]	[0.003]	[0.736]	[0.000]	[0.020]

Panel D: RESET Test

	Small	2	3	4	Big
Low	16.162***	14.704***	20.173***	14.816***	63.318***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
2	0.016	1.223	7.165***	1.011	15.435***
	[0.900]	[0.271]	[0.008]	[0.317]	[0.000]
3	4.511**	2.126	7.720***	10.097***	0.530
	[0.036]	[0.147]	[0.006]	[0.002]	[0.468]
4	0.010	12.596***	22.395***	0.767	2.011
	[0.919]	[0.001]	[0.000]	[0.383]	[0.159]
High	0.395	1.218	14.816***	18.356***	0.007
	[0.531]	[0.272]	[0.000]	[0.000]	[0.934]

Table 4.6b Diagnostic and Specification Checking for Set A Listed Market Value

Panel A: Normality Jarque-Bera Test

	Small	2	3	4	Big
Low	94.766***	894.179***	128.459***	28.289***	44.988***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
2	38.619***	256.240***	854.550***	16.160***	49.057***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
3	271.19***	138.25***	70.568***	30.450***	58.363***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
4	7.485**	9.445***	36.420***	154.586***	15101***
	[0.024]	[0.009]	[0.000]	[0.000]	[0.000]
High	2112.49***	35.414***	83.094***	9.236**	15.630***
	[0.000]	[0.000]	[0.000]	[0.010]	[0.000]

Panel B: Serial Correlation LM (1)

	Small	2	3	4	Big
Low	3.763***	14.950***	1.111	0.263	0.276
	[0.055]	[0.000]	[0.294]	[0.609]	[0.601]
2	0.176	7.569***	2.989*	0.221	0.035
	[0.675]	[0.007]	[0.086]	[0.639]	[0.851]
3	[0.000]	1.510	0.171	0.286	3.471*
	[0.991]	[0.124]	[0.680]	[0.594]	[0.065]
4	0.528	1.067	0.262	0.122	0.198
	[0.469]	[0.304]	[0.610]	[0.728]	[0.657]
High	0.026	0.095	0.006	3.436*	0.177
	[0.871]	[0.758]	[0.937]	[0.066]	[0.674]

Panel C: Heteroskedasticity White Test

	Small	2	3	4	Big
Low	0.993	6.762***	15.005***	1.143	27.682***
	[0.449]	[0.000]	[0.000]	[0.338]	[0.000]
2	11.208***	1.578	0.865	4.091***	14.671***
	[0.000]	[0.129]	[0.559]	[0.000]	[0.000]
3	22.372***	17.003***	6.779***	5.117***	7.763***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
4	2.251**	9.118***	17.680***	26.427***	1.266
	[0.023]	[0.000]	[0.000]	[0.000]	[0.262]
High	2.430**	5.016***	14.520***	6.044***	1.343
	[0.014]	[0.000]	[0.000]	[0.000]	[0.222]

Panel D: RESET Test

	Small	2	3	4	Big
Low	6.974***	20.483***	19.468***	21.001***	64.357
	[0.009]	[0.000]	[0.000]	[0.000]	[0.000]
2	0.366	9.134***	1.291	11.996***	14.86***
	[0.546]	[0.003]	[0.258]	[0.001]	[0.000]
3	13.750***	10.105***	16.948***	19.985***	5.717**
	[0.000]	[0.002]	[0.000]	[0.000]	[0.018]
4	0.336	20.148***	25.595***	18.516***	2.817*
	[0.563]	[0.000]	[0.000]	[0.000]	[0.096]
High	2.587	1.415	7.083***	7.035***	2.408
	[0.110]	[0.236]	[0.009]	[0.009]	[0.123]

Table 4.6c Diagnostic and Specification Checking for Set B Total Market Value

Panel A: Normality Jarque-Bera Test

	Small	2	3	4	Big
Low	80.104***	374.68***	186.25***	17.145***	477.27***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
2	175.19***	121.54***	36.619***	32.452***	64.38***1
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
3	48.968***	31.180***	308.87***	82.428***	34.314***
	[0.000]	[0.003]	[0.000]	[0.000]	[0.000]
4	87.007***	11.459	94.549***	35943. ***	4.702*
	[0.000]	[0.147]	[0.000]	[0.000]	[0.095]
High	217.76***	3.836***	37.449***	76.071***	60.261***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Panel B: Serial Correlation LM (1) Test

	Small	2	3	4	Big
Low	0.320	11.892***	0.245	1.309	2.727
	[0.573]	[0.001]	[0.621]	[0.255]	[0.101]
2	0.357	0.007	4.685**	1.111	6.946***
	[0.551]	[0.935]	[0.032]	[0.294]	[0.009]
3	2.493	0.343	0.656	0.013	0.018
	[0.117]	[0.559]	[0.420]	[0.908]	[0.894]
4	0.146	1.692	0.004	0.802	0.691
	[0.703]	[0.196]	[0.950]	[0.372]	[0.407]
High	2.413	12.444***	0.149	3.452*	0.140
	[0.123]	[0.001]	[0.700]	[0.066]	[0.709]

Panel C: Heteroskedasticity White Test

	Small	2	3	4	Big
Low	4.472***	8.942***	37.695***	3.638***	18.526***
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]
2	6.104***	5.456***	3.943***	2.264**	14.200***
	[0.000]	[0.000]	[0.000]	[0.022]	[0.000]
3	4.972***	4.366***	3.469***	10.314***	6.463***
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
4	1.039	1.275	16.163***	0.537	3.288***
	[0.413]	[0.257]	[0.000]	[0.845]	[0.001]
High	4.800***	7.812***	15.747***	3.768***	2.166
	[0.000]	[0.000]	[0.000]	[0.000]	[0.029]

Panel D: RESET Test

	Small	2	3	4	Big
Low	1.554	14.508***	37.838***	6.993***	64.016***
	[0.215]	[0.000]	[0.000]	[0.009]	[0.000]
2	10.346***	0.488	4.548**	7.141***	2.763*
	[0.002]	[0.486]	[0.035]	[0.009]	[0.099]
3	4.839**	11.980***	3.572*	10.049***	5.323**
	[0.030]	[0.001]	[0.061]	[0.002]	[0.023]
4	8.390***	13.550***	31.044***	2.429	0.180
	[0.004]	[0.000]	[0.000]	[0.122]	[0.673]
High	8.786***	15.580***	25.828***	7.121***	0.036
	[0.004]	[0.000]	[0.000]	[0.009]	[0.849]

Table 4.6d Diagnostic and Specification Checking for Set B Listed Market Value

	Panel A: Normality Jarque-Bera Test					**Panel B: Serial Correlation LM (1) Test**					
	Small	2	3	4	Big		Small	2	3	4	Big
Low	316.110***	493.128***	195.140***	301.101***	633.154***	Low	0.101	0.000	1.995	1.557	1.056
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		[0.751]	[0.994]	[0.160]	[0.214]	[0.306]
2	397.882***	299.834***	8893.84***	405.865***	994.305***	2	0.195	0.000	0.158	0.114	3.249
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		[0.660]	[0.990]	[0.692]	[0.736]	[0.074]
3	1404.27***	6629.2***	945.022***	945.430***	393.260***	3	1.397	0.486	0.606	2.712	1.209
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		[0.240]	[0.487]	[0.438]	[0.102]	[0.274]
4	893.686***	10473***	2691.92***	1142.21***	1890.33***	4	0.707	0.038	9.278***	0.888	0.053
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		[0.402]	[0.846]	[0.003]	[0.348]	[0.819]
High	586.503***	1302.65***	961.375***	811.823***	420.473***	High	4.062	0.585	2.520	0.453	2.534
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		[0.046]	[0.446]	[0.115]	[0.502]	[0.114]
	Panel C: Heteroskedasticity White Test					**Panel D: RESET Test**					
	Small	2	3	4	Big		Small	2	3	4	Big
Low	1.067	1.570	1.347	0.806	5.149***	Low	2.152	3.514*	7.214***	8.185***	31.462***
	[0.392]	[0.132]	[0.220]	[0.611]	[0.000]		[0.145]	[0.063]	[0.008]	[0.005]	[0.000]
2	1.182	1.035	1.122	1.100	0.920	2	1.860	7.166***	0.599	3.022*	4.038**
	[0.313]	[0.416]	[0.352]	[0.368]	[0.510]		[0.175]	[0.008]	[0.441]	[0.085]	[0.047]
3	0.916	1.110	0.828	1.491	1.369	3	1.482	2.744	3.588*	12.088***	2.777*
	[0.514]	[0.361]	[0.592]	[0.159]	[0.209]		[0.226]	[0.100]	[0.061]	[0.001]	[0.098]
4	1.491	1.762	0.799	1.439	1.270	4	1.821	9.812***	4.037**	7.443***	0.001
	[0.159]	[0.082]	[0.618]	[0.179]	[0.260]		[0.180]	[0.002]	[0.047]	[0.007]	[0.972]
High	1.359	1.322	0.555	0.756	1.331	High	6.364**	5.080**	1.918	2.723	1.989
	[0.214]	[0.232]	[0.832]	[0.657]	[0.228]		[0.013]	[0.026]	[0.169]	[0.101]	[0.161]

This table reports the descriptive statistics for residuals from the time-series regression of the Fama-French model. The first three resulting panels present the residual diagnostic statistics. Panel A reports the Jarque-Bera test of normality with the hypothesis that the estimated residuals are normally distributed; Panel B gives the first lag serial correlation LM test of residuals under the hypothesis that residuals are serially uncorrelated; Panel C shows the results of White tests of residual heteroskedasticity. Panel D reports the RESET test of model specification by adding square of the fitted value of portfolio excess returns from the regression as the omitted explanatory variable. F-statistics are reported with the corresponding probabilities in square brackets.

[*] Significant at a 90% confidence level.

[**] Significant at a 95% confidence level.

[***] Significant at a 99% confidence level.

The White tests reject the hypothesis of homoskedasticity for most portfolios in the first three samples. Heteroskedasticity may not seriously affect the coefficient estimates as the regressions are computed with consistent covariance matrices, but the results suggest that the standard Fama-French model does fail to capture possible time-variation in the variance of portfolio returns.

The Ramsey (1969) RESET test is a general test of this specification, and is run for each portfolio by adding the square of the fitted value of returns as the omitted variable (Panel D in each part of Table 4.6). In line with the results from the normality and homoskedasticity tests, the RESET tests reject the null hypothesis of no-mis-specification for most of the 25 size and book-to-market sorted portfolios. Overall, although the fit of the Fama-French model is very good, the residual diagnostic checks and misspecification tests indicate that the model fails to fully explain this sample of Chinese stock returns.

4.3.3.3 Time-varying Prices of Risks on the Fama-French Factor Loadings

The independent variables in the cross-sectional test are the estimated betas from the first pass time-series estimation in Equation (4.2). The estimated parameters (γ_i) are the prices of exposure to the three Fama-French factors. The equation is run for each year using the Generalized Method of Moments (GMM) estimation, in order to avoid problems of conditional heteroskedasticity in the joint distribution of returns and the three risk factors[28]. The cross-sectional model moment conditions are

[28] See Shanken and Zhou (2007) for the detailed discussion of the GMM estimation.

$$E\left[\varepsilon_i \otimes \begin{pmatrix}1\\ \boldsymbol{\beta}\end{pmatrix}\right] = E\begin{bmatrix}\bar{r}_i - \gamma_o - \boldsymbol{\gamma\beta} \\ (\bar{r}_i - \gamma_o - \boldsymbol{\gamma\beta}) \otimes \boldsymbol{\beta}\end{bmatrix} = 0$$

so that the estimated residuals have zero mean and no correlation with the factor loading betas. White's covariance matrix is used as the weighting matrix to make the estimation robust. There are four estimated parameters (γ_0, γ_M, γ_{SMB} and γ_{HML}) and four orthogonality restrictions (residuals have zero mean and residuals are uncorrelated with the three betas), therefore the overidentification restriction cannot be tested. Parameter estimates and adjusted R-squared statistics are presented in Table 4.7, for all four data sets.

Table 4.7 reveals that the annual average prices of risk are not constant over the tested periods, throughout the different sample sets. The adjusted R-squared statistics are very small and even negative in some years (1997, 2002, and 2006), which confirms that the model is a poor explanation of the cross-sectional variation of returns on Chinese A-shares stock portfolios in those years. In other years (1998, 2001 and 2003) a large proportion of variation in returns is successfully explained by the three-factor model.

The returns on the zero-beta asset (γ_0) are mostly insignificant, which should not be surprising because it is the excess returns that are to be explained. Prices of the Fama-French risks also show time-varying patterns. These time-varying patterns suggest more interesting results if considered together with Figure 3.3, the time plot of the market index.

Table 4.7 Annual Average Monthly Two-Pass Cross-sectional Prices on the Fama-French Factor Loadings.

This table presents Fama-MacBeth cross-sectional regressions using the annual average excess returns on 25 portfolios sorted by size and book-to-market. The variables of the 25 portfolio returns, SMB and HML are different in each sample set. In Set A, returns are calculated from all stocks listed in the Shanghai and Shenzhen stock exchanges. In Set B, firms with negative book-to-equity, special treatment stocks and firms from the financial industry are excluded. Within each set, weighted portfolio returns are calculated from total market capitalization (TMV) or listed market value (LMV). The independent variables in the regressions are the betas computed in the first-step OLS time-series regressions. The GMM estimates of the zero-beta returns and prices of risk associated with market risk, size risk and book-to-market risk are followed by the corresponding *t*-statistics in square brackets.

		γ_0	γ_M	γ_{SMB}	γ_{HML}	***Adj.R²***
1997	**Set A TMV**	0.317[0.097]	2.745[0.892]	0.989***[3.127]	0.232[0.363]	0.111
	Set A LMV	-4.789[-1.113]	7.181*[1.865]	0.613[1.544]	-0.426[-0.866]	0.059
	Set B TMV	3.539[1.099]	-0.172[-0.057]	0.517[1.634]	0.550[0.808]	-0.004
	Set B LMV	11.787**[2.193]	-0.529[-0.099]	-0.309[-0.472]	1.682[1.390]	-0.084
1998	**Set A TMV**	1.792[0.540]	-1.913[-0.634]	4.202***[8.405]	0.017[0.024]	0.770
	Set A LMV	4.023[1.257]	-3.970[-1.335]	3.393***[9.332]	0.239[0.459]	0.780
	Set B TMV	1.510[0.658]	-1.465[-0.686]	3.618***[13.324]	0.301[0.589]	0.845
	Set B LMV	3.144[1.703]	-2.865[-1.592]	3.720***[11.675]	-0.405[-0.766]	0.800
1999	**Set A TMV**	-5.863*[-1.800]	8.036**[2.667]	1.256***[3.349]	-0.861[-1.610]	0.355
	Set A LMV	-1.756[-0.531]	4.070[1.311]	0.641*[2.054]	-0.694[-1.453]	0.074
	Set B TMV	-5.863[-1.800]	8.036**[2.667]	1.256***[3.349]	-0.861[-1.610]	0.355
	Set B LMV	-0.508[-0.234]	3.287[1.500]	0.611*[2.034]	-1.101*[-2.076]	0.155
2000	**Set A TMV**	5.354*[2.018]	-0.960[-0.388]	2.921***[9.608]	0.339[0.699]	0.725
	Set A LMV	2.577[1.275]	1.777[0.972]	2.188***[8.741]	0.458[1.032]	0.723
	Set B TMV	7.507**[2.690]	-2.701[-1.018]	2.177***[5.372]	0.212[0.349]	0.571
	Set B LMV	0.501[0.167]	4.359[1.457]	1.890***[5.729]	0.127[0.153]	0.529
2001	**Set A TMV**	0.472[0.402]	-2.335**[-2.186]	0.582***[3.276]	0.353*[1.962]	0.488
	Set A LMV	2.835**[2.483]	-4.605***[-4.321]	0.746***[4.432]	0.722***[5.218]	0.611
	Set B TMV	0.371[0.374]	-2.169**[-2.445]	0.493***[3.172]	0.420***[2.963]	0.651
	Set B LMV	0.434[0.335]	-2.494*[-1.956]	0.839***[6.201]	0.646**[2.163]	0.577
2002	**Set A TMV**	1.243[0.840]	-2.383*[-1.761]	-0.249[-1.252]	-0.422*[-1.932]	0.113
	Set A LMV	-2.523[-1.317]	1.250[0.696]	-0.375[-1.563]	-0.100[-0.342]	-0.013
	Set B TMV	0.908[0.493]	-2.025[-1.194]	-0.270[-1.184]	-0.047[-0.166]	0.007
	Set B LMV	2.634[1.362]	-3.873*[-2.030]	-0.158[-0.799]	-0.016[-0.038]	0.039

		γ_0	γ_M	γ_{SMB}	γ_{HML}	***Adj.R²***
2003	**Set A**	4.637*[1.980]	-4.476*[-2.050]	-1.928***[-6.855]	1.802***[4.710]	0.741
	Set A	0.913[0.426]	-0.944[-0.471]	-1.686**[-7.716]	1.687***[5.330]	0.775
	Set B	4.376**[2.142]	-4.256**[-2.290]	-2.062***[-7.785]	2.009***[5.650]	0.788
	Set B	1.424[0.790]	-1.983[-1.133]	-2.271***[-9.993]	2.558***[8.129]	0.771
2004	**Set A**	-1.075[-0.945]	0.366[0.346]	-0.080[-0.592]	0.813***[4.467]	0.243
	Set A	-1.681[-0.835]	0.887[0.482]	0.143[0.639]	0.754***[2.889]	0.137
	Set B	0.211[0.172]	-0.769[-0.662]	-0.078[-0.521]	0.668**[2.461]	0.058
	Set B	-0.458[-0.328]	-0.212[-0.155]	-0.065[-0.343]	0.757*[1.976]	-0.005
2005	**Set A**	0.672[0.401]	-0.648[-0.425]	-0.362[-1.609]	-0.545**[-2.262]	0.246
	Set A	0.561[0.324]	-0.644[-0.403]	0.005[0.027]	-0.519*[-2.013]	0.041
	Set B	1.757[1.144]	-1.614[-1.152]	-0.017[-0.074]	-0.680**[-2.732]	0.174
	Set B	1.712[1.248]	-1.612[-1.191]	0.328[1.650]	-0.814***[-2.894]	0.090
2006	**Set A**	0.053[0.009]	7.416[1.456]	-1.027[-1.618]	0.516[0.542]	0.037
	Set A	4.282[0.994]	3.341[0.860]	-1.681***[-3.014]	0.329[0.495]	0.325
	Set B	2.236[0.424]	5.086[1.091]	-0.672[-1.117]	-0.027[-0.030]	-0.068
	Set B	6.497*[1.725]	0.946[0.261]	-2.550***[-4.062]	1.383[1.326]	0.462
2007	**Set A**	10.236[1.490]	0.779[0.124]	4.125***[4.257]	0.332[0.332]	0.592
	Set A	-6.595[-1.136]	16.870***[3.212]	3.125***[3.634]	1.413[1.520]	0.449
	Set B	15.378***[4.884]	-3.479[-1.234]	1.302**[2.270]	1.585**[2.256]	0.399
	Set B	3.142[0.815]	8.513**[2.205]	0.094[0.198]	2.244***[2.878]	0.279

Notes:

[*] indicates rejection of the null at the 10% significant level

[**] indicates rejection of the null at the 5% significant level

[***]indicates rejection of the null at the 1% significant level

Prices of market risks (γ_M) are not significant in some years (1998, 2004 and 2005) and are significant but negative in other years (2001-2003), rejecting the hypothesis of positive premiums for bearing more sensitivity to the aggregate market portfolio. The period of 2001 to 2003 was a period of market anxiety about the forthcoming non-tradable share reform. Thus it seems that the prices of market risks were negative in this period of uncertainty. But several years later (in 2004 and 2005) the uncertainty was dissipated and the cross-sectional variation of portfolio returns shows no premiums for bearing market risks. This time-varying market premiums show that the price for market risk is not positive and stable over time: it is subject to the bull and bear market regimes.

The size risk premiums are more important to portfolio returns than the market risk premiums and also exhibit time-varying patterns. They are independent of the contemporaneous market index but fluctuate – the prices of bearing size risks are high in 1998 but low in 1999, then high again in 2000 and low again in 2001. The prices became negative in 2003, and insignificant in 2002, 2004 and 2005, which shows that small size stocks did not always receive premiums against large size stocks. This finding is inconsistent with the expectation of the Fama-French model and the fundamental meaning of the size effect: that a premium is given for small size stocks.

The distress premiums are less significant in the first few years but become more important in later years of the sample period. They are also more significant in bear market periods. Again, the premiums on HML factor loadings are negative in 2005, after markets experience several years of downward movement. The negative distress premiums in 2005 indicate that stocks with low book-to-market ratios provide higher returns than high book-to-market stocks, which is against the theoretical expectation of distress risk.

To sum up, the prices for bearing fundamental market, size and distress risks should be positive and relatively stable over time if the traditional Fama-French model works successfully in Chinese markets. But the three Fama-French factor risk premiums are insignificant in some tested years and the prices always show time-varying patterns that appear to be linked to the contemporaneous market index: the prices of market risks are positive in up-market periods but negative in down-market periods; size risk premiums fluctuate over time; distress risk premiums are significant only in down-market periods. These findings are robust across data sets, not only challenging the explanatory power of the standard Fama-French factor models but also the theoretical 'fundamental' risks that the Fama-French factors represent. Overall these suggest the failure of the Fama-French model in Chinese stock markets.

4.3.4. The Effects of Market Capitalisation and Sample Selection

The estimated factor loadings on excess market returns, SMB and HML, and the adjusted R-squared values reported in Table 4.5 show some differences across the different samples. These differences are summarised in Table 4.8 and Table 4.9. Table 4.8 reports the summary statistics of the beta parameters. Table 4.9 presents the *t*-test on the difference in means. Results generated from Set A(TMV), Set A(LMV), Set B(TMV) and Set B(LMV) are presented together to compare the different effects when 'odd' stock are included or excluded, and when market capitalisation is measured in total form or listed form.

Generally, the Fama-French three factor model is a better fit to data when all listed stocks are included (Set A). The adjusted R-squared values do not differ much between the first three sample sets but it is surprising that the model fit is worst for Set B (LMV), when financial firms, firms with negative book values, and ST firms are excluded and the listed form capitalisation is used. The adjusted R-squareds have a relative high mean and the smallest volatility in Set A (LMV). Also, when listed market values are considered, the estimated residuals have fewer autocorrelation and heteroskedasticity problems (as shown in Table 4.6). This is especially true for Set B (LMV), where the model is robust to independence and homoskedasticity across all portfolios. An interesting result is that when listed market values are taken into account, the RESET tests are more likely to be significant, which indicates that the Fama-French model is misspecified and implies the need to consider omitted variables. Overall, these results suggest the estimates are more stable in sample set A when listed market values are applied.

Table 4.8 Summary Statistics for the sensitivities of the 25 size-BE/ME portfolios to the Fama-French Factors

This table summarises the descriptive statistics for the estimated factor loadings on the Fama-French factor from the first-pass time-series regression. The four resulting columns report summary statistics from the four data sets: Set A total market value, Set A listed market value, Set B total market value and Set B listed market value, respectively.

		SA (TMV)	SA(LMV)	SB(TMV)	SB(LMV)
β_M	Mean	1.041	1.062	1.056	1.012
	Maximum	1.168	1.194	1.188	1.104
	Minimum	0.958	0.971	0.929	0.893
	Std. Dev.	0.048	0.052	0.060	0.055
β_{SMB}	Mean	0.467	0.437	0.437	0.295
	Maximum	1.111	1.211	1.106	0.927
	Minimum	-0.594	-0.504	-0.532	-0.533
	Std. Dev.	0.451	0.482	0.479	0.447
β_{HML}	Mean	0.073	0.060	0.162	0.260
	Maximum	0.530	0.654	0.664	0.651
	Minimum	-0.551	-0.451	-0.575	-0.464
	Std. Dev.	0.315	0.333	0.305	0.263
Adj. R^2	Mean	0.900	0.897	0.887	0.645
	Maximum	0.964	0.950	0.955	0.753
	Minimum	0.706	0.785	0.596	0.531
	Std. Dev.	0.051	0.044	0.070	0.063

Factor loadings on excess market returns are not very distinct across sample sets. This is consistent with expectation since market returns are the same across sample sets (the S&P/CITIC A-share composite index weighted by the float-adjusted market value). The smallest mean market beta is in Set B (LMV), which is significantly different from the other three sample sets as shown in Table 4.9. This finding suggests that when float-adjusted market capitalisation is considered, financial firms and highly distressed stocks (those firms that are marked with special treatment and/or with negative book values) have higher volatilities than the aggregate market.

The slopes on HML are the strongest in Set B (LMV), which reveals that distress risk is better measured in terms of listed market value and, more importantly, when firms with negative book values are excluded from the sample (negative book values firms have strong distress probabilities but they will be ranked as the low book-to-market, in the other words, healthy firms). Set B excludes these firms, making the proxy for distress risk more meaningful.

Table 4.9 Tests on the Difference in Beta Means between Samples

This table reports the *t*-tests on the difference in the means of estimated betas between Set A (TMV), Set A (LMV), Set B (TMV) and Set B (LMV) with the null hypothesis that there is no difference between the parameter estimates. Each sample contains 25 observations that are the estimated factor loadings on the Fama-French three factors. The corresponding probabilities are reported in the square brackets below the *t*-statisitics.

Vs.	SA(TMV) SA(LMV)	SA(TMV) SB(TMV)	SA(TMV) SB(LMV)	SA(LMV) SB(TMV)	SA(LMV) SB(LMV)	SB(TMV) SB(LMV)
β_M	-1.522	-0.994	1.995*	0.404	3.348***	2.738***
	[0.135]	[0.325]	[0.052]	[0.688]	[0.002]	[0.009]
β_{SMB}	0.222	0.224	1.351	0.001	1.081	1.084
	[0.825]	[0.824]	[0.183]	[0.999]	[0.285]	[0.284]
β_{HML}	0.143	-1.016	-2.275**	-1.130	-2.352**	-1.213
	[0.887]	[0.315]	[0.027]	[0.264]	[0.023]	[0.231]

Notes:

* indicates rejection of the null at the 10% significant level

** indicates rejection of the null at the 5% significant level

*** indicates rejection of the null at the 1% significant level

On the other hand, loadings on SMB roughly show that a size effect is more pronounced in Set A than in Set B, and in TMV than in LMV although the differences are not significant. This implies that total market capitalisation is actually more likely to be used when investors evaluate size risk, because evaluations related to size, such as potential earnings, growth, economies of scale, etc. are dependent on actual operating size. Also, the effect in Set A is bigger when financial, negative book equity and ST firms are included, possibly because financial firms (especially banks) tend to be big, so that adding them to the sample enhances the relative performance of big firms.

4.3.5. Summary

This part provides an empirical study of the Fama-French three-factor model in Chinese A-share stock markets. Using monthly data from January 1997 to December 2007, the study finds a significant role for market, size and book-to-market equity in explaining portfolio returns on Chinese securities. However, although the regression estimates have good fit and joint significance, the model fails in some respects, as shown by diagnostic tests. The estimated residuals are non-normally distributed, with serial correlation and heteroskedasticity in some cases, and most of the regressions can imply the misspecification of the model.

Market risks are significant across portfolios, for all four data sets. Factor loadings on excess market returns are largest in Set A (LMV). Exposures on size risk exhibit a systematic pattern that is in line with the size risk statement, since small stocks have greater slopes on size premiums than big stocks. Comparing sample sets, size risks are stronger if weighting is by total market value. Loadings on HML are less significant than on the other two factors. To the extent that the HML slopes are significant, a pattern of distress risk is found since high book-to-market stocks show bigger distress betas than low book-to-market stocks. The HML risk factor is better constructed using listed market values and for Set B (without the noise generated by firms with negative book value of equity).

Based on these results, in the rest of the studies (the multi-beta asset pricing model, the sentiment-based conditional asset pricing model and the Markov-switching asset pricing model), I use only Set A data sample weighting by the listed market value for the 25 size-BE/ME sorted portfolios, Set A total market value for SMB and sample Set B listed market value for HML.

Prices for market, size and distress risks are not always significant during the sample period. The annual average risk premiums are strongly time-varying: market prices of risk are negative in down markets but positive in up markets; size risk premiums fluctuate; and distress risk premiums are only present in down markets. All these findings suggest that the Fama-French three factor is an incomplete model for Chinese stock markets and that omitted variables need to be specified to value Chinese stocks.

4.4 A Rational Explanation of the Failure – Missing Risk Factors

In addition to market-level and firm-level risks, stock returns are sensitive to macroeconomic and money market conditions, because these conditions affect the aggregate investment opportunity set. From this point of view, macroeconomic and money market variables (factors) are generally regarded as sources of systematic market risk. It is also reasonable to expect stocks to have different sensitivities in response to economic factors, because firms differ in their ability to adjust to changes in the economic environment. Chen *et al.* (1986) have reported research on the economic forces in stock markets. They find that innovations in macroeconomic variables are important risks that are priced in the U.S. stock markets. Shanken

(1992) argues that cross-sectional stock returns are a linear combination of general economic risks and market portfolio risk.

Additional risk factors include macroeconomic and money market variables that capture changes in aggregate industrial production, real discount rates, effects of globalisation and international cash flows, and fixed-income market interest rates. It is not assumed that the risk factors included in this section represent all alternative determinants of stock returns given the failure of the Fama-French model. However, because of the immaturity of Chinese financial markets and their limited financial products, other variables used the literature, such as the risk premium and term structure[29], are not available for Chinese stock market research. The variables applied in this section capture as much Chinese stock market information as possible.

4.4.1. The Multi-beta Asset Pricing Model

Asset pricing theories under the EMH indicate the trade-off between risk and return. Therefore, like the three-factor form of the Fama-French model, a multi-beta pricing model is the one such that the expected returns of securities are on the security market line in multi-dimension of risks that are as many as there are factors, which is in line with the arbitrage pricing theory (Ross, 1976). The multi-beta pricing model with K+1 dimensions of risks is:

$$E(r_i) = \beta_{M,i} E(R_M - R_f) + \sum_K \beta_{K,i} E(F_K) \qquad (4.6)$$

[29] These variables are thought to be significant sources of risks that are rewarded in stock markets. See Chen *et al.* (1986) and Campbell (1996).

Here $E(r_i)$ is the expected return on asset i in excess of the risk-free rate, $E(R_M - R_f)$ is the expected price of market risk, and the $E(F_k)$ (k=1….K) are the expected risk premiums on risk factors that capture the possible determinants of stock returns. $\beta_{k,i}$ is the risk loading of asset i on factor k.

For present purposes, the K+1 factors in Equation (4.6) include four macroeconomic and bond market variables, augmented by the three factors of the Fama-French model. These are: first, the monthly growth rate of the industrial production index (MP), as a proxy for the aggregate earnings ability of firms and changes in future dividends; second, retail price inflation (Inf), to capture changes in real discount rates and real cash flows; third, the monthly change in the exchange rate between the Chinese RMB and US Dollar (Ex), to capture the effect of globalisation and international capital flows; and fourth, the returns on a Chinese total bond index (Rf), to capture changes in money and debt market interest rates.

To be consistent with the Arbitrage Pricing Model (APT) and Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM), risk factors should represent risks affecting expected stock returns and should capture unexpected changes in investment opportunity sets. It is accepted in the literature that only unanticipated shocks to economic variables have an influence on stock prices. Following Sims (1980), Campbell (1996) and Petkova (2006), the innovations in the state variables and shocks to stock markets are generated from a second-order VAR system.

As was the case for the Fama-French Model, the multi-beta pricing model is tested using the Fama and MacBeth (1973) two-pass procedure. The procedure begins with a time-series estimation of factor loadings (betas) and the deviation factor (alpha). Cross-sectional regressions are then run using annual average portfolio excess returns.

The model to be tested is given by the 25 portfolio time series regressions:

$$r_{i,t} = \alpha_i + \beta_{M,i} r_{M,t} + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \beta_{u^{MP},i} u_t^{MP} + \beta_{u^{Inf},i} u_t^{Inf} + \beta_{u^{Ex},i} u_t^{Ex} + \beta_{u^{Rf},i} u_t^{Rf} + \varepsilon_{i,t} \quad (4.7)$$

followed by the cross-section regressions:

$$\bar{r}_i = \gamma_0 + \gamma_M \hat{\beta}_{M,i} + \gamma_{SMB} \hat{\beta}_{SMB,i} + \gamma_{HML} \hat{\beta}_{HML,i} + + \gamma_{u^{MP}} \hat{\beta}_{u^{MP},i} + \gamma_{u^{Inf}} \hat{\beta}_{u^{Inf},i} + \gamma_{u^{Ex}} \hat{\beta}_{u^{Ex},i} + \gamma_{u^{Rf}} \hat{\beta}_{u^{Rf},i} + e_i \quad (4.8)$$

As before, β_i and γ_i capture the sensitivity of asset returns to the specified risks and the prices of relevant risks. The residuals in Equations 4.7 and 4.8 should be i.i.d. normally distributed processes.

4.4.2. Data and the Econometric Approach to Generate Economic Shocks

4.4.2.1 Data on Macroeconomic and Bond Market Factors

The additional risk variables used in this section representing macroeconomic and bond market factors are summarised in Table4.10.

Industrial Production

Industrial production (IP) is a variable available at monthly intervals that captures macroeconomic growth and the aggregate earning ability of firms. Changes in industrial production have an effect on the real value of cash flows, which may result in changes in dividend payments.

The basic measure of industrial activity, IPI, is the Chinese Industrial Production Index. Designating IPI_t as the level of the industrial production index in month t, the monthly growth rate of industrial production (MP) is defined as

$$MP_t = \log IPI_t - \log IPI_{t-1}$$

CRR use monthly changes in an industrial production index to capture contemporaneous stock returns and monthly series of yearly growth rates of an industrial production index to measure the valuation of cash flows over long periods. Fama (1981) and CRR find evidence of an influence of industrial production on stock returns. Vassalou (2003) shows that news related to future GDP growth can also explain the cross-section of equity returns. Faugere and Erlach (2004) demonstrate theoretically and empirically that stock market returns should equate the expected sum of dividends, and the dividend payments, at an aggregate level, equal to GDP growth in the long run. Chou, Li, Rhee and Wang (2007) find that industrial production has a persistent effect on stock returns in both the short and long run. However, Black (2006) shows that stock markets precede GDP growth in the sense that conditional variation in the market risk premium has information about the future volatility of GDP growth.

Inflation

Inflation plays an important role in forecasts of future investment opportunity sets, and retail price inflation affects future real income (Flannery and Protopapadakis, 2002). As discussed by CRR and by Jorion (1991), expected inflation is thought to have an influence on future nominal cash flows, because firms appraise investments with reference to expected changes in retail price inflation. Unexpected inflation may play a more important role in generating stock returns as it creates shocks in stock markets and therefore indicates changes in returns.

Inflation is represented by the log first difference in the Chinese retail price index. Designating rpi_t as the level of the retail price index in month t, monthly inflation is defined as

$$Inf_t = \log rpi_t - \log rpi_{t-1}$$

Lee (1999) suggests the existence of a negative correlation between unexpected inflation and stock returns, where a higher level of inflation uncertainty makes future real earnings on investments more uncertain (thus discounting future dividends more heavily). Fama (1981) argues that inflation is negatively correlated with stock returns because it is a proxy for real activity, but this view is rejected by Lee (1992), who found that inflation explains little variation in real activity.

Changes in Exchange Rate

The exchange rate has been important to stock markets since the advent of the flexible exchange rate system and the development of globalization. At the level of firms, multinationals run business in, or trade with, foreign countries and devote resources to the management of foreign exchange risks. At the market level, globalisation in capital markets and the reduction of restrictions on capital flows leads to capital flows between economies. The exchange rate has been shown to be a priced factor in cross-sections of national stock indices (Brown and Otsuki, 1993; Ferson and Harvey, 1993). Jorion (1991) examines the relationship between exchange rate risk and the behaviour of the U.S. stock market and reports that although some equity values react to fluctuations in the trade-weighted value of the dollar, exchange rate exposure does not on average affect stock prices. However, Bailey and Chung (1995) find some evidence that equity market premiums are earned for exposure to exchange rate fluctuations in emerging markets.

Table 4.10 Glossary and Definition of Variables: Macroeconomic &bond market factors.

Panel A in Table4.10 presents the basic data used in the research. Panel B describes the series that are derived from the basic data and used in the VAR approach to generate the risk factors. Panel C show the detailed model specification for the VAR system and the generation of economic shocks. In the VAR, **A** and **B** are 7×7 coefficient matrices.

Symbol	**Variable**	**Definition and Source**
Panel A	**Basic Series**	
IPI	Industrial production index	DataStream
rpi	Retail price index	DataStream
Exp	Price of RMB against US dollar	State Administration of Foreign Exchange
BI	Total bond index	Citigroup China Total +S&P/CITIC Total bond Index, DataStream
Panel B	**Derived Series**	
MP	Monthly growth rate of industrial production	$\log IPI_t - \log IPI_{t-1}$
Inf	RPI Inflation	$\log rpi_t - \log rpi_{t-1}$
Ex	Rate of return in exchange rate	$\log Exp_t - \log Exp_{t-1}$
Rf	Interest rate	$\log BI_t - \log BI_{t-1}$
Panel C	**Risk Factors**	
R_{SMB}	SMB	$\begin{Bmatrix} r_{M,t} \\ R_{SMB,t} \\ R_{HML,t} \\ MP_t \\ Inf_t \\ Ex_t \\ Rf_t \end{Bmatrix} = \mathbf{A} \begin{Bmatrix} r_{M,t-1} \\ R_{SMB,t-1} \\ R_{HML,t-1} \\ MP_{t-1} \\ Inf_{t-1} \\ Ex_{t-1} \\ Rf_{t-1} \end{Bmatrix} + \mathbf{B} \begin{Bmatrix} r_{M,t-2} \\ R_{SMB,t-2} \\ R_{HML,t-2} \\ MP_{t-2} \\ Inf_{t-2} \\ Ex_{t-2} \\ Rf_{t-2} \end{Bmatrix} + \begin{Bmatrix} u_t^{r_M} \\ u_t^{SMB} \\ u_t^{HML} \\ u_t^{MP} \\ u_t^{Inf} \\ u_t^{Ex} \\ u_t^{Rf} \end{Bmatrix}$
R_{HML}	HML	
u_t^{MP}	Innovation in MP	
u_t^{Inf}	Innovation in Inf	
u_t^{Ex}	Innovation in Ex	
u_t^{Rf}	Innovation in Rf	

Taking Exp_t as the dollar price of domestic currency, RMB exchange rate appreciation with respect to the US Dollar (depreciation if negative) is given by

$$Ex_t = \log Exp_t - \log Exp_{t-1}$$

This variable is employed to capture two types of possible influence on stock markets. On one hand, the Chinese economy has a high degree of external dependence, given Chinese role as a world centre of production, so currency exposure has been a major source of concern for import and export companies and for foreign real investment. On the other hand, changes in exchange rates indicate potential international capital flows. In the case of China, the rapid growth of the domestic economy without commensurate exchange rate appreciation suggests that the RMB is under-valued. Potential appreciation of the Chinese RMB may affect the cost of international hedging and increase the total demand for assets in Chinese stock markets. This is especially true since the exchange rate reform of July 2005. Since the reform may have significantly affected the RMB exchange rate, a structural break is introduced taking July 2005 as the break point:

$$Ex\_1 = \begin{cases} Ex, \text{ before July 2005} \\ 0, \text{ after July 2005} \end{cases}, \text{ and } \quad Ex\_2 = \begin{cases} 0, \text{ before July 2005} \\ Ex, \text{ on and after July 2005} \end{cases}$$

Bond and Money Market Interest Rate

Bond and money market variables have attracted particular attention since money market products are commonly viewed as alternative investment instruments to stock market products. The return on a 3-month Treasury bill is commonly adopted as a risk free rate that provides minimum investment returns (Sharpe, 1964; Lintner, 1965; Fama and French, 1993, 1996). Bond market interest rates and the term structure[30] capture the level and slope of the yield curve (Fama and Schwert, 1977;

[30] Term Structure is captured by the difference between the return on a portfolio of long-term government bonds and the return on a portfolio of Treasury-bills.

CRR, 1986; Campbell, 1987). Campbell (1988a) also argues that the expected real term structure contains information about future consumption growth. Moreover, risk premium[31], otherwise referred to as the 'default spread', is argued to capture investor attitudes towards risks (CRR, 1986; Fama and French, 1989). Default spread and term spread variables are not used in this study because of the unavailability of data: short-term Chinese government bonds have been issued only since 2006, and there is no credit rating for immature corporate bonds in China.

Defining BI_t as the total bond index, the interest rate factor is

$$Rf_t = \log BI_t - \log BI_{t-1}$$

Higher interest rates refer to higher discount factors and therefore lower stock prices. Changes in the interest rate tend to be negatively correlated with asset returns because an increase in interest rate raises the cost of borrowing and may induce investors to shift from stock investment to fixed investment. Changes in the interest rate are also likely to affect consumer spending.

The Fama-French factors and tested portfolio returns

As mentioned briefly (see page 97 and 119), previous study shows that the listed market value is a more appropriate measure of market capitalisation as this is presumably most immediately relevant for asset pricing. However, when size is calculated, it would seem that an overall measure is better. Therefore, to simplify the research, the rest of the thesis uses only one set of data: the test portfolios are from

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[31] The risk premium is captured by the difference between the return on a "Baa and under" bond portfolio and the return on a portfolio of long-term government bonds.

Set A listed market value, SMB is calculated from Set A using total market value as weight, and HML is calculated in Set B weighted in listed market value.

Table 4.11 Summary of Portfolio Returns Sample Selection

	Set A	Set B
TMV	**SMB**	
LMV	**25 Portfolios**	**HML**

4.4.2.2 The Dynamic Approach to Generate Shocks

In order to define the *K* risk factors in Equation (4.6) as unexpected shocks to stock market and innovations to the state variables, SMB, HML and the four macroeconomic and money market factors are modelled as multivariate second-order Vector Autoregression (VAR), following Campbell (1996) and Petkova (2006), and the residuals from the VAR system are used as the innovation risks[32]. To be consistent with the definition of unexpected shocks, these residuals should be neither autocorrelated nor correlated with each other – achieved by triangularising the VAR system in Equation (4.9). Thus the innovation in excess market returns remains unchanged; the orthogonalised innovation in SMB is the component of the original SMB innovation that is orthogonal to the excess market returns; the orthogonalised innovation in HML is the component of the original HML innovation orthogonal to both excess market returns and SMB, and so on, ensuring that the shocks to the economic variables are orthogonal to the benchmark Fama-French risk factors.

[32] The VAR system was first estimated as a first-order system but this produced serial correlation in the residuals. The details of the first-order VAR residual diagnostic checking are reported in Appendix 4.2.

Excess market returns r_M form the first element of the state vector in the VAR, followed by SMB, HML, macroeconomic and money market factors respectively. The VAR is given by

$$\mathbf{Z}_t = \mathbf{A}\mathbf{Z}_{t-1} + \mathbf{B}\mathbf{Z}_{t-2} + \mathbf{u}_t \tag{4.9}$$

where $\mathbf{Z_t}$ denotes the matrix of all factors (r_M, SMB, HML, MP, Inf, Ex[33] and Rf). **A** is the 7×7 matrix of first-order dynamic coefficients and 7×7 **B** contains the second-order dynamic coefficients. The residual matrix $\mathbf{u_t}$ contains vectors of innovations. The detailed model for generating the economic shocks is presented in Panel C of Table 4.10. The results from the two-lag VAR process of innovations generation are presented in Table 4.12, where the dynamic relationship between the excess market return and the other variables is summarized.

Residual $\mathbf{u_t}$ represents the innovation vector for each element in the state vector. From $\mathbf{u_t}$ the six innovation series corresponding to SMB, HML, MP, Inf, Ex and Rf, are denoted u^{SMB}, u^{HML}, u^{MP}, u^{Inf}, u^{Ex} *and* u^{Rf}, respectively. The residuals in the second-order VAR system contain information on the Fama-French and economic risk factors that is not predicable using either own or other factor past values.

By triangularising the VAR system in Equation 4.9, $\boldsymbol{\mu}_t = \{\mu_t^{MP}, \mu_t^{Inf}, \mu_t^{Rf}, \mu_t^{Ex}\}'$ are orthogonalised with respect to the market, size and distress risk factors. Moreover, the innovation in Inf is the component of the unexpected inflation that is uncorrelated with contemporaneous MP, the innovation in Rf is the component of

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[33] Ex contains two parts of Ex_I (Ex) and Ex_II (Ex*Dex), where Dex is the dummy variable for the Chinese RMB exchange rate reform and takes the value of 1 since August 2005. Thus Ex_I represents the returns on exchange rate before the exchange rate reform and Ex_II takes the case after the reform. The innovation in Ex is composite by the residuals corresponding to Ex_I before the reform and the residuals corresponding to Ex_II after the reform.

the unexpected bond market returns uncorrelated with MP and Inf, and so on. Consequently, ordering in the VAR matters: if estimation results are insignificant for a state variable, it may not be that the variable is insignificant but that significant parts of the shocks are captured by variables that are higher in the VAR order.

Consistent with estimates elsewhere in the literature, there is minimal serial correlation in monthly stock excess returns. Only the one-period lagged value of Ex is correlated (positive and significant) with excess market returns after the exchange rate reform, suggesting that domestic currency appreciation positively predicts market returns, which is consistent with the suggested effects of an international trade surplus and international capital flows. SMB and HML are uncorrelated with the macroeconomic and bond market factors except inflation: an increase in retail price inflation has a positive impact on the next-period size premium; suggesting that the market requires higher returns on small firms facing an unexpected increase in price level; inflation has a positive impact on HML, although the effect is delayed.

On the other hand, the Fama-French factors do predict macroeconomic factors to some extent. High market returns predict the growth of production and lower inflation. SMB contains some information about inflation and changes in the exchange rate. HML predicts industrial production growth. These correlations suggest stock markets in China do have predictive power to Chinese macro economy.

Table 4.12 The Dynamics of the Risk Factors

This table reports the dynamics of the Fama-French factors and the additional four risk factors in the triangularised second-order VAR system. MP is the monthly changes, in natural logarithm differences, in the index of industrial production. Inf is retail price inflation. Rf is the logarithm return of Chinese total bond index. Ex is the changes in RMB to US Dollar exchange rate, before (Ex_I) or after (Ex_II) the exchange rate reform. The associated *t*-statistics are in square brackets below the coefficients.

	r_M	SMB	HML	MP	Inf	Rf	Ex_I	Ex_II
r_M (-1)	0.079	0.039	-0.063	0.018	0.000	-0.004	0.000	-0.001
	[0.850]	[0.746]	[-1.488]	[1.239]	[-0.183]	[-0.709]	[-0.357]	[-0.748]
r_M (-2)	0.047	0.033	0.014	0.026*	-0.005*	-0.003	0.000	0.002
	[0.492]	[0.598]	[0.317]	[1.703]	[-1.836]	[-0.448]	[0.695]	[1.568]
SMB(-1)	-0.030	0.272***	0.041	0.019	-0.008*	0.005	0.000	-0.009***
	[-0.171]	[2.746]	[0.503]	[0.651]	[-1.741]	[0.468]	[0.538]	[-3.363]
SMB(-2)	-0.287	-0.182*	-0.051	-0.025	0.012**	0.005	0.000	0.004
	[-1.557]	[-1.719]	[-0.592]	[-0.839]	[2.351]	[0.434]	[-0.081]	[1.366]
HML(-1)	0.079	-0.127	0.134	0.058*	0.000	0.005	0.000	0.000
	[0.377]	[-1.071]	[1.406]	[1.745]	[0.075]	[0.380]	[0.617]	[-0.072]
HML(-2)	0.405**	-0.177	-0.087	-0.006	-0.006	-0.020	0.000	0.002
	[2.001]	[-1.516]	[-0.920]	[-0.174]	[-1.130]	[-1.546]	[-0.446]	[0.642]
MP(-1)	0.670	0.078	-0.049	-0.776***	0.071***	-0.030	0.002	0.002
	[1.228]	[0.249]	[-0.196]	[-9.152]	[3.816]	[-0.631]	[0.709]	[0.182]
MP(-2)	0.076	-0.253	-0.136	-0.414***	0.030*	-0.084**	0.001	0.004
	[0.130]	[-0.765]	[-0.514]	[-4.587]	[1.826]	[-2.116]	[0.327]	[0.402]
Inf(-1)	5.475	3.299*	1.507	-0.015	0.298**	0.146	-0.004	0.044
	[1.575]	[1.652]	[0.934]	[-0.027]	[3.291]	[0.636]	[-0.392]	[0.839]
Inf(-2)	1.530	-1.365	2.665*	-1.204**	-0.117	-0.064	0.005	0.031
	[0.450]	[-0.707]	[1.725]	[-2.259]	[-1.301]	[-0.291]	[0.448]	[0.626]
Rf(-1)	-0.279	0.502	-0.617	-0.437*	-0.055	0.157*	-0.004	0.023
	[-0.187]	[0.592]	[-0.909]	[-1.885]	[-1.415]	[1.667]	[-0.819]	[1.044]
Rf(-2)	1.605	0.502	-0.093	0.618**	-0.055	0.233**	0.009*	0.004
	[1.065]	[0.583]	[-0.135]	[2.640]	[-1.375]	[2.409]	[1.927]	[0.156]
ExI(-1)	32.924	35.832*	11.069	2.377	-1.030	1.451	-0.202**	-0.246
	[1.013]	[1.932]	[0.736]	[0.463]	[-1.219]	[0.707]	[-2.094]	[-0.511]
ExI(-2)	35.844	18.800	15.562	2.698	-0.319	2.563	-0.170*	0.063
	[1.099]	[1.010]	[1.043]	[0.528]	[-0.380]	[1.264]	[-1.769]	[0.132]
ExII(-1)	12.401*	-5.743	-3.856	-0.463	0.294*	0.314	-0.006	0.300***
	[1.923]	[-1.542]	[-1.284]	[-0.448]	[1.729]	[0.755]	[-0.293]	[3.137]
ExII(-2)	3.885	1.208	5.986*	0.303	0.234	-0.157	0.001	0.306***
	[0.561]	[0.306]	[1.902]	[0.277]	[1.300]	[-0.358]	[0.033]	[3.045]

Table 4.12 (cont.)

	r_M	SMB	HML	MP	Inf	Rf	Ex_I	Ex_II
r_M		0.034	0.054	-0.010	0.001	-0.002	0.000	0.002
		[0.635]	[1.261]	[-0.673]	[0.570]	[-0.402]	[-0.534]	[1.154]
SMB			0.265***	-0.021	-0.006	-0.001	0.000	0.007***
			[3.496]	[-0.747]	[-1.264]	[-0.086]	[0.510]	[2.648]
HML				0.009	-0.004	0.024*	0.000	-0.001
				[0.277]	[-0.806]	[1.805]	[0.619]	[-0.343]
MP					-0.009	-0.036	-0.001	0.002
					[-0.554]	[-0.946]	[-0.399]	[0.281]
Inf						-0.165	0.006	-0.042
						[-0.707]	[0.545]	[-0.786]
Rf							0.001	0.001
							[0.219]	[0.055]
Ex_I								0.051
								[0.107]

Notes:

* indicates rejection of the null at the 10% significant level

** indicates rejection of the null at the 5% significant level

***indicates rejection of the null at the 1% significant level

4.4.3. Regression Results–with Additional Risk Factors

This section aims to identify whether the failure of the Fama-French three factor model is due to missing fundamental risk factors. The four additional economic shocks are added to the multi-beta pricing model in Equation 4.6 and, as before, the Fama-Macbeth two-pass process is used to test the model.

4.4.3.1 Patterns of Factor Loadings on Innovation Risks

In the first step, the 25 size and book-to-market sorted portfolio excess returns are regressed on the constant, excess market returns, SMB, HML and the additional four innovations in MP, Inf, Ex and Rf, using Newey-West standard errors. The betas are the risk factor loadings on the excess market return, SMB, HML, and the innovations in economic state variables MP, Inf, Rf and Ex. The alpha is the constant term and the residual is the idiosyncratic error term that should be an i.i.d. normally distributed series for each portfolio regression.

The estimated results of risk exposures of the 25 portfolios are presented in Table 4.13, with the adjusted R-squared and the jointly significant *F*-statistics. Results are similar to the Fama-French model, in that the constant terms remain positive and significant, loadings on the excess market return remain the most significant, and size risk patterns and distress risk patterns are systematically informative. The average of the 25 adjusted R^2 statistics is 89.5% and the *F*-statistics for all regressions reject the joint hypothesis that the explanatory variables are insignificant at the 99% confident level.

The positive constant terms indicate that over the period of 132 months from January 1997 to December 2007, stock portfolios earn returns in excess of the three-month bank deposit rate that cannot be explained by the Fama-French risk factors. This result is different from the Fama-French (1996) estimation where only a small 0.093% average absolute intercept was found in the U.S. data.

Loadings on the excess market return remain the most significant, indicating that the sensitivity of portfolios to the aggregate market return plays a leading role among the risk variables. Size risk exposures show that portfolios of smaller size stocks have bigger betas within each book-to-market group, suggesting that small stocks require higher returns than big stocks. Likewise, portfolios of higher book-to-market stocks (those with higher distress risk) have bigger betas than portfolios of stocks with lower book-to-market equity in the same size group. The factor loadings on SMB and HML reveal that portfolio returns are sensitive to size and distress risks even with control of economic risks.

Contrary to the expectations of a traditional model, portfolio returns are not significantly exposed to macroeconomic and bond market risks: only 3 portfolios show significant factor loadings on unexpected industrial production growth; 6 portfolios are sensitive to inflation changes; and 5 portfolios are sensitive to shocks in bond market interest rates. This lack of significance suggests that innovations in economic risks have little empirical influence on portfolio returns, even though there are strong theoretical reasons for expecting them to contribute to explanations of asset pricing. Moreover, the signs of the risk exposures are inconsistent. For instance, companies should benefit from positive shocks to the growth of industrial production but Table 4.13 shows that S1B5 portfolio has negative correlation with innovations in MP. The coefficient signs on innovations in retail price inflation and bond market interest rate are also inconsistent across portfolios.

The only exception is exchange rate risk: loadings on innovations in this variable are positive and significant for more than half of the portfolios, which suggests that stock markets in China tend to benefit from domestic currency appreciation, which is in line with the 'world factory' view of China (where industrial firms export a significant proportion of their output). This is especially true for small size and high book-to-market stocks. It is possible that small firms tend to be export firms and are therefore more sensitive to RMB exchange rate appreciation. However, there is no good reason for high book-to-market stocks to be significantly influenced by innovations in exchange rates. Probably a more forceful explanation is that small size and high book-to-market stocks attract more speculative trading, triggered by international hot money inflows that chase benefits from potential RMB exchange rate appreciation.

Table 4.13 Factor Loadings on the Fama-French factors and innovations in economic risk factors.

This table reports the 25 size and book-to-market sorted portfolio's sensitivities to the excess market return, SMB, HML, and innovations in monthly growth rate in industrial production, retail price inflation, changes in exchange rate and market interest rate. Factor loading betas are computed in least square regression, with controlling of possible serial correlation and Heteroskedasticity using Newey-West consistent covariance with 4 lags. The asymptotic *t*-statistics are reported in square brackets.

$$r_{i,t} = \alpha_i + \beta_{M,i} r_{M,t} + \beta_{SMB,i} SMB_t + \beta_{HML,i} HML_t + \beta_{u^{MP},i} u_t^{MP} + \beta_{u^{YP},i} u_t^{Inf} + \beta_{u^{EX},i} u_t^{Ex} + \beta_{u^{RF},i} u_t^{Rf} + \varepsilon_{i,t}$$

	Small	2	3	4	large	Small	2	3	4	large
			α					***β_M***		
Low	1.557***	0.815**	0.515	0.997***	1.584***	0.881***	1.016***	0.949***	1.023***	1.219***
	[3.907]	[2.374]	[1.637]	[3.502]	[4.191]	[13.930]	[17.392]	[11.291]	[20.783]	[13.526]
2	0.574*	1.037***	1.400***	1.005***	0.954***	0.950***	1.004***	1.087***	1.073***	1.035***
	[1.746]	[4.684]	[4.328]	[4.181]	[3.947]	[17.227]	[20.669]	[20.927]	[29.530]	[19.478]
3	1.173***	0.737***	0.458*	0.926***	0.991***	1.031***	1.016***	0.983***	1.037***	1.062***
	[4.302]	[3.365]	[1.784]	[3.377]	[3.405]	[18.912]	[20.021]	[28.475]	[22.544]	[20.346]
4	0.755***	1.164***	0.795***	0.939***	1.540***	0.932***	1.026***	1.037***	1.121***	1.042***
	[3.348]	[6.392]	[4.589]	[3.772]	[3.537]	[29.058]	[36.164]	[28.926]	[16.490]	[14.578]
High	0.946***	0.709***	0.723***	0.409*	0.769***	0.945***	1.005***	1.015***	0.998***	0.900***
	[2.898]	[2.946]	[3.078]	[1.806]	[3.180]	[21.433]	[18.414]	[21.450]	[23.608]	[28.087]
			β_{SMB}					***β_{HML}***		
Low	1.057***	0.839***	0.411***	0.208***	-0.343***	-0.039	-0.063	-0.248*	-0.306***	-0.568***
	[9.866]	[8.369]	[4.895]	[2.995]	[-3.112]	[-0.317]	[-0.779]	[-1.772]	[-3.374]	[-5.116]
2	0.854***	0.607***	0.263***	0.194***	-0.564***	0.095	0.045	0.023	-0.157*	-0.287***
	[8.824]	[6.852]	[3.908]	[2.680]	[-9.724]	[0.504]	[0.626]	[0.305]	[-1.754]	[-4.815]
3	0.881***	0.718***	0.490***	0.239***	-0.323**	0.381***	0.222***	0.093	0.088	0.140**
	[8.725]	[10.735]	[6.233]	[3.083]	[-2.473]	[3.757]	[3.325]	[1.036]	[1.017]	[2.334]
4	0.793***	0.608***	0.495***	0.158	-0.293***	0.428***	0.307***	0.190***	0.212***	0.353**
	[11.715]	[11.094]	[7.636]	[1.527]	[-2.926]	[7.461]	[6.419]	[3.089]	[2.972]	[2.044]
High	0.840***	0.691***	0.481***	0.305***	0.904***	0.454***	0.576***	0.562***	0.478***	0.216***
	[10.081]	[11.319]	[7.099]	[3.707]	[11.828]	[5.335]	[9.893]	[6.119]	[8.270]	[2.723]

Table 4.13 (cont.)

			β_u^{MP}					β_u^{Inf}		
Low	-0.301	0.215	0.129	0.090	0.667***	1.129	-1.212	0.449	-0.986	-5.143***
	[-1.386]	[0.821]	[0.730]	[0.485]	[2.892]	[0.598]	[-0.695]	[0.356]	[-0.647]	[-2.898]
2	0.376	0.227	0.042	0.094	-0.153	3.216**	1.674	-0.614	0.519	0.052
	[1.604]	[1.411]	[0.280]	[0.545]	[-1.255]	[2.034]	[1.416]	[-0.443]	[0.496]	[0.049]
3	0.235	0.124	0.025	0.208	0.314	-1.594	0.193	2.889**	0.101	-0.598
	[0.956]	[0.870]	[0.180]	[1.197]	[1.435]	[-1.018]	[0.178]	[2.173]	[0.067]	[-0.431]
4	0.114	0.391**	0.088	0.072	-0.123	1.926*	1.272	-1.562*	0.012	-2.119
	[0.473]	[2.329]	[0.702]	[0.350]	[-0.444]	[1.800]	[0.963]	[-1.919]	[0.009]	[-0.644]
High	-0.475*	-0.159	0.127	0.073	-0.059	-1.010	0.687	-0.943	1.041	2.235*
	[-1.916]	[-1.277]	[0.925]	[0.421]	[-0.254]	[-0.529]	[0.651]	[-0.878]	[0.746]	[1.688]
			β_u^{Rf}					β_u^{Ex}		
Low	0.841	-0.460	0.246	-0.390	-1.021*	11.038	6.963***	-0.137	8.147	-2.358
	[0.950]	[-0.808]	[0.537]	[-0.935]	[-1.717]	[1.635]	[2.826]	[-0.057]	[1.404]	[-0.434]
2	0.938	-0.429	0.631	0.186	-0.048	17.272**	11.020**	3.119	1.154	0.652
	[1.573]	[-0.850]	[0.991]	[0.433]	[-0.084]	[2.367]	[2.235]	[0.997]	[0.427]	[0.241]
3	-0.078	0.060	0.670	0.040	-0.018	8.462**	5.089**	5.086*	4.953	1.722
	[-0.093]	[0.173]	[1.210]	[0.084]	[-0.034]	[2.074]	[2.048]	[1.786]	[1.422]	[0.547]
4	0.781*	0.108	-0.320	-0.670	-1.357**	7.309***	4.834**	6.656***	4.430	4.659
	[1.731]	[0.250]	[-1.096]	[-1.031]	[-2.063]	[3.536]	[2.562]	[2.830]	[1.295]	[1.286]
High	-0.210	0.336	1.072**	-0.582	1.210***	11.034**	6.474***	4.668**	5.666***	9.222***
	[-0.274]	[0.871]	[2.163]	[-1.490]	[3.032]	[2.052]	[3.405]	[2.370]	[2.722]	[6.021]
			Adj. R^2					***F-Statistics***		
Low	0.826	0.899	0.853	0.873	0.871	86.195***	160.977***	105.852***	124.511***	122.932***
2	0.861	0.914	0.883	0.915	0.911	112.563***	193.279***	137.361***	195.102***	184.562***
3	0.895	0.929	0.906	0.898	0.885	153.621***	237.792***	175.163***	159.349***	139.470***
4	0.917	0.949	0.952	0.909	0.767	200.006***	335.879***	356.862***	181.248***	60.375***
High	0.851	0.928	0.938	0.929	0.913	103.772***	234.620***	271.293***	235.314***	190.932***

* Significant at a 90% confidence level.

** Significant at a 95% confidence level.

*** Significant at a 99% confidence level.

To sum up, the Fama-French factor exposures remain significant when macroeconomic and money market variables are added to the multi-beta pricing model as extra risk factors. However, risk exposures on the added factors tend to be insignificant. The exposure coefficients appear to be insignificant for innovations in monthly growth of industrial production, retail price inflation and bond index return. Only exchange rate innovations show any systematic relation to portfolio returns. The fact that exchange risk exposures are generally positive indicates that stock markets benefit from domestic currency appreciation[34].

4.4.3.2 Tests of Diagnostics

The diagnostic checks tend to confirm that adding additional risk factors does not improve the theoretical asset pricing model for Chinese stock market data. Although the adjusted R^2s indicate that the multi-beta pricing model explains about 90% of the variation in average portfolio returns, the extended asset pricing model still fails to achieve desirable properties for the residuals. Indeed, normality and homoskedasticity are strongly rejected, suggesting further missing variables. The diagnostic checks and misspecification tests are reported in Table 4.14.

The diagnostic tests are the same as those reported for the basic Fama-French model. In general, the Jarque-Bera tests reject the normality of the residuals. There is relatively little evidence of serial correlation but substantial evidence of heteroskedasticity, although as before the estimates are unaffected as robust (Newey-West) standard errors are calculated for the model.

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[34] Since there is a structure change in the RMB exchange rate, this effect may only appear after the RMB exchange rate was launched.

More important, the Ramsey tests continue to show the significance of omitted variables in most of the portfolios. The omitted variables are again proxied by the fitted values of the portfolio excess returns (from the regressions using the Fama-French factors and the innovations in the four economic variables).

The regression results and diagnostic tests suggest that economic risk factors (ie. rational risks) are not the reason for the failure of the Fama-French model in Chinese stock markets and lend further support to a possible explanatory role for ‘irrational’ factors.

Table 4.14 Diagnostic Tests of the Factor Loading estimations of Multi-Beta Pricing Model

This table reports descriptive statistics for residuals from the time-series regression of the Fama-French model. The first three panels present residual diagnostic checks. Panel A reports the Jarque-Bera test of normality with the null hypothesis that the estimated residuals are normally distributed; Panel B gives the first lag serial correlation LM test of residuals under the null hypothesis that residuals are serially uncorrelated; Panel C shows the results of White tests of residual heteroskedasticity. Panel D reports the RESET test of model specification (adding the square of the fitted value of portfolio excess returns from the regression as the omitted explanatory variable). The F-statistics are reported with the corresponding probabilities in square brackets.

	Panel A: Normality Jarque-Bera Test					**Panel B: Serial Correlation LM (1) Test**				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	85.117***	221.780***	103.869***	9.862***	84.981***	0.015	4.106**	1.514	0.645	0.680
	[0.000]	[0.000]	[0.000]	[0.007]	[0.000]	[0.902]	[0.045]	[0.221]	[0.424]	[0.411]
2	14.839***	119.663***	1192.48***	15.558***	196.882***	0.197	4.717**	5.039**	0.210	0.206
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.658]	[0.032]	[0.027]	[0.647]	[0.651]
3	24.178***	30.412***	25.137***	16.057***	179.908***	1.492	0.413	0.193	0.161	0.764
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.224]	[0.522]	[0.661]	[0.689]	[0.384]
4	4.332	1.275	8.150**	161.511***	11413. ***	0.977	0.772	0.129	0.009	0.004
	[0.115]	[0.529]	[0.017]	[0.000]	[0.000]	[0.325]	[0.382]	[0.720]	[0.924]	[0.948]
High	48.696***	29.794***	52.829***	14.766***	11.095***	0.612	1.424	2.112	7.688***	0.533
	[0.000]	[0.000]	[0.000]	[0.001]	[0.004]	[0.436]	[0.235]	[0.149]	[0.007]	[0.467]
	Panel C: White Test of Heteroskedasticity					**Panel D: RESET Test**				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	1.208	8.098***	3.582***	1.553**	7.798***	2.669	18.016***	9.442***	11.210***	92.699***
	[0.235]	[0.000]	[0.000]	[0.050]	[0.000]	[0.105]	[0.000]	[0.003]	[0.001]	[0.000]
2	5.977***	2.924***	3.053***	2.135***	7.438***	0.001	2.709	0.065	9.852***	38.250***
	[0.000]	[0.000]	[0.000]	[0.002]	[0.000]	[0.981]	[0.102]	[0.800]	[0.002]	[0.000]
3	6.258***	2.145***	0.907	2.826***	4.719***	14.269***	5.439**	9.117***	16.110***	4.605**
	[0.000]	[0.002]	[0.619]	[0.000]	[0.000]	[0.000]	[0.021]	[0.003]	[0.000]	[0.034]
4	1.450*	0.984	2.473***	5.673***	2.281***	0.224	7.386 ***	16.424***	15.812***	1.108
	[0.082]	[0.506]	[0.000]	[0.000]	[0.001]	[0.637]	[0.008]	[0.000]	[0.000]	[0.295]
High	1.510*	2.169***	3.380***	1.588**	2.736***	1.426	0.715	2.977*	1.758	4.060**
	[0.062]	[0.002]	[0.000]	[0.042]	[0.000]	[0.235]	[0.399]	[0.087]	[0.188]	[0.046]

* Significant at a 90% confidence level.

** Significant at a 95% confidence level.

*** Significant at a 99% confidence level.

4.4.3.3 Time-varying Risk Premiums from the Multi-beta Model

In the second-pass of the Fama-MacBeth approach, annual average portfolio returns formed on size and book-to-market ratios are regressed on the factor loadings estimated in the first-pass time-series regressions. The factor loading betas are taken as exposure to the corresponding risk factors, and the cross-sectional regression prices the premiums for bearing such risks. The prices of risks are estimated from Equation (4.8), where the γ_i are the prices of the corresponding risks. Equation (4.8) is again estimated by GMM using White's diagonal weighting matrix to obtain estimators robust to heteroskedasticity of unknown form. The results are presented in Table 4.15.

Table 4.15 shows the estimated annual average zero-beta returns and annual risk premiums on market, size, distress, and innovations risks. The time-varying adjusted R^2 confirms the results of the basic Fama-French model that this asset pricing model fails to capture the cross-sectional variations in the average returns in some years.

In these estimates, the zero-beta returns in excess of the three-month bank deposit rate are mostly not distinguishable from zero, being significant only in 2000, 2002 and 2004. Significant market prices of risk appear just twice: in 1997 (7.67%) and 2001 (-3.27%). Given that the factor loadings on the excess market returns are all significant, the insignificant price of the associated risk suggests that stock returns in China move with aggregate market returns, but that the market risk is not rationally priced. In other words, the rational explanation of market beta and price – the higher the beta, the more volatile the security returns – does not exist in China's stock markets.

Table 4.15 Time-varying Prices of Risks from the Multi-beta Pricing Model

This table presents the premiums of bearing risk loadings on the Fama-French factors and four additional economic shocks, which are estimated from the Fama-MacBeth cross-sectional regressions using the annual average of monthly excess returns on 25 portfolios formed on size and book-to-market. The independent variables in the regressions are computed in the first-step LS time-series regression. The GMM estimates of prices of risks on factor loadings of the excess market return, SMB, HML, and the innovations in MP, Inf, Ex and Rf are reported followed by the corresponding *t*-statistics in square brackets. The GMM estimators are corrected using White covariance.

	γ_0	γ_M	γ_{SMB}	γ_{HML}	γ_u^{MP}	γ_u^{Inf}	γ_u^{Rf}	γ_u^{Ex}	Adj.R
1997	-5.724	7.666*	0.021	-0.011	-0.650	-0.336**	0.750**	0.178***	0.227
	[-1.264]	[1.763]	[0.041]	[-0.017]	[-0.781]	[-2.306]	[2.449]	[3.662]	
1998	1.449	-1.288	3.430***	-0.153	-0.896	0.065	0.385	-0.035	0.762
	[0.548]	[-0.511]	[5.360]	[-0.226]	[-1.135]	[0.528]	[1.164]	[-0.768]	
1999	-2.672	5.062	0.862	-0.938	-1.234	-0.092	0.394	0.033	-0.085
	[-0.492]	[1.010]	[1.395]	[-1.650]	[-1.433]	[-0.873]	[1.453]	[0.366]	
2000	4.502*	-0.169	2.059***	0.705	0.596	-0.051	0.188	0.017	0.693
	[2.085]	[-0.084]	[3.664]	[1.238]	[1.113]	[-0.534]	[0.768]	[0.398]	
2001	1.364	-3.274*	0.210	0.923***	0.555	0.076	0.042	0.001	0.599
	[0.724]	[-1.790]	[0.735]	[4.049]	[1.168]	[1.272]	[0.276]	[0.080]	
2002	-5.615**	4.111	-0.590*	0.100	0.475	-0.003	0.500***	0.040	0.060
	[-2.215]	[1.680]	[-1.853]	[0.248]	[0.657]	[-0.032]	[3.079]	[1.123]	
2003	-1.828	1.582	-2.19***	2.239***	0.431	0.068	-0.280	0.017	0.726
	[-0.668]	[0.596]	[-5.679]	[5.423]	[0.694]	[0.776]	[-1.275]	[0.560]	
2004	-3.443**	2.359	-0.306	1.057***	0.391	-0.006	0.074	0.063**	0.174
	[-2.230]	[1.625]	[-0.903]	[3.228]	[0.937]	[-0.081]	[0.388]	[2.350]	
2005	1.347	-1.407	-0.100	-0.466	0.447	-0.074	0.401**	-0.005	0.092
	[0.681]	[-0.752]	[-0.382]	[-1.247]	[1.164]	[-1.475]	[2.621]	[-0.247]	
2006	0.321	7.108	-1.678**	0.431	-2.534**	-0.297*	0.148	0.081	0.548
	[0.055]	[1.255]	[-2.165]	[0.651]	[-2.800]	[-2.017]	[0.482]	[1.696]	
2007	0.728	9.915	4.223**	1.210	-2.666	-0.375	-0.683	0.062	0.447
	[0.080]	[1.142]	[2.504]	[1.149]	[-1.311]	[-1.654]	[-1.175]	[0.736]	

Notes:

* indicates rejection of the null at the 10% significant level

** indicates rejection of the null at the 5% significant level

***indicates rejection of the null at the 1% significant level

Loadings on SMB and HML behave more similarly to their equivalents in the basic Fama-French model. The size premium is positive in up markets but negative in down markets, in line with the findings from the Fama-French model. Again, if size risk is rationally priced, the premium should be constant and positive. However, the negative prices in 2002 and 2003 suggest that when stock markets are falling, small size stocks are more risky than big size stocks, as the downward pressure reduces the returns of small stocks more than big stocks. This leads to the question of whether size price is fundamentals-driven or sentiment-driven.

The distress premium becomes less a significant explanation of cross-sectional variation of portfolio returns. The distress price is significant only in 2001, 2003 and 2004, again within the bear market period. In these three years, distress premiums have positive sign although the magnitudes vary. The time-varying yearly distress premiums suggest that a book-to-market strategy may be inefficient in the China's stock markets. This is in line with the investigation of Fama and French (1996), who found that the annual difference in returns of HML was not always positive in 1964-1993 U.S. stock markets.

Exposure to shocks in economic variables does not predict the cross-section of portfolio returns. Loadings on innovations in MP are almost all not significantly priced. The only exception is in 2006 but the sign is negative. The factor loadings on the innovations in MP are also insignificant in the time-series regression. Overall this suggests that portfolio returns in Chinese stock markets do not accurately reflect the growth of the Chinese national economy. Innovations in retail price inflation also fail to explain the cross section of asset returns in China. The premium on inflation risk is significant only in 1997 and 2006, but with a consistently negative sign as expected. Loadings on Rf innovations seem to be only slightly more important in determining the cross-section of annual average portfolio excess returns. There are three years (1997, 2002 and 2005) when money and bond market risks are priced in stock markets and these risk premiums are all positive. Exchange rate innovations do have significant risk loadings, but it seems from Table 4.14 that these are not an important determinant of cross-sectional portfolio returns. The only two significant yearly premiums appear in 1997 and 2004. Surprisingly perhaps, in 2006 and 2007, after the RMB exchange rate reform, exchange rate risk is not a significant determinant of the cross-sectional variation of portfolio returns.

Given the generally insignificant estimated factor risk loadings on economic shocks, the time-varying adjusted R^2s, insignificant or negative prices of market, size and distress risks, and the insignificant prices on risks of economic shocks, it seems that adding extra theoretical risk factors does not solve the problems of the Fama-French model when applied to Chinese stock market data.

4.5 Robustness Results

The results so far suggest that macroeconomic and money market variables play insignificant roles in the determinants of cross-sectional variation of 25 size-BE/ME portfolio returns. However, there is an important qualification to this conclusion. This is connected with the process of estimating the innovations. In the VAR, shocks are orthogonalised by triangularising the VAR with variables taken in the order $R_{M,}$ SMB, HML, MP, Inf, Ex and Rf. That is, innovations in the excess market return remain unchanged while the orthogonalised innovations in SMB consist of the components of the original innovations in SMB that are incremental to the innovations in R_M. Similarly, the orthogonalised innovations in HML consist of the components of the original innovations of HML that are incremental to the innovations in R_M and SMB, and so on. Therefore, the insignificant contribution of innovations in MP may not be because the factor has no explanatory power but because the actual contribution of the factor has been incorrectly ascribed to R_M, SMB or HML.

Therefore, to check the robustness of the previous results, the order of the triangularised VAR system is changed. More precisely, the excess market return is retained as the first element, followed by Rf, MP, Inf, Ex, SMB and HML. The model used to generate innovations is:

$$\begin{Bmatrix} r_{M,t} \\ Rf_t \\ MP_t \\ Inf_t \\ Ex_t \\ SMB_t \\ HML_t \end{Bmatrix} = \mathbf{A} \begin{Bmatrix} r_{M,t-1} \\ Rf_{t-1} \\ MP_{t-1} \\ Inf_{t-1} \\ Ex_{t-1} \\ SMB_{t-1} \\ HML_{t-1} \end{Bmatrix} + \mathbf{B} \begin{Bmatrix} r_{M,t-2} \\ Rf_{t-2} \\ MP_{t-2} \\ Inf_{t-2} \\ Ex_{t-2} \\ SMB_{t-2} \\ HML_{t-2} \end{Bmatrix} + \boldsymbol{\mu}_t \qquad (4.10)$$

The orthogonalised innovations in Rf, MP, Inf, Ex, SMB and HML created from equation (4.10) are again used as the risk factors in the multi-beta model. Notice that this test uses the innovations in SMB and HML rather than the raw data to proxy size and distress risks. This application has no special meaning but shows simply whether the unexpected changes in size and distress premiums can predict stock returns. The patterns of risk exposure and risk premiums are reported in Tables 4.16 and 17.

Table 4.16 shows that the pattern of factor loadings does not change much with changing ordering of the risk variables. The mis-pricing and aggregate market risk coefficients ($\boldsymbol{\alpha}$ and βr_M respectively) are as positive and as highly significant as in the original model. Size and distress risk exposures remain significant in spite of coming last in the VAR ordering. Furthermore, loadings on innovations in SMB and HML show explicit size and distress effects: portfolios with small stocks have higher loadings (are exposed to higher risks) than portfolios with large stocks; portfolios with high book-to-market stocks have higher loadings than portfolios with low book-to-market stocks.

Table 4.16 Factor Loadings on R_M and Innovations on Rf, MP, Inf, Ex, SMB and HML with Re-Ordering in the VAR

This table reports the time-series regression of 25 size-book-to-market portfolio returns against the excess market return and innovations in excess market return, market interest rate, monthly growth of industrial production, retail price inflation, changes in exchange rate, SMB, and HML. Factor loading betas are computed by least square regression with robust estimators using Newey-West consistent covariance, with the corresponding *t*-statistics on the right.

$$r_{i,t} = \alpha_i + \beta_{i,M} r_{M,t} + \beta_{i,u^{RF}} u_t^{Rf} + \beta_{i,u^{MP}} u_t^{MP} + \beta_{i,u^{YP}} u_t^{Inf} + \beta_{i,u^{EX}} u_t^{Ex} + \beta_{i,u^{SMB}} u_t^{SMB} + \beta_{i,u^{HML}} u_t^{HML} + \varepsilon_{i,t}$$

	Small	2	3	4	Large	Small	2	3	4	Large
			α					t_α		
Low	1.927	1.109	1.062	0.685	1.516	4.628	2.664	2.550	1.645	3.640
2	1.401	1.070	1.529	0.900	1.129	3.365	2.569	3.672	2.161	2.711
3	1.425	0.776	0.688	0.921	0.924	3.421	1.865	1.653	2.213	2.219
4	1.306	1.022	0.831	1.539	1.069	3.136	2.455	1.995	3.696	2.568
High	1.407	0.617	0.471	1.425	1.310	3.380	1.482	1.130	3.423	3.147
			β_{rM}					$t_{\beta rM}$		
Low	0.956	1.037	1.056	1.007	1.097	18.447	20.017	20.381	19.440	21.168
2	1.014	1.070	1.151	1.061	0.984	19.561	20.649	22.215	20.474	18.993
3	1.104	1.065	1.007	1.058	0.958	21.313	20.553	19.436	20.419	18.482
4	1.115	1.083	1.182	1.023	1.003	21.507	20.897	22.811	19.740	19.347
High	1.132	1.077	1.085	1.502	1.067	21.841	20.777	20.935	28.976	20.600
			β_u^{Rf}					$t_{\beta uRf}$		
Low	-0.013	-0.057	-0.016	-0.015	-0.091	-0.242	-1.041	-0.284	-0.280	-1.657
2	0.007	0.005	-0.038	0.040	-0.011	0.132	0.095	-0.692	0.736	-0.198
3	0.004	0.058	0.041	-0.003	0.032	0.065	1.058	0.751	-0.053	0.585
4	0.054	0.051	0.017	-0.028	0.005	0.982	0.925	0.310	-0.512	0.089
High	0.042	0.064	0.053	0.116	0.072	0.757	1.159	0.959	2.115	1.310
			β_u^{MP}					$t_{\beta uMP}$		
Low	-0.035	-0.055	0.026	-0.045	0.062	-0.632	-1.013	0.475	-0.820	1.140
2	0.000	-0.007	-0.012	0.010	0.015	-0.009	-0.135	-0.213	0.175	0.280
3	0.010	-0.032	0.005	-0.012	0.029	0.181	-0.586	0.098	-0.223	0.524
4	0.035	-0.001	0.025	-0.081	0.015	0.636	-0.027	0.451	-1.485	0.278
High	0.001	-0.026	-0.017	0.178	0.034	0.011	-0.468	-0.314	3.245	0.615

Table 4.16 (cont.)

	β_u^{Inf}					$t_{\beta uInf}$				
Low	-0.105	-0.062	-0.117	0.014	-0.030	-1.915	-1.135	-2.139	0.257	-0.554
2	-0.055	-0.049	-0.004	-0.044	0.047	-1.012	-0.904	-0.068	-0.806	0.849
3	-0.132	-0.047	-0.012	0.014	0.035	-2.402	-0.866	-0.216	0.264	0.642
4	-0.122	-0.057	-0.103	-0.125	0.048	-2.232	-1.042	-1.887	-2.275	0.881
High	-0.152	-0.059	-0.037	0.096	-0.130	-2.781	-1.086	-0.677	1.759	-2.382
	β_u^{Ex}					$t_{\beta uEx}$				
Low	0.076	0.190	-0.010	0.073	-0.014	1.394	3.470	-0.183	1.338	-0.264
2	0.139	0.156	0.011	0.056	-0.013	2.530	2.852	0.198	1.022	-0.230
3	0.115	0.093	0.088	0.086	0.029	2.107	1.692	1.608	1.564	0.531
4	0.082	0.067	0.048	0.099	0.044	1.496	1.230	0.875	1.814	0.810
High	0.117	0.080	0.078	0.234	0.135	2.134	1.454	1.431	4.266	2.455
	β_u^{SMB}					$t_{\beta uSMB}$				
Low	0.465	0.418	0.264	0.165	-0.253	8.491	7.625	4.818	3.005	-4.621
2	0.479	0.291	0.274	0.054	-0.282	8.745	5.305	5.003	0.982	-5.152
3	0.540	0.371	0.203	0.115	-0.186	9.862	6.768	3.711	2.094	-3.402
4	0.411	0.313	0.255	0.089	-0.133	7.497	5.716	4.663	1.618	-2.427
High	0.378	0.329	0.185	0.122	0.476	6.909	6.013	3.386	2.233	8.692
	β_u^{HML}					$t_{\beta uHML}$				
Low	-0.130	-0.145	-0.111	-0.229	-0.281	-2.376	-2.649	-2.025	-4.176	-5.129
2	-0.008	0.001	-0.099	-0.044	-0.153	-0.138	0.027	-1.811	-0.804	-2.803
3	-0.015	0.086	0.023	0.021	0.087	-0.279	1.574	0.424	0.380	1.588
4	0.144	0.138	0.177	0.152	0.150	2.627	2.529	3.234	2.780	2.748
High	0.236	0.269	0.246	1.156	0.122	4.304	4.918	4.490	21.110	2.229

Loadings on innovations in Rf and MP are insignificant even if they are orthogonalised only to the excess market return. However, the 25 size-BE/ME portfolio returns are slightly more exposed to shocks in Inf after the re-ordering of variables in the VAR. Loadings on inflation are now significant and negative, which is consistent with the empirical evidences in the published literature. These results imply that portfolio returns are, to some extent, sensitive to shocks in retail price inflation and exchange rate, but that this can be captured by innovations in SMB and HML. In other words, innovations in Inf and Ex influence not only the stock market index but also the differential returns between small-stock and large-stock portfolios and between high-book-to-market and low-book-to-market portfolios.

Table 4.17 Cross-Sectional Estimation of the Multi-Beta Model with Re-Ordered Factor Loadings in the VAR

This table presents cross-sectional GMM estimates of the annual average monthly excess returns of 25 size-BE/ME portfolios on the deviation factor, market excess return and innovations in macroeconomic, money market and Fama-French risk factors. The corresponding *t*-statistics are reported in square brackets. The regression is corrected using White's covariance correction to eliminate any potential heteroskedasticity.

Cross-sectional Tests of the Multi-Beta Pricing Model with Re-Ordering									
	γ_0	γ_M	γ_u^{Rf}	γ_u^{MP}	γ_u^{Inf}	γ_u^{Ex}	γ_u^{SMB}	γ_u^{HML}	Adj. R^2
1997	0.624	2.506***	11.123**	0.179	-10.710**	2.619	-1.057	-2.016*	0.405
	[1.052]	[4.414]	[3.255]	[0.068]	[-2.920]	[0.963]	[-1.147]	[-2.627]	
1998	2.222***	-2.001***	16.882***	1.709	-0.678	-0.151	7.108***	-1.334	0.887
	[5.325]	[-4.060]	[4.044]	[0.520]	[-0.247]	[-0.060]	[9.995]	[-1.879]	
1999	0.157	2.764***	-7.720	6.306*	-4.040	-7.445**	2.750**	-0.113**	0.557
	[0.571]	[11.621]	[-1.817]	[2.868]	[-1.780]	[-3.315]	[3.235]	[-0.175]	
2000	1.298***	2.650***	9.430*	6.295**	-3.640*	0.661	5.466***	-1.527*	0.820
	[4.461]	[8.606]	[2.354]	[3.059]	[-2.411]	[0.389]	[8.256]	[-2.428]	
2001	0.429**	-2.095***	2.971	-0.757	1.670	-0.482	1.482***	0.591*	0.491
	[2.942]	[-12.986]	[1.641]	[-0.580]	[1.695]	[-0.366]	[4.492]	[2.250]	
2002	0.548*	-1.553**	-0.065	2.369	1.864	-2.716	0.459	0.036	0.157
	[2.344]	[-6.473]	[-0.033]	[1.703]	[1.093]	[-1.652]	[0.952]	[0.077]	
2003	-0.001	-0.421	-0.026	-3.459	-0.101	-0.287	-2.229**	2.102**	0.458
	[-0.004]	[-1.178]	[-0.006]	[-1.815]	[-0.052]	[-0.170]	[-3.257]	[2.978]	
2004	-0.326	-0.257	-0.763	-1.445	0.240	0.489	0.185	0.643	-0.166
	[-1.468]	[-0.884]	[-0.337]	[-1.072]	[0.146]	[0.386]	[0.628]	[1.694]	
2005	0.583**	-0.366	4.133	0.809	1.440	-1.145	-0.709	-1.003*	0.336
	[3.254]	[-1.909]	[1.927]	[0.531]	[1.386]	[-1.198]	[-1.638]	[-2.300]	
2006	1.803*	6.297***	3.457	-32.075***	-9.252*	2.121	-8.314***	2.012	0.482
	[2.306]	[8.484]	[0.484]	[-6.219]	[-2.713]	[0.523]	[-5.888]	[1.640]	
2007	2.219	8.312***	-18.875	3.035	16.324*	13.448	7.293*	7.358***	0.752
	[1.165]	[4.800]	[-1.655]	[0.445]	[2.814]	[1.893]	[2.852]	[4.335]	

Notes:

* indicates rejection of the null at the 5% significance level

** indicates rejection of the null at the 1% significance level

***indicates rejection of the null at the 0.1% significance level

The next step is to estimate the cross-sectional variation in risk premia among the 25 size-BE/ME portfolios (Table 4.17). These can be compared with the results in Table 4.15 (using the original VAR ordering). It is evident that the ordering of variables in the triangularised VAR has little effect on the estimated risk premiums. The premiums from the re-ordering show similar sign and significance to the original ordering. There is still a significant constant term (γ_0), indicating mis-pricing. Aggregate market risk remains an important determinant of cross-sectional variation in average portfolio returns in all years except 2003 and 2005. Economic risks are priced in only a few years, and these are the same as in the original ordering. Interestingly, the loading on innovations in HML become more significant after re-ordering. These results suggest that the conclusions in the previous section reflect not random chance but economic content. In other words, the ordering of elements in the triangularised second-order VAR system does not appear to affect estimates of the risk exposure betas and the risk premium gammas.

4.6 A Further Consideration: Stability of the Fama-French Factor Loadings

4.6.1. Test for Stability

A further issue of robustness concerns the parameter stability of the basic three-factor Fama-French factor pricing model. The results in this chapter assume that the factor loading parameters are constant over January 1997 and December 2007. This may be regarded as a strong assumption given that Chinese stock markets are young and have been subject to frequent regulatory and policy changes. These reforms may have changed the profile of investors, especially institutional investors, and could have caused structural breaks in the returns-generating process. In this section the stability of the Fama-French factor loadings are tested with two possible break points taken into account. More specifically, February 2001 and June 2001, both located in the middle of the test period, are considered separately as break points. The former captures the policy change that allowed domestic investors to trade B-shares. The latter picks the beginning of the discussion on SOE non-tradable share reform[35].

Table 4.18 shows the stability results of the Fama-French three factors for 25 size-BE/ME portfolio returns. 19 portfolios reject or marginally reject the hypothesis that factor loadings are constant using February 2001 as the break point, and 20 portfolios reject or marginally reject the hypothesis using June 2001 as the break point. These rejections clearly reveal that market risk, size risk and distress risk are NOT constant. The non-stability of factor loading parameters is more significant when June 2001 is selected as the break point. This finding is in line with our general expectation that the SOEs non-tradable share reform has a greater impact upon the return generating process in China’s stock markets, whereas the B-share market reform has relative less impact on A-share markets since the market capitalisation and liquidity of the B-share market are both much lower than the main domestic A-share markets.

[35] The detailed descriptions of the B-share market reform and the non-tradable share reform have been discussed in Chapter 3 (page 71, 72)

Table 4.18 Stability Test for Fama-French Factor Loadings

The table shows the results of Chow stability tests based on two separate break points: February 2001, when domestic investors were allowed to trade B-shares; June 2001, when there was the announcement that SOE shares would enter the market. The F-statistics and log likelihood ratio estimators of Chow stability tests are reported, with the corresponding probabilities in square brackets.

	Feb. 2001		**Jun. 2001**	
	F-statistic	**LR test**	**F-statistic**	**LR test**
S1B1	4.473***	17.792***	4.231***	16.888***
	[0.002]	[0.001]	[0.003]	[0.002]
S1B2	1.739	7.206	2.169*	8.928 *
	[0.146]	[0.125]	[0.076]	[0.063]
S1B3	2.199*	9.045*	1.900	7.850*
	[0.073]	[0.060]	[0.115]	[0.097]
S1B4	2.139*	8.807*	2.057*	8.481*
	[0.080]	[0.066]	[0.091]	[0.076]
S1B5	1.325	5.526	1.645	6.825
	[0.264]	[0.237]	[0.167]	[0.146]
S2B1	3.208**	13.000**	3.279**	13.272**
	[0.015]	[0.011]	[0.014]	[0.010]
S2B2	1.199	5.011	1.195	4.991
	[0.315]	[0.286]	[0.317]	[0.288]
S2B3	0.358	1.517	0.374	1.584
	[0.838]	[0.824]	[0.827]	[0.812]
S2B4	2.281*	9.373*	1.997 *	8.242*
	[0.064]	[0.052]	[0.099]	[0.083]
S2B5	1.962	8.100*	2.015*	8.314*
	[0.104]	[0.088]	[0.096]	[0.081]
S3B1	7.164***	27.443***	7.345***	28.069***
	[0.000]	[0.000]	[0.000]	[0.000]
S3B2	2.027*	8.359*	2.187*	8.999*
	[0.095]	[0.079]	[0.074]	[0.061]
S3B3	4.097***	16.386***	4.116***	16.458***
	[0.004]	[0.003]	[0.004]	[0.003]
S3B4	6.232***	24.178***	6.962***	26.743***
	[0.000]	[0.000]	[0.000]	[0.000]
S3B5	6.334***	24.543***	6.385***	24.721***
	[0.000]	[0.000]	[0.000]	[0.000]

Table 4.18 (cont.)

	Feb. 2001	Jun. 2001	Feb. 2001	Jun. 2001
	F-statistic	**LR test**	**F-statistic**	**LR test**
S4B1	2.963**	12.051**	3.449**	13.924***
	[0.022]	[0.017]	[0.010]	[0.008]
S4B2	4.884***	19.311***	4.631***	18.379***
	[0.001]	[0.001]	[0.002]	[0.001]
S4B3	1.954	8.068*	2.162*	8.901*
	[0.106]	[0.089]	[0.077]	[0.064]
S4B4	5.143***	20.261***	5.440***	21.342***
	[0.001]	[0.000]	[0.001]	[0.000]
S4B5	4.609***	18.298***	6.084***	23.655***
	[0.002]	[0.001]	[0.000]	[0.000]
S5B1	8.668***	32.547***	8.319***	31.381***
	[0.000]	[0.000]	[0.000]	[0.000]
S5B2	1.761	7.294	1.445	6.012
	[0.141]	[0.121]	[0.223]	[0.198]
S5B3	2.924**	11.897**	3.314**	13.407**
	[0.024]	[0.018]	[0.013]	[0.010]
S5B4	6.272***	24.321***	6.462***	24.993***
	[0.000]	[0.000]	[0.000]	[0.000]
S5B5	0.448	1.894	0.467	1.972
	[0.774]	[0.755]	[0.760]	[0.741]
Reject	17	19	19	20

Notes:

*: Significant at 10%,

**: Significant at 5%,

***: Significant at 1%

4.6.2. Structural Break of Fama-French Factor Loadings

Table 4.19 reports the factor loading parameters on the constant term and the Fama-French three risk variables for January 1997 to May 2001 and June 2001 to December 2007. At first glance, all the parameters are significant in both subsample periods, indicating that the Fama-French factors are important determinants of stock returns during the whole tested period.

Table 4.19 Structural Break of the Fama-French Factor Loadings

Fama-French factor loadings are shown before and after a June 2001 break point. C is the estimated constant term and the r_M, SMB, HML columns give factor loadings on the excess market return, small-minus-big and high BE/ME-minus-low BE/ME. The associated *t*-statistics are in square brackets below the coefficients.

	Jan. 1997- May 2001				Jun. 2001- Dec. 2007			
	C	**r_M**	**SMB**	**HML**	**C**	**r_M**	**SMB**	**HML**
S1B1	1.820**	0.652***	1.113***	-0.329**	1.642***	1.024***	0.982***	-0.116
	[2.157]	[9.393]	[6.149]	[-2.462]	[3.602]	[14.522]	[8.127]	[-0.616]
S1B2	1.365**	0.981***	0.861***	-0.169*	0.484	0.890***	0.816***	0.262
	[2.127]	[15.964]	[4.229]	[-1.784]	[0.877]	[11.371]	[5.426]	[0.919]
S1B3	1.246**	0.952***	0.610***	0.309*	1.535***	1.068***	0.928***	0.289**
	[2.314]	[16.250]	[3.533]	[1.947]	[4.549]	[16.739]	[10.227]	[2.300]
S1B4	0.613	0.982***	0.939***	0.530***	0.983***	0.934***	0.739***	0.306***
	[1.073]	[18.318]	[5.090]	[5.595]	[3.317]	[24.263]	[10.700]	[3.144]
S1B5	1.450**	0.907***	0.724***	0.672***	1.631**	1.075***	1.067***	0.203
	[2.316]	[12.579]	[4.262]	[7.286]	[2.311]	[14.810]	[5.422]	[1.323]
S2B1	-0.059	0.924***	0.970***	-0.404***	1.262**	1.043***	0.906***	-0.025
	[-0.118]	[13.676]	[7.378]	[-3.320]	[2.224]	[12.454]	[6.553]	[-0.219]
S2B2	1.005**	1.058***	0.585***	-0.084	1.141***	0.943***	0.632***	0.093
	[2.237]	[13.718]	[3.869]	[-0.895]	[3.367]	[19.175]	[7.787]	[0.946]
S2B3	0.653	1.048***	0.679***	0.198*	0.888***	0.988***	0.753***	0.211**
	[1.478]	[10.973]	[5.300]	[1.804]	[3.058]	[25.106]	[12.031]	[2.425]
S2B4	0.792**	1.103***	0.754***	0.284***	1.327***	0.983***	0.604***	0.333***
	[2.111]	[35.326]	[4.126]	[2.968]	[6.270]	[24.175]	[11.889]	[4.365]
S2B5	1.270**	0.984***	0.434***	0.709***	0.964***	1.047***	0.739***	0.437***
	[2.540]	[10.582]	[2.831]	[9.340]	[3.006]	[19.595]	[14.303]	[6.075]
S3B1	0.960	0.991***	0.248	-0.506***	0.358	0.833***	0.525***	0.039
	[1.462]	[8.072]	[1.293]	[-4.031]	[1.398]	[20.540]	[8.249]	[0.677]
S3B2	1.507**	1.040***	0.038	0.027	1.893***	1.133***	0.357***	-0.033
	[2.585]	[20.384]	[0.194]	[0.183]	[4.986]	[16.576]	[4.562]	[-0.760]
S3B3	0.173	0.924***	0.387***	-0.063	1.152***	1.023***	0.590***	0.117**
	[0.300]	[21.058]	[3.054]	[-0.393]	[3.915]	[29.234]	[6.226]	[2.453]
S3B4	1.158***	1.123***	0.192*	0.346***	1.107***	1.009***	0.635***	0.116*
	[3.707]	[26.236]	[1.800]	[5.182]	[5.562]	[37.190]	[14.394]	[1.766]
S3B5	1.222***	1.119***	0.238*	0.828***	1.048***	0.990***	0.560***	0.430***
	[4.803]	[15.042]	[2.002]	[9.204]	[5.416]	[28.168]	[11.083]	[6.738]

Table 4.19 (cont.)

	Jan. 1997- May 2001				Jun. 2001- Dec. 2007			
	C	r_M	**SMB**	**HML**	**C**	r_M	**SMB**	**HML**
S4B1	-0.120	1.002***	0.300	-0.456***	1.777***	1.047***	0.293***	-0.327***
	[-0.204]	[15.520]	[1.558]	[-3.990]	[4.313]	[17.001]	[3.591]	[-3.048]
S4B2	1.447***	1.009***	-0.052	-0.313***	1.014***	1.061***	0.252***	-0.060
	[3.510]	[26.921]	[-0.438]	[-5.046]	[3.623]	[19.839]	[4.211]	[-0.692]
S4B3	0.403	1.074***	0.229	-0.020	1.382***	0.992***	0.317***	0.150**
	[1.107]	[29.654]	[1.540]	[-0.136]	[4.846]	[15.407]	[4.728]	[2.418]
S4B4	1.197***	1.211***	-0.157	0.219***	1.282***	1.043***	0.350***	0.307***
	[3.083]	[12.897]	[-1.165]	[3.339]	[4.667]	[24.515]	[3.973]	[4.144]
S4B5	0.574	0.984***	-0.022	0.564***	0.943***	1.029***	0.475***	0.380***
	[1.250]	[13.822]	[-0.143]	[6.736]	[4.612]	[28.008]	[7.527]	[6.628]
S5B1	1.683***	1.370***	-0.738***	-0.636***	1.585***	1.048***	-0.115	-0.330***
	[3.266]	[10.471]	[-4.675]	[-7.395]	[3.435]	[16.279]	[-1.381]	[-3.342]
S5B2	1.139**	1.102***	-0.542***	-0.218***	0.791**	0.984***	-0.579***	-0.284***
	[2.594]	[12.124]	[-5.057]	[-3.395]	[2.481]	[23.875]	[-6.699]	[-3.935]
S5B3	0.939**	1.023***	-0.530***	0.088	1.455***	1.088***	-0.166	0.156*
	[2.629]	[29.123]	[-4.527]	[1.128]	[3.818]	[15.244]	[-1.124]	[1.727]
S5B4	1.265***	1.155***	-0.656***	0.125	1.851***	0.880***	-0.084	0.591*
	[3.618]	[35.746]	[-7.694]	[1.612]	[3.276]	[6.762]	[-0.864]	[1.763]
S5B5	0.988**	0.936***	0.961***	0.251**	1.046***	0.908***	0.864***	0.152
	[2.516]	[19.726]	[6.657]	[2.645]	[3.125]	[20.503]	[10.147]	[0.955]

Notes:

*: Significant at 10%,

**: Significant at 5%,

***: Significant at 1%

Looking at the individual parameters, the constant term in the second period is both more significant and greater in value, which indicates that stock portfolios after June 2001 achieved relatively higher returns in general. Figures 4.1 to 4.3 plot the significant factor loadings on excess market returns, SMB and HML from Table 4.19 in order to provide a clear comparison of the parameters before and after the June 2001 break.

Loadings on the excess market returns become less diversified across the portfolios. This probably shows that the degree of co-movement among stock portfolio returns increases, caused by some common factors in markets. Arguably, the June 2001 SOE non-tradable share reform discussions triggered anxiety and fear in markets even though the reform was back to the drawing board soon after. After 2005 China experienced a dramatic bull market until in 2007 the rise was stopped by the global financial crisis. A reasonable conjecture is that investor sentiment was a common influence producing co-movement of all stocks – through anxiety, fear and over-confidence. This conjecture will be tested in Chapter 5.

Figure 4.1 Market Risk Before and After June 2001

This figure plots the significant factor loadings on r_M from the Fama-French model (from Table 4.18) based on Chinese A-share stock market data during January 1997 – May 2001 and June 2001 – December 2007. RM1 is the exposed market risk in the period from January 1997 to May 2001 and RM2 is the exposed size risk in the period from June 2001 to December 2007. S1 to S5 refer to size-sorted portfolios from small to big; B1 to B5 refer to book-to-market sorted portfolios from low to high.

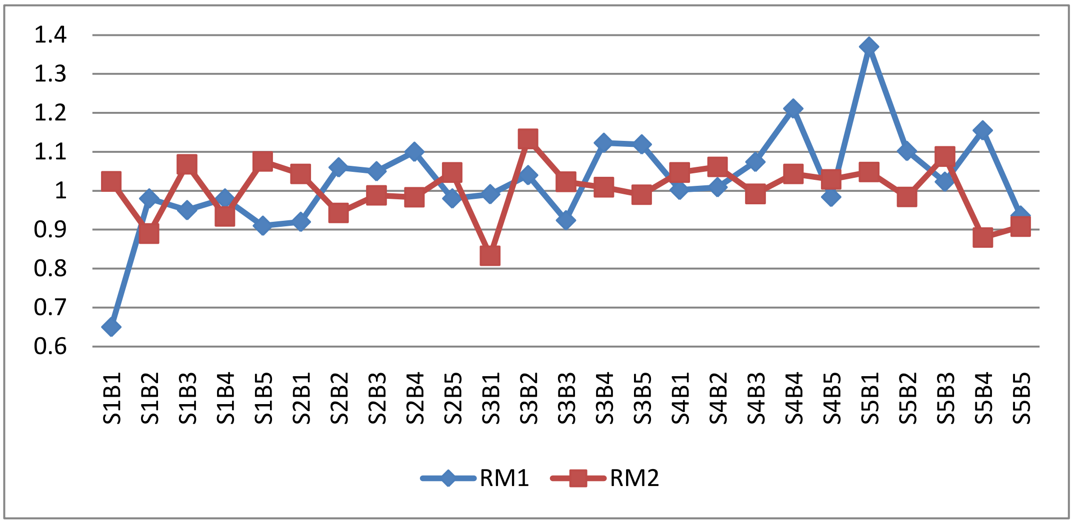


Figure 4.2 Size Risk Before and After June 2001

This figure plots the significant factor loadings of 25 size-BE/ME portfolio returns on SMB from the Fama-French model (from Table 4.18) based on China's A-share stock market data from January 1997 to May 2001 and June 2001 to December 2007. SMB1 is the size risk from January 1997 to May 2001 and SMB2 is the size risk from June 2001 to December 2007. S1 to S5 refer to size-sorted portfolios from small to big; B1 to B5 refer to book-to-market sorted portfolios from low to high.

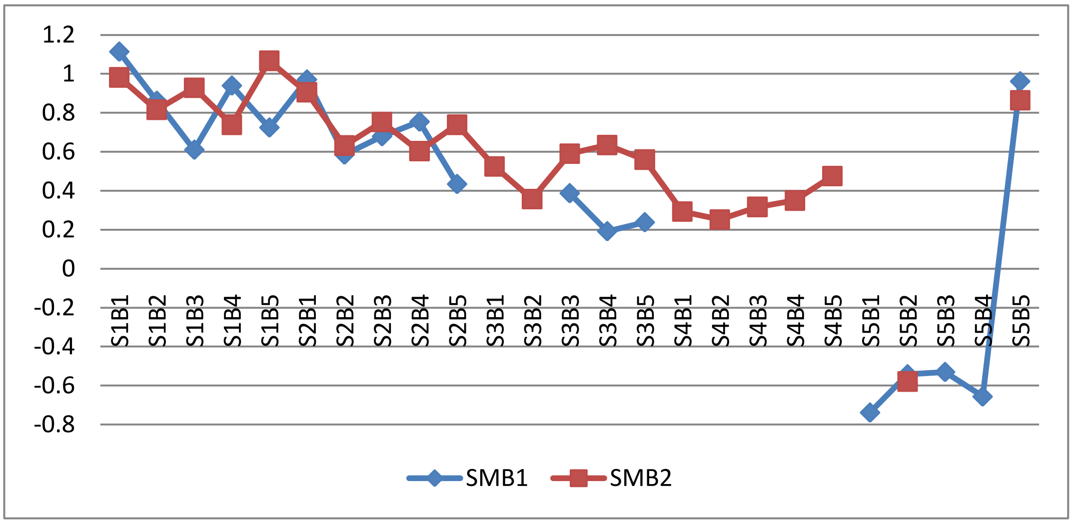
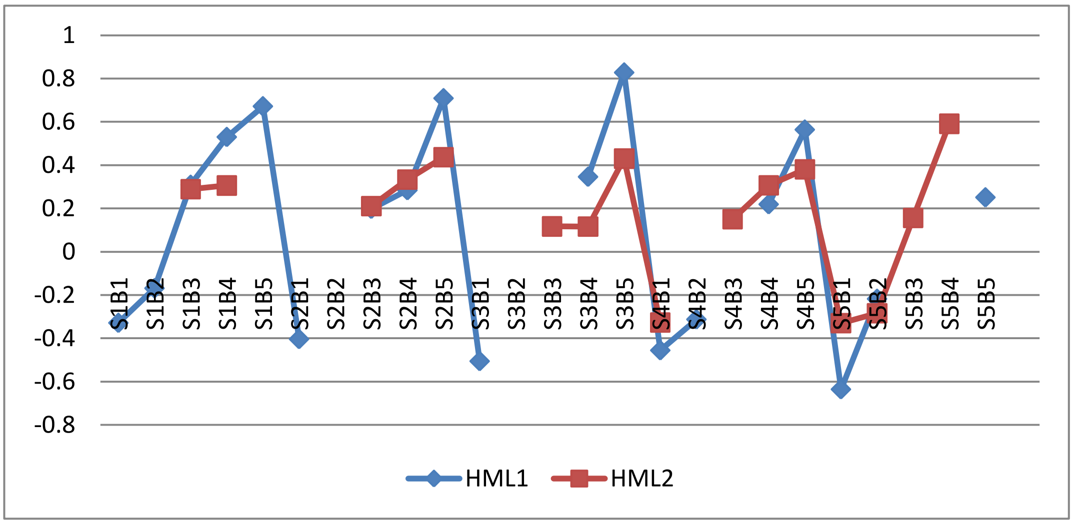


Figure 4.1 Distress Risk Before and After June 2001

This figure plots the significant factor loadings of 25 size-BE/ME portfolio returns on HML from the Fama-French model (from Table 4.18) based on China's A-share stock market data from January 1997 to May 2001 and June 2001 to December 2007. HML1 is the size risk from January 1997 to May 2001 and HML2 is the size risk from June 2001 to December 2007. S1 to S5 refer to size-sorted portfolios from small to big; B1 to B5 refer to book-to-market sorted portfolios from low to high.



After June 2001, size risk seems to be more important as a determinant of stock returns. Seven portfolios have returns that show no size risk during January 1997-May 2001, but this falls to 3 from June 2001-December 2007 (Figure 4.2). Another change in the later period for the SMB loadings is that it appears that mid-large size (S2 to S4) stocks are exposed to greater size risks than before, although the systematic size risk pattern observed in the basic model[36] can still be observed. The change following the June 2001 reform suggests that middle to large stocks increase in size elasticity post-reform while the size elasticity for small stocks tends to be unchanged, reducing the difference between small and large stocks in their size risk exposure.

Unlike the size effect, the significance of distress risk falls slightly in the second period. Six portfolio returns have no correlation with HML (the distress premium) before the break while this number increases to 9 after the break. Across the 25 size-BE/ME sorted portfolios, high book-to-market stock returns still show greater factor loadings on HML than low book-to-market stock returns. However, this difference declines because the returns of high book-to-market stocks show less distress risk whereas those of low book-to-market stocks how relative higher distress risk.

4.7 Conclusion

This chapter sheds light on the success of rational asset pricing models in Chinese stock markets. The test begins by investigating the Fama-French three factor model that has received empirical support in other markets. The results show that the

[36] See Table 4.5 and page 101.

Fama-French factors are important determinants of cross-sectional variation in portfolio returns. However, there is a significant part of the return that cannot be explained by the Fama-French model, which suggests the existence of mis-pricing and challenges the success of the model. Give time-invariant factor loadings, the risk premiums with respect to excess market returns, SMB and HML are strongly time-varying over years and sensitive to the contemporaneous market condition. Also, using June 2001 as the break point, the stability of the Fama-French model is rejected in Chinese A-share stock markets, indicating time-variation and herding patterns of the risk factor loadings.

Four additional risk factors are employed in order to investigate whether the failure of the Fama-French model is caused by missing risk factors. A multi-beta asset pricing model is estimated that contains excess market returns, SMB, HML, and also innovations in the growth rate of industrial production, retail price inflation, the change in the RMB/$US exchange rate, and money market interest rates. The results show that the multi-beta asset pricing model does not work better than the Fama-French model. The residuals from the factor loading regressions are still nonnormally distributed with time-varying variances, while the RESET tests show that there are still omitted variables that could significantly determine the 25 portfolio returns. Moreover, regressing the annual average portfolio returns on the factor loadings show that the prices of market, size and distress risks still vary over time and that the premiums are negative in some years. The prices on the economic risks are insignificant in most years.

In summary, the Fama-French three factor model exhibits a systematic change in parameters following the JUNE 2001 SOE non-tradable share reform. Stock returns show equally significant market risks, but more significant size risks and less significant distress risks. Moreover, there is a consistent pattern of changes in the market, size and distress factor loadings, implying reduced differences in market, size and distress risks across portfolios. These reduced differences reveal that stock returns tended to move more closely together after June 2001, possibly driven by some common influences. Next chapter extends this issue by considering that investor sentiment is the common reason that drives the co-movement between stocks and the deviation in returns away from the fundamentals.

Appendix 4.1 . Number of companies in Sample Sets

Set A includes stocks in Chinese A-share stock markets (Shanghai and Shenzhen) that has listed for more than one year. Set B includes stocks from Set A but excludes stocks marked ST (special treatment) or S, stocks with negative book value of equity, and companies from financial industries.

Year	Set A	Set B
1997	459	373
1998	650	536
1999	748	622
2000	842	693
2001	973	815
2002	1052	885
2003	1123	947
2004	1190	1012
2005	1290	1108
2006	1304	1124
2007	1354	1174

Appendix 4.2 The VAR System Specification

Campbell (1996) and Petkova (2006) apply a first-order VAR system to generate the innovations in economic state variables. The first-order VAR process is followed and autocorrelation in the residuals is checked using Lagrange Multiplier (LM) tests. Results of the LM tests are presented in Panel A of Table A4.2.1. There is serial correlation in the innovations for MP and Inf when a first-order VAR is used, suggesting that changes in MP and Inf can be predicted using the past values. This is inconsistent with the concept of an unexpected shock. The serial correlations are absent when the second-order lags are introduced, as shown in Panel B of Table A4.1. As a result, a second-order VAR is used.

Table A 4.1 Serial Correlation Tests of the VAR Residuals

The vectors in the first- and second-order VAR systems are the same. They include the excess market returns (r_M), the Fama-French factors (SMB and HML), monthly growth rates of a production index (MP), retail price inflation (Inf), changes in the RMB to US Dollar exchange rate (Ex)[37] and the returns of the total bond index (Rf). LM test results are computed as the numbers of observation times the R-squared from the equation estimation, approximately distributed as Chi-squared statistics with 2 degrees of freedom.

Residual Serial Correlation LM Tests								
		R_M	SMB	HML	MP	Inf	Ex	Rf
Panel A: 1st-order VAR	SATMV	3.80	13.67**	2.45	19.34***	8.63*	3.09	0.00
	SALMV	4.49	7.19*	7.22*	18.71***	7.13*	4.36	0.00
	SBTMV	3.16	7.05*	9.33**	19.11***	8.38*	5.20	0.00
	SBLMV	4.44	5.46	14.59***	18.28***	6.95*	5.40	0.00
Panel B: 2nd-order VAR	SATMV	1.43	0.60	0.00	3.44	2.83	2.63	0.00
	SALMV	0.41	0.00	0.00	3.25	3.23	2.85	0.00
	SBTMV	1.32	1.95	0.92	3.26	1.98	2.49	0.00
	SBLMV	1.87	0.48	0.00	3.09	2.46	3.91	0.00

* The result is significant at 95% confidence level. ** The result is significant at 99% confidence level. *** The result is significant at 99.9% confidence level.

[37] The innovation in Ex is composite by the residuals of Ex before August 2005 and the residuals of Ex*Dex afterwards, where Dex is the dummy variable for the Chinese RMB exchange rate reform, which takes the value of 1 after the reform.

Chapter 5 CONDITIONAL ASSET PRICING WITH INVESTOR SENTIMENT

"*…the market has a psychology, more specifically it has a character. It has thoughts, beliefs, moods, and sometimes stormy emotions. The main characteristic of the market is extreme nervousness. It is full of hope one moment and full of anxiety the next moment. … In short, the market closely resembles a stereotypical individual investor.*"

— Kahneman, *January 2000*[38]

5.1 Introduction

Results from the previous chapter suggest that although the Fama-French and multi-beta asset pricing models fit Chinese data as well as to be expected, the structural diagnostics are of more concern with rejections in 18 Reset tests and 19 Chow tests at the date of the SOEs non-tradable share reform. It should be emphasized that there is abundant evidence that variables other than the three Fama-French factors help explain stock returns in a statistical sense (for example Clare and Thomas, 1994). Moreover, taking additional risk factors into account holds out little hope of remedying this defect, since the economic factors do not matter in the determination of asset returns. Furthermore, if the factor loadings are constant over time, the prices of associated risks appear to vary over time. This variation shows some patterns that correlate to some extent with contemporaneous

— [38] These remarks are from Daniel Kahneman's presentation at a conference on behavioural finance held by Northwestern University and quoted by Shefrin (2005: 203–204) in his book "*A Behavioral Approach to Asset Pricing*".

market conditions. This correlation suggests that the theoretical foundation of the three Fama-French factors may be open to doubt.

One argument from behavioural finance attributes mis-pricing and market inefficiency to the effects of investor sentiment. Behavioural economics and finance state that economic agents cannot achieve rational utility maximisation: from one aspect, they may maximise a utility function but employ wrong information; from another aspect, they may gain welfare not only from consumption utility but also from emotions. These provide an illuminating insight into the role of investor psychology in stock pricing.

Investor sentiment may play a more important role in the Chinese stock market. One reason stems from the short (20 years) history of these markets. Chinese stock exchanges are less developed than those of mature markets in developed countries. Less experienced investors, lack of investment instruments, frequent policy changes and the other factors, provide circumstances that hardly satisfy the market efficiency requirement. Another reason is the large number of individual investors, as discussed in Chapter 3. The total number of investors in the A-share markets is sensitive to market conditions. From end 2001 to end 2005 when markets fell, the number of trading accounts in the two stock exchanges increased from 66.5m to 73.4 m. But the number increased substantially more dramatically when the market index rose: in 2006 5.2m new accounts were opened; in 2007 over 60.3m new accounts were opened, and almost doubled the total number of accounts outstanding[39]. It is hard to say how "rational" the new investors can be, as they were almost certainly motivated by the increase in the market index and feedbacks from others. This behaviour exactly describes the definition of trend followers.

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[39] Source from DataStream .

This chapter incorporates investor sentiment as a third dimension (see Figure 2.1, P32) beside risk and returns in the determination of stock returns in China. Investor sentiment is incorporated using the framework of the Fama-French three-factor model already estimated. The role of sentiment is first investigated by focusing on two hypotheses. First, sentiment can be viewed as an additional pricing factor if it directly helps explain the mis-pricing component of returns, that is: the part of the return series not explained by a traditional asset pricing model such as the Fama-French model. Second, sentiment may influence asset prices indirectly *via* its effect on the risk factors themselves in a traditional asset pricing model. Tests of these two hypotheses provide information about the direct and indirect effects of sentiment on asset pricing in the context of a well-established traditional model. Thereupon, a sentiment-based conditional asset pricing model is introduced and tested.

The plan of the chapter is as follows: section 5.2 briefly reviews the relevant literature; section 5.3 provides the theoretical background and develops the motivation for combining sentiment with a conditional beta pricing model; section 5.4 describes the data; section 5.5 investigates the impact of sentiment; the sentiment-based conditional asset pricing model is estimated in section 5.6; section 5.7 provides concluding remarks and direction for further research.

5.2 Literature of Emotional Decision Making and Sentiment Effects on Asset Pricing

Traditional finance theory argues that asset prices are determined purely by investors' unbiased cognitive evaluation and maximisation of expected utility, and leaves no role for investor sentiment. DeLong, *et al.* (1990) challenge this approach with the argument that arbitrageurs have short time horizons and are subject to risks and costs, which implies that there are limits to their abilities to arbitrage away price anomalies.

They also argued that prices would be determined in part by noise traders: investors whose decisions are not based on an analysis of fundamentals or of arbitrage opportunities, but more on sentiment and possibly “irrational” beliefs. In addition, noise traders may tend to trade in concert rather than to diversify because of the effects of common background emotions and feedbacks from their social interactions (Kumar and Lee, 2006). Thus the two assumptions that the traditional asset pricing models are based on — unlimited arbitrage and investor rationality as a whole — may not in fact be true.

The biases involved in people’s judgments and decision making can be categorised into two aspects. First, investors judge in response to information and make decisions heuristically using the rule of thumb (Kahneman, *et al.*, 1982; Kahneman and Tversky, 1996). Second, economic agents cannot always make judgements and decisions objectively. Instead, emotions, mood and feelings play an important role. The former refers to the cognitive bias and the latter refers to the affective bias. A good review for the psychological application on asset pricing was given by Hirshleifer (2001), who summarised that the investors are subject to heuristic simplification (fail to receive and update in response to information fully and rationally), self-deception (to be too confident to evaluate rationally given receiving information and be biased self-attributed), emotional loss of control (emotional effects throughout the decision-making process, such as distaste for ambiguity and time preference), and social interaction (interpersonal communication). Similar work was done later by Stracca (2004), who also addressed the role of decision heuristics and emotions in behavioural asset prices.

5.2.1. Measuring Investor Sentiment

Baker and Wurgler (2007) define investor sentiment as “…a belief about future cash flows or investment risks that is not justified by the facts at hand.” Thus, investor sentiment is not derived from fundamental changes in stock markets but from heuristic and/or emotional reactions to available information.

A straightforward way to measure investors' sentiment is to ask them how optimistic or pessimistic they are. There are two survey data for direct sentiment conducted by the American Association of Individual Investors (AAII) [40] and the Investor Intelligence (II) [41]. Both of them are dealing with the U.S. stock markets. The AAII quantifies individual investors' response survey and the II index aims at the attitudes of newsletters and institutional investors. Since 1996, the UBS and Gallup companies jointly produce a poll of investor attitudes called the UBS/Gallup index of investor optimism. Brown and Cliff (2005) adopt the Investor Intelligence as the sentiment measure and conclude that market pricing errors are positively correlated with the II sentiment index, while over multiyear horizons returns are negatively related to sentiment.

Alternatively, investor sentiment can be measured using some observable market data. Recent researches on the U.S. market define investor sentiment by the direct measures and the indirect indicators interchangeably. For instance, Brown and Cliff (2004) investigate the relationship between direct sentiment measures (AAII and II) and the indirect sentiment indices and report significant correlations with expected sign. This finding suggests that a direct survey of investor sentiments can be proxied and substituted by indirect market variables. This will especially facilitate research in countries with no direct survey data available. Wang, Keswani and Taylor (2006) jointly study both the direct sentiment survey from American Association of Individual Investors (AAII) and the II, and the indirect sentiment proxies of put-call

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[40] The survey is conducted by the American Association of Individual Investors (www.aaii.com).

[41] Investor Intelligence (www.investorsintelligence.com) provides the data.

volume ratio and ARMS index[42]. They find no difference between these sentiment indicators except that ARMS predicts market returns but derivative market products are driven by market returns.

Baker and Wurgler (2006) construct a composite sentiment index using the closed-end fund discount, market share turnover, the number of initial public offerings (in short, IPOs), the IPOs first-day returns, the share of equity issues in total equity and debt issues, and dividend premium. In 2007, they extended the sentiment indicators by arguing that potential sentiment proxies can include investor surveys, investor mood, retail investor trades, mutual fund flows, trading volume, dividend premium, closed-end fund discount, option implied volatility, IPO first-day returns and volume, equity issues over total new issues and insider trading. They found that closed-end fund discount and dividend premium enter the composite sentiment index negatively while turnover, the number of IPOs and IPOs first-day return enter with the positive sign.

5.2.2. Sentiment and Asset Pricing

Sentiment influences expected future cash flows and investment risks and thus affects investment decisions and stock returns. Positive sentiment induces investors to be more confident about their abilities to evaluate situations and more willing to take risks. Negative sentiment usually has the opposite effects (Kuhnen and Knutson, 2008).

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[42] ARMS takes the ratio of scaled advancing issues to scaled declining issues, which is argued to reflect the relative market strength of oversold or overbought.

Empirically, investment sentiment may affect both the aggregate market and the cross-section of returns. In aggregate, periods of high positive sentiment should yield contemporaneously high returns, followed later by low returns as sentiment eventually reverts to a more normal level. Many previous papers have broadly confirmed such a pattern in aggregate market returns: they are typically positively autocorrelated over short time horizons (1-2 months), and negatively autocorrelated over the longer-run (3-5 years)[43]. In cross-sections of shares, sentiment-based behaviour is also expected to vary among firms: the dot-com bubble being one possible example. Baker and Wurgler (2006) find that sentiment particularly drives excess returns for stocks that are: small, young, highly volatile, unprofitable, non-dividend-paying, distressed, or with extreme growth prospects. The crucial characteristic of stocks that are more easily influenced by sentiment is the difficulty and subjectivity of determining these stocks' true valuation. For example, compared with firms with a long earning history and stable dividend payments, small and young firms usually have less available information or at least information that is more costly to access. Currently unprofitable but potentially highly profitable firms imply a greater degree of deferred consumption, and are therefore more difficult to value. Extreme growth and distressed stocks also involve a greater degree of uncertainty than others.

Dealing with Chinese stock markets, Li and Zhang (2008) study the sentiment effect on the aggregate market, where sentiment is captured by the newly opened accounts, and find a positive relationship between shifts in sentiment and stock returns. This proxy is a good measure of individual sentiment because it tells directly how willing people are to trade. Li and Zhang use weekly and monthly data. However, new

---

[43] See DeBondt and Thaler (1985), Hirshleifer (2001) and Barberis and Thaler (2003).

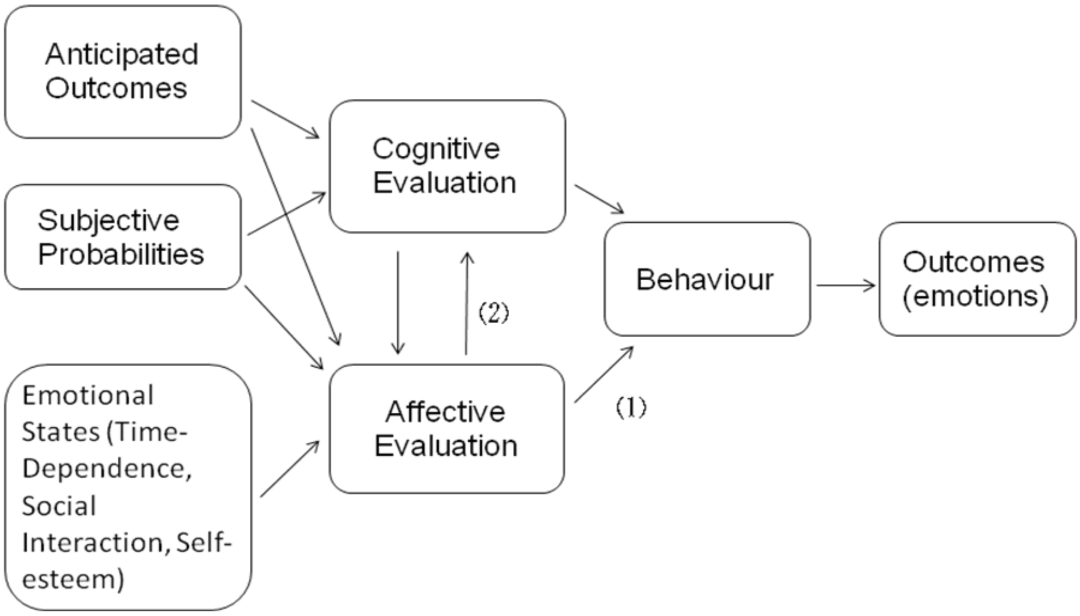
investors crowd into markets mainly motivated by the gains and feedbacks of others *via* social interaction. Such social interaction takes times. Thus the newly opened account may be a good sentiment proxy with quarter or annual frequency but higher frequency data may be less reliable. Also, their sample periods cover May 30, 2005- June 8, 2007 for weekly data and December 2003- April 2007 for monthly data. The data periods are short and, especially for the weekly data, cover only the periods of strong bull market. Consequently, the relationship between sentiment and market returns is hardly expected to be constant over time or under different market circumstances.

5.3 Methodology: Emotional Decision-Making in Stock Markets

5.3.1. Sentiment-based Decisions

Traditional asset pricing models utilise a standard pricing equation derived from expected utility maximisation based on purely cognitive judgements in risky situations. Agents make "rational" decisions using essentially exogenous information and rational forecasting; emotion or sentiment has no role to play. "Economics ignores passions like greed…by transmuting them to allegedly more predictable, less emotional and completely rational motives of self-interest" (Pixley, 2002:69). An alternative schematic description of a decision-making process that specifically allows for the impact of emotion is suggested *inter alia* by Loewenstein, Weber, Hsee and Welch (2001) (figure 5.1).

Figure 5.1 Cognitive and Affective Biases in Decision-Making Process



(Edit from Loewenstein *et al.*,2001)

This suggests that economic agents form their beliefs, make decisions and behave not just on the basis of a cognitive evaluation of anticipated outcomes and probabilities, but also on an affective evaluation from the information at hand and the states that aroused emotional regularities. Psychological theories show that the strength of pessimistic emotion increases when agents face ambiguous situations but decreases when the anticipated outcomes are described or represented in a way which is mentally vivid (Nisbett and Ross, 1980; Einhorn and Hogarth, 1986). In addition, social interaction indicates that people learn to adhere to social norms. Zafar (2009) finds that individuals like to conform: people gain emotional well-being simply by making the same decision as those with whom they make their social comparisons.

Emotional reaction results in people behaving in ways which are biased rather than the unbiased decisions postulated by expected utility theory. Thus, even if they do seek to maximize utility, they may employ “wrong” information. In addition, people may update their beliefs according to their affective evaluation of emotional well-being as well as or instead of their cognitive evaluation of consumption well-being. Applied to asset pricing, this suggests that investor sentiment may be a direct determinant of asset prices and also of the risk factors that investors recognise cognitively.

5.3.2. The Theoretical Hypotheses for Sentiment

According to behavioural finance theory, the measures of investor sentiment are expected to have certain specific effects in stock markets. The main hypotheses regarding sentiment are proposed as the following:

> ***H1*****:** Sentiment helps explain the mis-pricing component of returns in the Fama-French three-factor asset pricing model.
>
> ***H2:*** Sentiment helps explain the Fama-French factors.
>
> ***H3:*** Sentiment affects aggregate and cross-sectional returns. In aggregate, sentiment helps explain the Fama-French factors; in cross-sections, the sentimental effect is stronger for small stocks, distressed stocks (high book-to-market), non-profitable stocks and high volatility stocks.
>
> ***H4*****:** Positive sentiment has a different effect on asset returns from normal sentiment.
>
> ***H5:*** Sentiment affects asset pricing through its impact on variations in the risk loadings of pricing factors; including the Fama-French factors.

H1 is a test of whether sentiment has direct explanatory power for asset returns insofar as it helps explain any mis-pricing in the Fama-French model. ***H2*** is about the indirect effects of sentiment on stock returns through its impact on the risk factors in the Fama-French model. ***H3*** characterises in more detail the distinction between the aggregate (market) and cross-sectional effects of sentiment, following Baker and Wurgler (2006). ***H4*** postulates the existence of a non-linearity in the response of returns to variations in sentiment following for example Odean (1998). ***H5*** postulates that sentiment may conditionally affect the loadings of risk factors in a conventional asset pricing model.

5.3.3. Methodology: Testing Sentimental Effects

The benchmark is the Fama-French model tested in Chapter 4 in which excess portfolio returns ($r_{i,t}$) are regressed on the three Fama-French factors: the excess return on a broad market portfolio (r_M); the difference between returns on small stock portfolios and those on big stock portfolios (*SMB*); and the difference between returns on high book-to-market stock portfolios and those on low book-to-market portfolios (*HML*):

$$r_{i,t} = \alpha_i + \beta_{i,M} r_{M,t} + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + e_{i,t}$$

where: α_i, $\beta_{i,j}$ ($j = M, SMB, HML$), and $e_{i,t}$ are the intercept, coefficients and residuals from the least square regression. The model errors and the Fama-French three factors are used to investigate the sentiment effects on the mis-pricing component of the Fama-French model, and on the characteristic features of the Fama-French three factors. These tests are processed as following.

5.3.3.1 Direct Sentiment Effects

The direct sentiment effects ***H1*** are investigated by regressing the Fama-French pricing errors on the Fama-French factors and three measures of sentiment ($Sent_j$, j=1,…,3)[44]:

$$\begin{aligned} e_{i,t} &= a_{i,t} + \omega_{M,i} r_{M,t} + \omega_{SMB,i} SMB_t + \omega_{HML,i} HML_t + \sum_j b_{i,j,o} Sent_{t,j} \\ &+ \sum_j h_{i,j,0}(Sent_{t,j} D_{Sent,t,j}) + [\sum_j b_{i,j,1} Sent_{t-1,j} + \sum_j h_{i,j,1}(Sent_{t-1,j} D_{Sent,t-1,j})] + \varepsilon_{i,t} \end{aligned} \tag{5.1}$$

where: $D_{sent,j}$, j = 1,…,3 is a sentiment dummy variable equal to unity if sentiment is positive, and zero otherwise. $b_{i,j,k}$ measures the impact of current ($k=0$) or recent ($k=1$) sentiment on the mis-pricing components of returns for symmetric sentiment, and $h_{i,j,k}$ measures the extra impact of sentiment on returns when sentiment is positive ("high"). The recent sentiment, which is the term in square brackets, is only included when the level of investor sentiment is measured[45]. The Fama-French factors included in the model because Maddala (2001: 467) suggests that the existing explanatory variables should also be considered if using residuals to test observed omitted variables[46].

If $b_{i,j,k}$ or $h_{i,j,k}$ are significant, ***H1*** can be accepted, and investor sentiment explains at least part of the portfolio returns that are not explained by the FF factors. If $h_{i,j,0}$ and $h_{i,j,1}$ are both significant, this also provides evidence for ***H4*** which allows for positive sentiment to have a different marginal effect on stock returns than normal

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[44] These are set out in section 5.4 below. An alternative method is to regress the portfolio returns instead of the pricing errors on the FF and sentiment variables. These regressions show robust results.

[45] Sentiment effects are studied and compared between the level of sentiment (raw data) and the changes in sentiment (log difference of sentiment level). When sentiment is measured by the changes, the lagged term is except from the model.

[46] Maddala states that the estimated coefficients of the omitted variables in the residual regression will not be the consistent estimator without the pre-specified explanatory variables, unless the omitted variables have zero coefficients.

sentiment.

5.3.3.2 Indirect Sentiment Effect

Baker and Wurgler (2006) conclude that positive (or negative) sentiment contemporaneously overprices (or underprices) small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks and distressed stocks. They state that the sentiment effects on cross-sections of stock returns can be tested by regression for short-minus-long portfolios[47], such as small-minus-big and high BE/ME-minus-low BE/ME. ***H2*** asserts that sentiment may have an indirect impact on asset pricing in that it helps explain the Fama-French factors. ***H3*** postulates that sentiment effects vary across portfolios. These hypotheses are tested by estimating:

$$Fact_t = \rho_0 + \sum_j \rho_{j,N,0} Sent_{t,j} + \sum_j \rho_{j,H,0} Sent_t D_{Sent,t} + \sum_j \rho_{j,N,1} Sent_{t-1,j} + \sum_j \rho_{j,Sent,1} Sent_{t-1} D_{H,t-1} + u_t \quad (5.2)$$

for each of the FF factors and two new short-minus-long portfolio returns: $Fact_t$ = RM_t, SMB_t, HML_t, $NPMP_t$, $HVMLV_t$.[48] $\rho_{j,N,k}$ and $\rho_{j,H,k}$ represent the normal and positive sentimental effects on the factor portfolios; k = 0, 1 correspond to the current and lagged values of *Sent*. These regressions model time-series and cross-sectional effects of sentiment. For the time series, if $\rho_{j,N,k}$ and $\rho_{j,H,k}$ are

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[47] Short portfolios represent such as small size, high book-to-market, high volatile, and non profitable stocks; long portfolios are, on the contrary, large size, low book-to-market, low volatile and profitable stocks. Short-minus-long portfolios are the differences in returns between the short portfolios and the associated long portfolios.

[48] See P177 for the definitions of NPMP and HVMLV.

significant, ***H2*** can be accepted, indicating that investor sentiment may affect asset prices indirectly by affecting the cognitive risk factors of the pricing model. In the cross-section, the coefficients provide a test of ***H3***, that short (small, distressed, non-profitable and high volatility) stocks are more likely to be prone to sentiment than the long (big, healthy, profitable and low volatility) stocks. For example if small firms are regarded as more speculative than big firms, $\rho_{j,N,k}$ and $\rho_{j,H,k}$ will be positive in the SMB regression, reflecting that positive sentiment increases returns on small firms more than on large firms, while negative sentiment reduces returns on small firms more than on large ones. ***H4*** implies that there is a different marginal effect as between positive and negative sentiment, and this can be checked by investigating the size and significance of $\rho_{j,N,k}$ and $\rho_{j,H,k}$.

5.3.4. Methodology: The Sentiment-based Conditional Asset Pricing Model

If investor sentiment helps explain stock returns even when the FF factors are included in the regression, it suggests that sentiment can be viewed directly as an omitted factor in the model. In addition, if investor sentiment is a determinant of the pricing factors themselves, sentiment also drives asset returns indirectly by affecting the cognitive pricing factors that are the fundamental measures of risk in classical finance. Thus, sentiment has a conditioning effect on the pricing model which, following Baker and Wurgler, can be measured by the interaction between factors and sentiment. In this extended model, portfolio returns are linearly related to the unconditional cognitive factors, the direct sentimental factors, and the conditional sentiment-driven cognitive factors:

$$r_{i,t} = \alpha_i + \lambda_{i,M} RM_t + \lambda_{i,S} SMB_t + \lambda_{i,H} HML_t + \sum_j \delta_{i,N,j} Sent_{t,j} + \sum_j \delta_{i,H,j} Sent_t D_{Sent,t} + \sum_j \sum_k \theta_{i,N,j,k} Sent_{t,j} Fact_{t,k} + \sum_j \sum_k \theta_{i,H,j,k} Sent_t D_{Sent,t} Fact_{t,k} \quad (5.3)$$

As before, $Sent_j$ is the *j-th* sentiment proxie (j=1,…,3), $D_{Sent,t}$ is the dummy variable equal to 1 if sentiment is positive, and $Fact_t$ denotes the cognitive FF factors ($Fact_{t,k} = RM_t, SMB_t, HML_t$). λ_i are the return sensitivities to the Fama-French factors after controlling for sentiment effects, $\delta_{i,N,j}$ and $\delta_{i,N,j}$ pick up the irrational effects of normal and positive sentiment. Conditional sentiment effects are captured by the $\theta_{i,N,j,k}$ for normal sentiment and $\theta_{i,H,j,k}$ for positive sentiment[49]. The null of ***H5*** is that $\theta_{i,N,j,k} \neq 0$ and/or $\theta_{i,H,j,k} \neq 0$ if the conditional sentiment effect is significant; under ***H4*** we may also expect that $\theta_{i,H,j,k} \neq 0$ as positive sentimental effects are different from normal effects. Finally, we check ***H3*** by investigating differences in response to sentiment among the *N* different portfolios.

5.4 Data

5.4.1. Tested Portfolios and Short-Minus-Long Cognitive Factors

The test assets are the same as those in the multi-beta pricing model. The sample stocks are formed into (*N=25*) portfolios differentiated according to size and book-to-market ratios, using sample Set A that includes all stocks with longer than a one year listing history, and the portfolio weighting is by listed market value. SMB is by Set A total market value, and HML is from Set B and weighted by listed market value. The mis-pricing term used in the analysis of direct sentiment effect is from the standard Fama-French model regression errors.

To test the sentiment effects on the cross-section of stock returns, two more variables are studied. NPMP denotes "non-profitable-minus-profitable": the

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[49] Lagged sentiment is omitted from equation (5.3) as lagged sentimental effects turn out to be less significant than current effects in equations (5.2) and (5.1). See the discussion in section 5.5 below.

difference in returns between the equal weighted non-profitable stocks and profitable stocks, where "profitable" indicates firms that have positive accounting earnings before tax. HVMLV denotes high volatility-minus-low volatility: returns on the equal weighted high volatility stocks minus returns on the equal weighted low volatility stocks. High volatility and low volatility portfolios are constructed by sorting stocks into three groups according to their volatility in returns using 30% and 70% as the breakpoints.

5.4.2. Sentiment Proxies

The behavioural pricing literature suggests various proxies for sentiment indicators, but according to Baker and Wurgler (2006), "…there are no definitive or uncontroversial measures…." Brown and Cliff (2004) give a comprehensive overview of different proxies, but our choice is limited to a considerable extent by the availability of data, as in Chinese stock markets the proxies for sentiment are limited. There is no survey data on investor sentiment available in China. Also, stock index futures were firstly introduced in February 2010. Derivative market data is not available within the data period. Besides, data from the IPO market is not continuous, since the IPO mechanism changed three times with suspension of the IPO process[50]. Moreover, as mentioned in Chapter 3, corporate bonds remain undeveloped and few corporations issue corporate bonds to fund operations. Thus the indirect sentiment indicator of equity share in new issues is not available in Chinese stock markets.

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[50] The IPO mechanism experiences six changes that suspended the IPO process for at least 3 months, which are March-July 1991, August 1994-January 1995, January-June 1995, August-November 2001, August 2001-January 2005, and May 2005-June 2006. The later three are within the testing period.

This thesis employs the following sentiment indicators: market turnover (*TURN*); the ratio of advancing to declining issues (*ADVDEC*); and the dividend premium (*DPNP*), comparing payers with non-payers[51].

1. Market Turnover (TURN)

Market liquidity has been argued to be a sentiment indicator as large trading volumes come from noise trading. Black (1986) states noise traders are "willing to trade even when from an objective point of view they would be better off not trading." Baker and Stein (2004) provide a discussion which shows that under a short-sales constraint, market liquidity can be a sentiment barometer: high liquidity is a symptom that the market is overvalued while low sentiment drives investors to quit the market as they cannot short-sell. Baker and Wurgler (2007) confirm that turnover is a proxy for liquidity and sentiment.

Turnover (*TURN*) is the ratio of total reported A-share trading volume in Shanghai and Shenzhen to total shares listed in the two markets. Data of the trading volume and listing shares of Shanghai and Shenzhen stock exchanges are obtained from WindDB (wind financial database). Sentiment is positive (D_{turn}=1) if turnover increases in comparison with some reference point, defined here as the three-period backward moving average. The positive turnover dummy is:

$$D_{turn,t} = \begin{cases} 1, \text{ for turnover} > 3\text{-month moving average of turnover} \\ 0, \text{ otherwise} \end{cases}$$

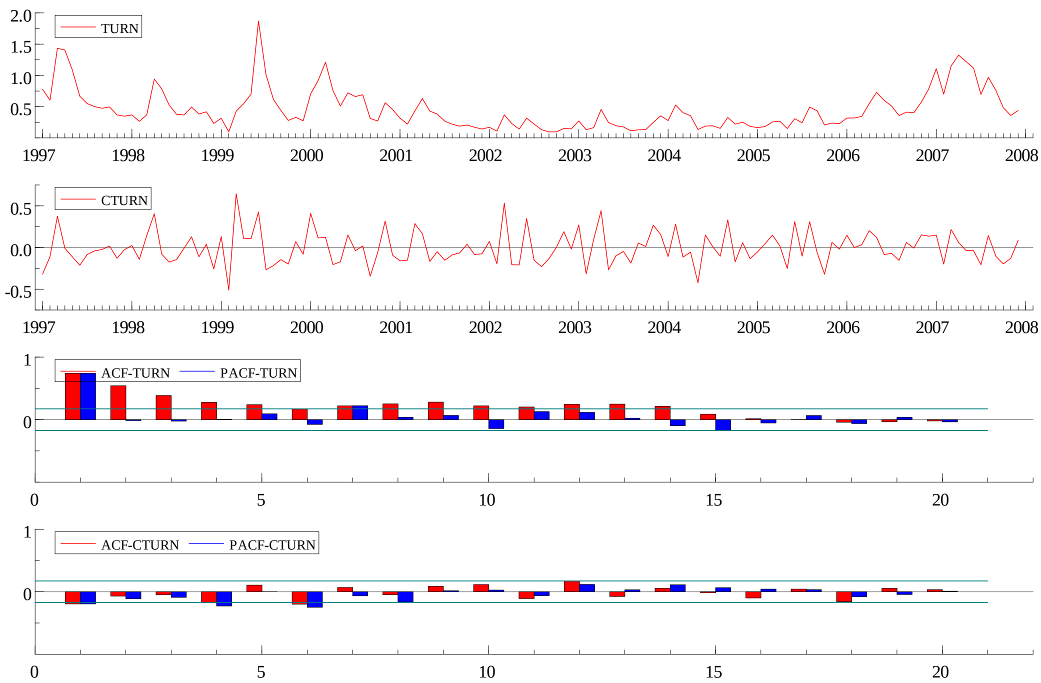
This study tests two turnover variables - the raw turnover ratio (*TURN*) and the

[51] Baker and Wurgler (2006) use the closed-end fund discount (CEFD) but this is available for China only from October 1998, 21 months after the beginning of our sample data. The detailed discussion of CEFD is presented in Appendix 5.1. We checked the closed-end discount as a sentiment proxy using the shortened dataset. Our estimates suggest that it is not a significant determinant of the risk factors, and therefore we do not report these results.

changes in turnover (*CTURN*, defined by the log difference of the raw turnover ratio). The time plot of *TURN* and *CTURN* and their time-series analyses are presented in Figure 5.2. The autocorrelation function (ACF) of turnover shows that the raw turnover ratio has strong serial correlation thus transforming turnover to the log difference may reduce noise in linear regressions.

Figure 5.2 Turnover and log difference of turnover, January 1997- December 2007

This figure plots turnover (*TURN*) and the log difference of turnover (*CTURN*) over the period of January 1997 to December 2007. The autocorrelation function and partial autocorrelation function for the two liquidity indicators are reported following the time plots.



2. Advances-declines Ratio (ADV/DEC)

The second proxy is the ratio of the number of advancing issues to declining issues (*ADV/DEC*), which is a common technical indicator that captures the relative strength of the market in terms of buying-selling imbalance (Brown and Cliff, 2004).

The number of advancing issues is the monthly average number of A-shares from Shanghai and Shenzhen that close at prices above their opening. Similarly, declining issues measure the number of issues that close at prices below their opening. Data on advancing issues and declining issues are from the WindDB.

Several studies used a modified advances-to-declines ratio to capture investor sentiment, see Brown and Cliff (2004) and Wang *et al.* (2006). These studies define a ratio of standardised advancing issues to declining issues, by scaling the advancing and declining issues using the associated trading volumes. Wang *et al.* (2006) point out that this index interprets the ratio of volume per declining issue to the volume in each advancing issue. This research uses the standard ADV/DEC ratio to measure the buying-selling imbalance rather than the scaled one for two reasons. Firstly, the standard ADV/DEC ratio tells directly the relative strength of buying stocks over selling stocks: investors are more willing to purchase stocks at higher prices to match the trading[52] when they are bullish, resulting in stocks closing at higher prices. Secondly and more importantly, the two stock exchanges in China have a price limit regime that restricts daily price changes to be within the -10% to +10% ranges. This constrains trading volumes since trading will be locked once the price reaches the +10% or -10% boundary, leaving no important role for scaling the measure by trading volumes again.

Figure 5.3 reports the *ADV/DEC* and its log difference (*CADV*). During 2006 and 2007 when the market experienced a dramatic increase, the buying-selling pressure remained relatively high in terms of both mean and volatility. But this ratio is lower during mid 2001 to 2005, when the market faced a declining trend. This suggests

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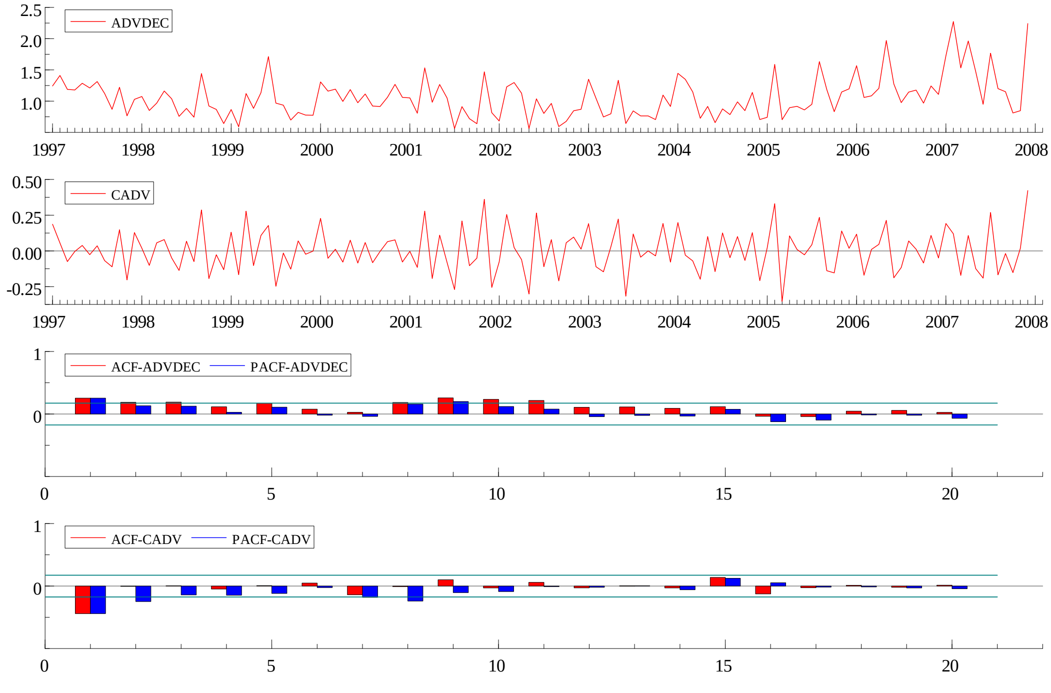
[52] Shanghai and Shenzhen stock exchanges adopt the electronic communications network to match trading using the "price priority and time priority" principle of automatic brokered transactions.

that the advances-declines ratio could be a good sentiment indicator. Since ADV/DEC ratio is serial correlated, the log difference (CADV) is also used as the measure of changes in buying-selling imbalance. The time-series property of CADV shows that the change of ADV/DEC still has first-order autocorrelation but higher order autocorrelation eliminated.

Figure 5.3 *ADV/DEC* and the log difference of ADV/DEC, January 1997-December 2007

This figure plots *ADV/DEC* and the log difference of ADV/DEC (*DADV*) over the period of January 1997 to December 2007. The autocorrelation function and partial autocorrelation function for the two buying-selling imbalance indicators are reported following the time plots.



An ADV/DEC ratio greater than unity indicates that there are on average more buying commissions than selling commissions during the month, and therefore reflects positive sentiment level; and *vice-versa*. The positive sentiment dummy for

ADV/DEC (D_{ADVDEC}) is defined as

$$D_{ADVDEC,t} = \begin{cases} 1, \text{if } ADV / DEC_t > 1 \\ 0, \text{otherwise} \end{cases}$$

3. Dividend Premium ($D^{p\text{-}np}$)

The dividend premium is the difference between the returns on dividend-paying shares and those on non-payers. The theoretical argument of the Modigliani-Miller proposition states that a firm's payout policy should have no effects on its value. Thus the premium of dividend payers should reflect investors' attitudes to these different firms. Non-payers are on average those of small, less profitable firms with strong growth opportunities, while dividend-paying stocks are the reverse (Fama and French, 2001; Baker and Wurgler, 2004). When sentiment is negative, investors become more anxious about the future. This increases time preference so that immediate income from dividend-payers is preferred over deferred income from capital gains from non-payers. Thus the dividend premium captures investor sentiment in the sense of time-dependent emotions: an increase in the premium indicates increased caution and therefore a decrease in investor sentiment[53].

Dividend data is from the WindDB. It has to be noticed that dividend paying in Chinese stock markets is not as common as that in mature markets. In fact, investors care less about firms' dividend policies — they pay more attention to capital gains. Figure 5.4 shows the proportion of payers to non-payers. There were fewer firms paying dividends until 2002, when the number of payers exceeds that of non-payers.

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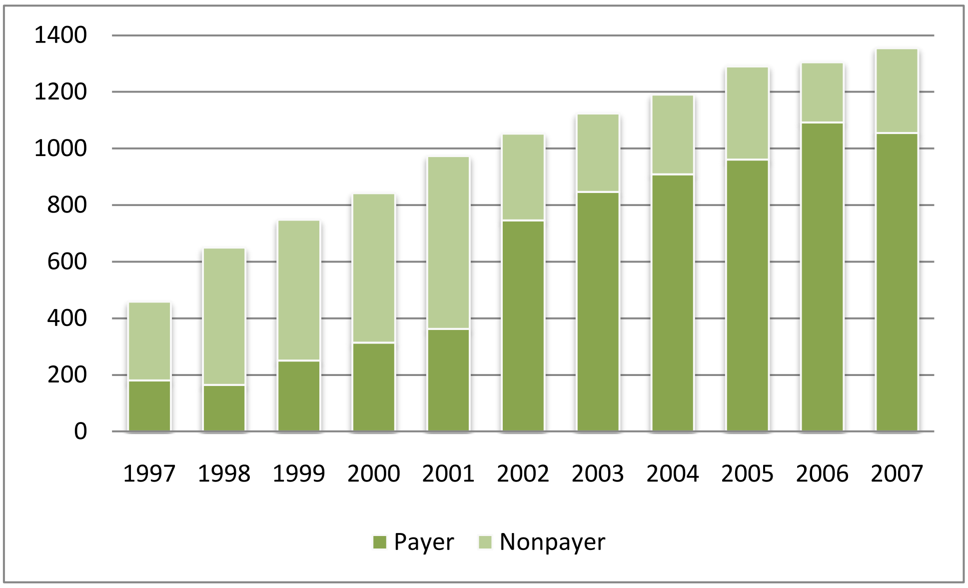
53 Note that this differs from Baker and Wurgler (2004). They use market-book ratios rather than returns.

Figure 5.4 The Proportion of Dividend Payers to Non-payers, 1997-2007

This Figure presents the number of dividend paying companies against the number of non-paying companies. The vertical axis interprets the number of firms.



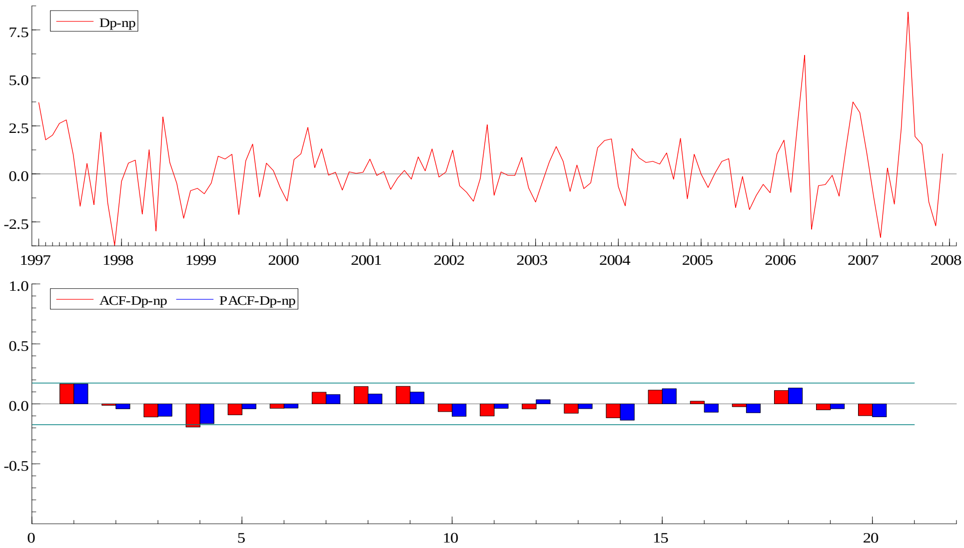
Sentiment is defined to be positive when the current dividend premium is smaller than the 3-months backward moving average, and *vice-versa*. This gives

$$D_{D^{p-np},t} = \begin{cases} 1, \text{if } \ D^{p-np}{}_t < 3-\text{month backward moving avarage of } D^{p-np} \\ 0, \text{otherwise} \end{cases}$$

Figure 5.4 presents the time plot of $D^{p\text{-}np}$ and its time-series properties. Unlike TURN and ADV/DEC, the dividend premium is not serially correlated. Hence the first difference is not used. The serial independence of the dividend premium is to be expected since it is closely related to the stock returns time series.

Figure 5.5 Dividend Premium, January 1997- December 2007

This figure plots $D^{p\text{-}np}$ over the period of January 1997 to December 2007. The autocorrelation function and partial autocorrelation function are reported following the time plot.



5.4.3. Summary Statistics of Sentiment Proxies

The summary statistics for the sentiment proxies are presented in Table 5.1. Data for turnover shows that on average 45.4% of listed shares are traded in a month, indicating a relatively liquid market, possibly because speculative investors trade frequently to earn short-period capital gains. Turnover ranges from 9.7% to 187.0%, with a standard deviation of 32.3%, suggesting that turnover is relatively volatile.

Average ADV/DEC is close to unity, reflecting that buying and selling are broadly matched as we should expect. In the rest of the studies, (ADV/DEC-1) is used to create a zero-mean variable. The volatility of ADV/DEC is high too: buying can be twice as large as selling, or vice-versa. Log changes in *ADV/DEC* do reduce this variance. There are positive premiums for dividend paying stocks, averaging 24.6%.

Table 5.1 Summary Statistics of Sentiment Proxies (in percentage)

TURN is the market turnover obtained as the ratio of total reported A-share trading volumes to the number of shares listed in Shanghai and Shenzhen stock exchanges. *ADV/DEC* is a ratio of monthly average advancing issues to declining issues. D^{p-np} is dividend premium, calculated by the differences in returns between dividend payers and non-payers. *CTURN* and *CADV* stand for the nature log differences in *TURN* and *ADV/DEC*, respectively. For each sentiment proxy, the table shows the mean, maximum, minimum, standard deviation, and *t*(mean), which is the ratio of the mean to its standard error [t(mean) = Mean/(Std. Dev/$132^{1/2}$)]. Panel A reports the summary statistics of the sentiment level, Panel B substitutes *TURN* and *ADV/DEC* by their changes, remaining dividend premium unchanged.

Panel A:	***TURN***	***ADV/DEC***	D^{p-np}
Mean	0.454	1.062	0.246
Maximum	1.870	2.273	8.434
Minimum	0.097	0.563	-3.719
Std. Dev.	0.323	0.323	1.674
t(mean)	16.176	37.749	1.690
Panel B:	***CTURN***	***CADV***	D^{p-np}
Mean	-0.004	0.003	0.246
Maximum	0.644	0.422	8.434
Minimum	-0.510	-0.353	-3.719
Std. Dev.	0.197	0.150	1.674
t(mean)	-0.250	0.257	1.690

Table 5.2 Relations between the Sentiment Proxies, January 1997-December 2007

This table reports the covariances and correlations between the market turnover (*TURN*), advances-declines ratio (*ADV/DEC*) and dividend premium (D^{p-np}). Panel A shows the relations of the level of turnover, ADV/DEC and dividend premium. Panel B shows the relations of the changes in turnover and ADV/DEC, and the level of dividend premium. The diagonal and upper triangular matrices report the covariances among the three sentiment proxies. The lower triangular matrices with bold marking report the correlations among them.

Panel A: Covariances and Correlations between Sentiment Level			
	TURN	*ADV/DEC*	D^{p-np}
TRUN	0.103	0.052***	0.068
ADV/DEC	**0.502*** **	0.104	0.019
D^{p-np}	**0.126**	**0.035**	2.782
Panel B: Covariances and Correlations between Sentiment Changes			
	CTURN	*CADV*	D^{p-np}
CTURN	0.039	0.008***	-0.009
CADV	**0.289*** **	0.022	0.032
D^{p-np}	**-0.027**	**0.127**	2.782

*Note:** Significant at 10% level.** Significant at 5% level.*** Significant at 1% level

Studies of sentiment commonly construct a single composite measure of sentiment from different indicators, using methods such as principal components (Brown and Cliff, 2004; Baker and Wurgler, 2006). This conforms intuitively to the idea of a unified concept of "sentiment". However, since sentiment is not directly observed, the weightings in any empirical measure of sentiment and therefore the whole time series of sentiment are vulnerable to change as new observations of its components become available. In this thesis instead the postulated components are used directly in the regressions. This permits the weight on each component to vary across portfolios and makes it possible to check on the robustness of these variables as sentiment measures. We do not claim that this method is "better" than the received approach, but that it is an important alternative which deserves exploration. Indeed, a first look at the data shows that, apart from TURN and ADVDEC there is a relatively low correlation and covariance among the sentimental factors, giving some confidence that all the sentiment measures can rightfully be interpreted as independent factors

5.5 Impact of Investor Sentiment on Chinese Stock Returns

This section provides some preliminary evidence on sentiment by investigating first, whether investor sentiment explains the mis-pricing component of returns in the Fama-French model, and second, whether investor sentiment helps explain the Fama-French factors. These empirical investigations reveal the direct and indirect sentiment effects on stock returns and guide the sentiment-based asset pricing model. In addition, the appropriate measure of the sentiment proxies, in terms of the levels or the changes, and the current or the lagged, are also studied.

5.5.1. Sentiment Effect on the Fama-French Model Mis-pricing Returns

Results from chapter 4 show that, although the Fama-French model fits as well as to be expected, estimated residuals are non-normally distributed with heteroskedasticity. The structural diagnostics using Reset tests and Chow tests are also of concern. Moreover, adding more fundamental risk factors fails to remedy these defects.

Alternatively, the irrational factor of investor sentiment may help to explain stock returns. This section tests whether investor sentiment helps explain the mis-pricing component of returns in the Fama-French model by equation 5.1.

Both the levels and the changes of investor sentiment are used in the estimation of (5.1). The estimated parameters, the adjusted R-squareds, and the *F*-statistics for testing the joint significance of all the explanatory variables are reported in Table 5.3 and 5.4. for the levels and changes, respectively.

5.5.1.1 Effects of Sentiment Levels on Pricing Errors

When sentiment levels are considered, this mis-pricing regression shows that investor sentiment helps to explain some part of stock returns that cannot be modelled by the Fama-French (table 5.3). This marginally accepts ***H1*** although the sentiment effects are absent for some portfolios. The adjusted R-squareds are small in general, revealing that the three sentiment proxies can capture only a fraction of the Fama-French pricing errors. In 11 out of 25 portfolios, sentiment effects jointly differ from zero.

In those significant cases, market liquidity and buying-selling imbalance are positively related to stock returns. Positive turnover as markets become more active, have no extra explanatory power on average. Another interesting finding is that the one-month lag of turnover always has the opposite signs to the contemporaneous turnover to the extent that the effects are significant: returns increase with current sentiment but decrease subsequently, implying that monthly market liquidity has no momentum effects. This result is in line with the theoretical argument by Baker and Stein (2004) that expected returns are decreasing in liquidity over time[54].

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[54] Given the informative results of the current and lagged sentiment levels, an alternative way is to test the "level plus change" effect: suppose b_o and b_1 are the correlation coefficients on the current and lagged turnover, the level plus change model is that $b_0 TURN_t - b_1 TURN_{t-1} = (b_0 - b_1) TURN_t + b_2 \Delta TURN$. This transformation enables to

The imbalance between buying and selling commissions is the reason of explaining the mid to large size stock returns but the explanatory power disappears for small size (S1) stocks. ADV/DEC has no correlation with the pricing errors on the smallest size stock, but do show some significant correlations as stock size increases. This effect is more likely to come from the current advances-declines ratio. The positive sentiment (buying over selling) has the opposite effect only in the largest size (S5) group. The impact of dividend premium is significant but with inconsistent signs across portfolios, reducing the explanatory power of dividend premium to the mis-pricing components of returns from the Fama-French model.

5.5.1.2 Effects of Sentiment Changes on Pricing Errors

This estimation uses the changes in turnover and advances-declines ratio instead of the levels, with the dividend premium remaining unchanged. Lagged sentiment proxies are excluded from the regressions. Comparing the adjusted R-squareds as between Table 5.3 and 5.4, the levels of sentiment generally model a larger proportion of the pricing errors, as the adjusted R^2 in Table5.3 are almost greater than or equal to those in Table 5.4. Also, only 4 pricing errors can be jointly explained by the three changes in sentiment proxies, as compared to the level of sentiment, where 11 *F*-statistics are significant. This suggests that sentiment levels are more likely to be the direct determinants of stock returns.

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estimate the effect of sentiment level and changes simultaneously. However since the estimation in this step of research is a preliminary test for the sentiment based pricing model and mainly to find the most relevant sentiment effect, the “level plus change” model is not run in this research.

Table 5.3 Sentiment Effects on Mis-pricing Components of the Fama-French Model (LEVEL)

25 Size-BE/ME portfolio return pricing errors in standard Fama-French three factor model are regressed on the constant, Fama-French three factors, symmetrical and positive investor sentiment over 1997:01 – 2007:12. S1 to S5 refer to size sorted portfolios from small to big; B1 to B5 refer to book-to-market ratio sorted portfolios from low to high. *TURN*, *ADV/DEC* and $D^{p\text{-}np}$ are market turnover, advances-declines ratio and dividend premium, respectively. The resulting columns report the sentiment effects with the corresponding *t*-statistics in square brackets below the coefficients. Under each sentiment proxy, "all" is labelled as the symmetric sentiment effects, and "high" indicates the extra effects generated by positive sentiment. Adjusted R-square and the *F*-statistics for testing the joint hypothesis of all explanatory variables are presented in the last two columns. The values in square brackets below the *F*-stat. are the corresponding probabilities of the *F*-tests. The time-series estimations are robust using Newey-West consistent covariance.

	TURN		***TURN(-1)***		***ADV/DEC***		***ADV/DEC(-1)***		$D^{p\text{-}np}$		$D^{p\text{-}np}(-1)$		***Adj. R^2***	***F-stat.***
	All	High	All	High	All	High	All	High	All	High	All	High		
S1B1	-0.092	-0.175	2.403	-0.034	1.046	0.176	2.751	-0.996	-0.574	0.742	-0.468	0.858	-0.018	0.845
	[-0.017]	[-0.059]	[0.462]	[-0.016]	[0.330]	[0.155]	[1.014]	[-0.850]	[-1.102]	[1.086]	[-0.767]	[1.084]		[0.626]
S1B2	-3.804	1.797	4.712	-1.942	0.761	0.508	0.451	-0.612	-0.824	1.374	0.627	-1.164	0.014	1.121
	[-0.722]	[0.699]	[1.246]	[-1.409]	[0.235]	[0.519]	[0.188]	[-0.456]	[-1.482]	[1.581]	[1.202]	[-1.597]		[0.346]
S1B3	-7.989*	4.121*	5.424	-0.016	2.697	-1.224	1.667	0.057	-0.269	0.684	0.265	-0.276	-0.018	0.844
	[-1.905]	[1.706]	[1.620]	[-0.012]	[0.923]	[-1.127]	[0.664]	[0.049]	[-0.609]	[1.363]	[0.529]	[-0.494]		[0.628]
S1B4	0.086	0.997	0.405	-0.166	0.573	0.842	2.089	-0.703	-0.300	0.943**	0.370	-0.567	0.011	1.094
	[0.025]	[0.463]	[0.131]	[-0.152]	[0.265]	[1.028]	[1.096]	[-0.845]	[-0.648]	[2.273]	[1.349]	[-1.185]		[0.370]
S1B5	8.314**	-1.984	-2.541	-2.329	0.975	-0.330	11.311	-2.290	-1.469	2.519**	0.498	-1.098*	0.254	3.948***
	[2.377]	[-0.725]	[-0.798]	[-0.965]	[0.281]	[-0.240]	[1.533]	[-0.967]	[-1.617]	[2.141]	[1.235]	[-1.763]		[0.000]

Table 5.3 (cont.)

	TURN		***TURN(-1)***		***ADV/DEC***		***ADV/DEC(-1)***		$D^{p\text{-}np}$		$D^{p\text{-}np}(-1)$		***Adj.*** R^2	***F-stat.***
	All	High	All	High	All	High	All	High	All	High	All	High		
S2B1	-0.273	1.982	5.703**	-3.486**	2.051	-0.294	5.074	-1.778*	-1.033**	0.844	-0.716	0.201	0.188	3.010***
	[-0.100]	[0.791]	[2.449]	[-2.109]	[0.824]	[-0.316]	[1.523]	[-1.658]	[-2.192]	[1.490]	[-1.188]	[0.291]		[0.000]
S2B2	4.029	-1.041	-1.094	0.686	2.862	-0.808	-2.162	0.498	-0.475	0.819*	0.418	-0.889	0.074	1.693 *
	[1.459]	[-0.446]	[-0.528]	[0.558]	[1.254]	[-0.856]	[-1.062]	[0.596]	[-1.116]	[1.738]	[1.030]	[-1.468]		[0.062]
S2B3	6.379*	-2.011	-5.339**	1.927**	1.868	-0.095	0.395	-0.464	-0.099	0.741**	-0.528**	0.196	0.113	2.101**
	[1.800]	[-1.050]	[-1.980]	[2.112]	[1.036]	[-0.126]	[0.199]	[-0.669]	[-0.269]	[2.007]	[-2.557]	[0.694]		[0.014]
S2B4	0.541	3.038**	0.063	-0.033	2.595	-0.176	2.831*	-1.741***	0.144	0.338	0.109	-0.312	0.139	2.394***
	[0.304]	[2.271]	[0.038]	[-0.049]	[1.517]	[-0.223]	[1.883]	[-2.989]	[0.382]	[0.762]	[0.607]	[-1.262]		[0.005]
S2B5	1.566	1.072	-2.008	1.814	0.869	1.177*	-1.839	0.526	-0.543	0.639	0.634	-0.486	0.098	1.945**
	[0.538]	[0.910]	[-0.966]	[1.401]	[0.457]	[1.817]	[-1.296]	[0.688]	[-1.334]	[1.075]	[1.643]	[-0.831]		[0.025]
S3B1	3.982	-0.095	-1.637	1.240	2.491	-0.926	-0.292	-0.388	-0.613	0.039	-0.020	0.350	0.009	1.081
	[1.047]	[-0.051]	[-0.611]	[1.226]	[1.003]	[-1.130]	[-0.130]	[-0.390]	[-1.244]	[0.080]	[-0.047]	[0.578]		[0.382]
S3B2	0.532	0.125	0.108	-0.737	1.463	0.505	1.540	-0.171	-0.117	-0.236	-0.106	0.997*	0.045	1.409
	[0.143]	[0.076]	[0.052]	[-0.852]	[0.754]	[0.559]	[0.671]	[-0.196]	[-0.177]	[-0.294]	[-0.507]	[1.859]		[0.155]
S3B3	3.008	-1.943	-1.723	0.088	6.781***	-1.229	-1.644	0.501	-0.135	0.022	-0.818**	0.808*	0.062	1.569*
	[0.946]	[-0.921]	[-0.479]	[0.077]	[4.358]	[-1.533]	[-0.553]	[0.490]	[-0.275]	[0.039]	[-2.484]	[1.804]		[0.093]
S3B4	4.605**	0.196	-3.148*	1.024	3.188**	-0.253	-0.212	-0.223	0.290	-0.433	-0.128	-0.248	0.105	2.015**
	[2.047]	[0.107]	[-1.728]	[1.539]	[2.597]	[-0.390]	[-0.136]	[-0.351]	[1.147]	[-1.190]	[-0.597]	[-0.742]		[0.020]
S3B5	3.925**	0.313	-3.148**	2.682***	3.056*	-0.342	-5.416***	1.879***	-0.040	-0.037	0.000	-0.529**	0.247	3.850***
	[2.175]	[0.256]	[-2.043]	[3.405]	[1.926]	[-0.505]	[-3.939]	[3.200]	[-0.210]	[-0.103]	[0.003]	[-2.020]		[0.000]

Table 5.3 (Cont.)

	TURN		***TURN(-1)***		***ADV/DEC***		***ADV/DEC(-1)***		***D^{p-np}***		***$D^{p-np}(-1)$***		***Adj. R^2***	***F-stat.***
	All	High	All	High	All	High	All	High	All	High	All	High		
S4B1	8.137***	-1.959	-5.990***	-0.293	4.665***	0.106	-0.292	0.181	-0.237	0.893*	-0.321	0.819**	0.129	2.286***
	[3.961]	[-0.948]	[-3.056]	[-0.361]	[3.232]	[0.120]	[-0.165]	[0.227]	[-0.693]	[1.762]	[-1.055]	[1.981]		[0.007]
S4B2	-1.048	0.757	1.121	1.043	5.229***	-0.653	-0.504	-0.393	-0.279	0.797***	-0.244	0.645*	0.163	2.688***
	[-0.492]	[0.604]	[0.647]	[1.306]	[2.849]	[-0.940]	[-0.333]	[-0.518]	[-1.049]	[2.686]	[-1.496]	[1.807]		[0.002]
S4B3	-0.455	1.628	0.453	1.083	4.739*	-0.847	-0.960	0.427	-0.303	0.590	-0.330	-0.053	0.050	1.452
	[-0.159]	[0.999]	[0.207]	[0.928]	[1.952]	[-0.993]	[-0.535]	[0.596]	[-0.822]	[1.160]	[-1.246]	[-0.144]		[0.136]
S4B4	0.825	0.789	-1.230	0.686	3.350	-0.831	0.706	0.335	-0.150	-0.087	0.344	-0.643*	-0.028	0.764
	[0.172]	[0.417]	[-0.432]	[0.512]	[1.598]	[-0.821]	[0.364]	[0.417]	[-0.328]	[-0.200]	[1.559]	[-1.882]		[0.714]
S4B5	-0.334	0.906	-1.291	0.582	2.581	0.176	1.937	-0.313	0.211	-0.308	0.364	-0.597*	-0.022	0.812
	[-0.138]	[0.549]	[-0.668]	[0.448]	[1.315]	[0.236]	[1.210]	[-0.425]	[0.572]	[-0.574]	[1.299]	[-1.659]		[0.662]
S5B1	8.175	1.798	-4.500	0.176	6.631**	-2.382**	-1.093	0.341	0.474	0.121	-0.213	0.346	0.184	2.950**
	[1.612]	[0.792]	[-1.201]	[0.159]	[2.452]	[-2.520]	[-0.460]	[0.324]	[1.002]	[0.196]	[-0.562]	[0.675]		[0.001]
S5B2	2.019	1.488	2.480	-1.423	-2.620**	1.155**	-1.744	0.905	-1.461***	1.224***	0.344**	-0.409	0.273	4.248***
	[0.564]	[0.895]	[1.022]	[-1.532]	[-2.114]	[2.112]	[-0.927]	[1.251]	[-3.181]	[2.942]	[2.064]	[-1.572]		[0.000]
S5B3	6.686***	-2.598	-4.646**	1.967**	3.447	-0.651	2.500	-1.160	0.911*	-0.962	-0.489	0.587	0.059	1.543
	[2.859]	[-1.357]	[-2.404]	[2.223]	[1.332]	[-0.607]	[1.588]	[-1.502]	[1.788]	[-1.280]	[-1.343]	[1.442]		[0.102]
S5B4	6.956	-2.148	-1.717	-1.220	6.595**	-2.665*	-1.451	0.770	0.816**	-1.763***	-0.418	0.659*	0.036	1.319
	[1.402]	[-0.893]	[-0.685]	[-0.682]	[2.028]	[-1.739]	[-0.593]	[0.533]	[2.319]	[-2.711]	[-1.446]	[1.794]		[0.202]
S5B5	-3.275	1.214	3.758	-0.934	-1.494	0.814	1.055	-0.105	-0.124	0.487	0.427	-0.793*	-0.025	0.787
	[-0.939]	[0.650]	[1.209]	[-0.837]	[-0.518]	[0.851]	[0.512]	[-0.118]	[-0.217]	[0.752]	[1.189]	[-1.769]		[0.689]

Notes:

*Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Table 5.4 Sentiment Effects on Mis-pricing Components of the Fama-French Model (CHANGE)

25 Size-BE/ME portfolio return pricing errors in standard Fama-French three factor model are regressed on the constant, Fama-French three factors, symmetrical and positive investor sentiment over 1997:01 – 2007:12. S1 to S5 refer to size sorted portfolios from small to big; B1 to B5 refer to book-to-market ratio sorted portfolios from low to high. C*TURN*, C*ADV* and D^{p-np} are changes in market turnover, changes in advances-declines ratio and dividend premium, respectively. The resulting columns report the sentiment effects with the corresponding *t*-statistics in square brackets below the coefficients. Under each sentiment proxy, "all" is labelled as the symmetric sentiment effects, and "high" indicates the extra effects generated by positive sentiment. Adjusted R-square and the *F*-statistics for testing the joint hypothesis of all explanatory variables are presented in the last two columns. The values in square brackets below the *F*-stat. are the corresponding probabilities of the *F*-tests. The time-series estimations are robust using Newey-West consistent covariance.

	CTURN		***CADV***		D^{p-np}		***Adj.*** R^2	***F-stat.***
	All	High	All	High	All	High		
S1B1	-1.373	2.703	-4.616	1.837	-0.762*	1.364**	-0.009	0.864
	[-0.395]	[0.621]	[-1.280]	[0.357]	[-1.676]	[2.142]		[0.559]
S1B2	-4.960	8.525*	0.533	4.369	-0.789	1.351*	0.030	1.454]
	[-1.440]	[1.695]	[0.179]	[0.953]	[-1.485]	[1.728]		[0.173]
S1B3	0.317	-2.490	-3.520	0.825	-0.210	0.730*	-0.031	0.569
	[0.126]	[-0.662]	[-1.107]	[0.205]	[-0.551]	[1.815]		[0.821]
S1B4	-0.242	1.024	-0.890	-0.224	-0.482	1.202***	0.020	1.304
	[-0.101]	[0.296]	[-0.303]	[-0.063]	[-1.157]	[3.089]		[0.242]
S1B5	-1.701	4.322	-5.288	-10.958	-1.658	2.764**	0.139	3.350***
	[-0.455]	[0.594]	[-1.622]	[-1.057]	[-1.551]	[2.356]		[0.001]
S2B1	0.372	-0.711	-5.670	1.380	-1.142**	1.360**	0.033	1.495
	[0.168]	[-0.200]	[-1.441]	[0.282]	[-2.293]	[2.148]		[0.157]
S2B2	1.485	-1.612	-2.397	5.117	-0.576	1.056**	0.016	1.231
	[0.788]	[-0.585]	[-1.148]	[1.456]	[-1.641]	[2.457]		[0.283]
S2B3	-0.600	3.623	-2.635	3.264	-0.316	0.982***	0.046	1.704*
	[-0.337]	[1.479]	[-1.288]	[1.010]	[-0.855]	[2.711]		[0.095]
S2B4	1.184	0.709	-1.557	1.859	0.061	0.493	0.008	1.111
	[0.572]	[0.257]	[-0.847]	[0.880]	[0.168]	[1.141]		[0.360]
S2B5	3.734*	-2.916	1.981	-3.169	-0.707	0.947	0.025	1.375
	[1.882]	[-0.827]	[0.745]	[-0.905]	[-1.575]	[1.345]		[0.206]

Table 5.4 (cont.)

	CTURN		***CADV***		D^{p-np}		***Adj. R^2***	***F-stat.***
	All	High	All	High	All	High		
S3B1	-1.958	3.945	-2.590	1.426	-0.806	0.502	-0.003	0.957
	[-0.770]	[1.132]	[-1.085]	[0.429]	[-1.601]	[0.942]		[0.479]
S3B2	0.433	0.012	-0.642	-2.680	-0.016	-0.146	-0.058	0.196
	[0.249]	[0.004]	[-0.268]	[-0.571]	[-0.026]	[-0.205]		[0.994]
S3B3	-0.765	0.569	-0.401	4.826	-0.406	0.473	-0.034	0.521
	[-0.340]	[0.162]	[-0.152]	[1.099]	[-0.810]	[0.867]		[0.857]
S3B4	1.867	0.260	-3.740*	5.803**	0.322	-0.422	0.005	1.070
	[1.480]	[0.138]	[-1.827]	[2.768]	[1.418]	[-1.523]		[0.389]
S3B5	1.317	-0.813	-0.114	1.752	0.122	-0.123	-0.063	0.132
	[0.791]	[-0.340]	[-0.056]	[0.605]	[0.410]	[-0.315]		[0.999]
S4B1	3.656	-3.002	-1.948	2.696	-0.375	1.109**	0.020	1.296
	[1.584]	[-1.013]	[-0.808]	[0.942]	[-1.127]	[2.502]		[0.246]
S4B2	0.434	-3.900	-1.509	6.302**	-0.229	0.989***	0.092	2.481**
	[0.270]	[-1.500]	[-0.747]	[2.063]	[-0.916]	[3.646]		[0.012]
S4B3	0.343	-1.375	-3.180	4.635	-0.302	0.735	-0.023	0.675
	[0.200]	[-0.350]	[-0.995]	[1.126]	[-0.973]	[1.583]		[0.730]
S4B4	-2.889	4.002	-2.055	-0.299	-0.159	-0.125	-0.041	0.431
	[-1.292]	[1.192]	[-0.716]	[-0.091]	[-0.409]	[-0.330]		[0.916]
S4B5	-1.098	3.280	-0.288	-1.243	-0.138	0.014	-0.055	0.237
	[-0.601]	[1.214]	[-0.125]	[-0.442]	[-0.321]	[0.024]		[0.988]
S5B1	3.773	-4.782	-6.358*	1.909	0.520	0.231	0.010	1.141
	[1.495]	[-1.256]	[-1.719]	[0.427]	[1.006]	[0.441]		[0.340]
S5B2	-2.344	3.709	-3.761*	-0.614	-1.064**	1.052**	0.103	2.679***
	[-1.015]	[1.156]	[-1.946]	[-0.219]	[-2.237]	[2.561]		[0.007]
S5B3	4.015*	-4.984	-3.132	0.971	0.704	-0.551	-0.009	0.876
	[1.741]	[-1.173]	[-1.061]	[0.280]	[1.568]	[-0.996]		[0.549]
S5B4	4.474*	-4.918	-5.680	5.136	0.668*	-1.291**	-0.018	0.747
	[1.756]	[-1.438]	[-1.423]	[1.161]	[1.854]	[-2.265]		[0.665]
S5B5	-4.632]*	7.183*	-0.440	-0.614	0.021	0.377	-0.021	0.702
	[-1.761]	[1.714]	[-0.159]	[-0.159]	[0.040]	[0.647]		[0.706]

Notes: *Significant at 10%. ** Significant at 5%***. Significant at 1%.

5.5.2. Impact of Sentiment on Cognitive Factors

Investor sentiment also affects stock returns indirectly *via* impacting on the Fama-French cognitive factors. This section investigates the impact of sentiment on the Fama-French factors (equation 5.2). Here strong evidence is found for supporting ***H2***: even though many of the sentiment proxies are individually insignificant, collectively, they help explain the time-variation in r_M, SMB, and to a lesser extent HML. *F*-statistics are significant for all cases, indicating that sentiment effects on the excess market and the short-minus-long portfolio returns are jointly different from zero. From another point of view, ***H3*** is accepted as positive relations between sentiment and short-minus-long portfolios (small-minus-big, high BE/ME-minus- low BE/ME, non-profit-minus-profit, and high volatility-minus low volatility) indicate the sentiment effect is stronger for the "short" portfolios. The results are reported in Table5.5 and 5.6, again different in terms of the sentiment measure (levels or changes).

Similar to the effects on pricing errors, sentiment levels have an effect than changes in explaining the Fama-French factors. The regressions for the excess market return, SMB, HML, NPMP and HVMLV all show higher adjusted R-squareds when regressed on the sentiment levels than they do when regressed on the changes. Also, given the model specification, ie. the "other" variables are the same), serially correlated residuals are found in the r_M and HML regressions when the changes in sentiment are used.

Table 5.5: Impacts of Sentiment upon the Fama-French Factors and two more Short-minus-long Portfolio Returns (LEVEL).

Panel A reports the sentiment effects on FF factors (r_M, SMB, HML), non-profit-minus-profit (NPMP) and high volatility-minus-low volatility (HVMLV). "*Other*" reports the additional autoregressive coefficients for the first-order lag of SMB, second-order lag of HML and NPMP[55]. "All" is for normal sentiment and "High" is for positive sentiment. The corresponding *t*-statistics are shown in square brackets. Adjusted R-squareds and *F*-statistics that test the joint significance of all explanatory variables are reported in the last to columns. The corresponding probabilities are given below the *F*-statistics, also in the square brackets. Estimates are robust using the Newey-West procedure with 4 lags. Panel B reports some diagnostic tests of residual normality, serial correlation with two lags, and heteroskedasticity.

Panel A: Setiment Effects on Short-minus-long portfolios

	Sent	*C*	*TURN*	*TURN (-1)*	*ADV/DEC*	*ADV/DEC (-1)*	$D^{P\text{-}NP}$	$D^{P\text{-}NP(-1)}$	*Other*	*Adj.*R^2	*F-test*
r_M	All	-13.12***	5.318	-4.381*	9.809***	0.37	0.291	-0.265		0.786	40.82***
		[-4.585]	[1.499]	[-1.960]	[3.829]	[0.129]	[0.733]	[-0.583]			[0.000]
	High		6.81***	0.023	2.687**	-1.296	0.255	0.494			
			[2.628]	[0.015]	[2.254]	[-1.047]	[0.578]	[0.977]			
SMB[a]	All	1.422	-5.555	5.409*	5.145**	-7.936***	-0.91***	0.088	0.73***	0.508	9.879***
		[1.492]	[-1.582]	[1.846]	[2.320]	[-3.577]	[-3.003]	[0.230]	[7.073]		[0.000]
	High		3.405	-0.026	0.237	1.18	-0.734	1.067**			
			[1.546]	[-0.019]	[0.287]	[1.186]	[-1.300]	[2.459]			
HML	All	-7.329*	-6.21	3.179	8.004**	1.647	0.883***	0.253	-0.252**	0.195	3.402***
		[-1.733]	[-1.137]	[0.743]	[2.031]	[0.644]	[2.670]	[0.727]	[-2.584]		[0.000]
	High		3.056	-1.164	-1.957	-0.041	0.014	-0.347			
			[0.913]	[-0.780]	[-1.462]	[-0.034]	[0.018]	[-0.828]			
NPMP	All	6.185	1.53	-3.094	-4.031	-2.134	-0.015	1.214*	-0.149*	0.211	3.656***
		[1.460]	[0.250]	[-0.533]	[-1.357]	[-0.529]	[-0.028]	[1.684]	[-1.722]		[0.000]
	High		2.55	0.228	-0.254	0.613	1.439**	-1.750*			
			[0.608]	[0.126]	[-0.205]	[0.401]	[2.499]	[-1.871]			
HVMLV	All	-1.503	1.192	0.21	0.256	0.344	-0.387	-0.554**		0.24	4.426***
		[-1.079]	[0.417]	[0.107]	[0.235]	[0.229]	[-1.523]	[-2.158]			[0.000]
	High		-2.56	-0.787	1.365**	-0.72	-0.156	1.08***			
			[-1.607]	[-0.904]	[2.125]	[-1.040]	[-0.507]	[2.948]			

Panel B: Diagnostic Checking

	Normality	LM(2)	White
r_M	25.786***	0.425	3.300***
	[0.000]	[0.655]	[0.000]
SMB	9.366***	0.918	2.601***
	[0.009]	[0.402]	[0.002]
HML	14.773***	0.759	5.272***
	[0.001]	[0.471]	[0.000]
NPMP	6.559**	1.875	2.610***
	[0.038]	[0.158]	[0.002]
HVMLV	27.459***	1.59	1.504*
	[0.000]	[0.208]	[0.066]

Notes:

*: Significant at 10% , **: Significant at 5% , ***:Significant at 1%

[a]: The regression for SMB on the sentiment levels involves ARMA(1,1) errors to correct the regression out of serial correlation in residuals.

[55] "Other" variable in each regression is specified based on the model specification and residual diagnostics.

Table 5.6 Impacts of Sentiment upon the Fama-French Factors and two more Short-minus-long Portfolio Returns (Changes)

Panel A reports the sentiment effects on the excess market returns, SMB, HML, NPMP and HVMLV. All variables are defined the same as those in Table5.5, except the sentiment measures of turnover and advances-declines ratio: here the changes in these two proxies are used, denoted by *CTURN* for the changes in turnover and *CADV* for the changes in ADV/DEC. Lagged sentiment proxies are excepted from the model as changes are used. Panel B reports the diagnostic checking for each regression.

Panel A: **Setiment Effects on Short-minus-long portfolios**

	Sent	Constant	*CTURN*	*CADV*	$D^{P\text{-}NP}$	Other	$Adj.R^2$	*F-test*
r_M	All	0.091	5.206	26.813***	0.058		0.37	13.826***
		[0.086]	[1.536]	[5.332]	[0.064]			[0.000]
	High		12.840**	-8.143	0.735			
			[2.171]	[-1.058]	[0.772]			
SMB	All	0.227	-5.651**	10.621***	-1.089***	0.354***	0.323	9.874***
		[0.402]	[-2.160]	[3.909]	[-2.636]	[4.760]		[0.000]
	High		6.309**	0.051	-0.036			
			[1.649]	[0.013]	[-0.059]			
HML	All	0.652	-0.391	6.481**	0.681*	-0.264***	0.146	4.155***
		[1.300]	[-0.149]	[2.184]	[1.876]	[-2.997]		[0.000]
	High		-0.98	-3.535	0.228			
			[-0.283]	[-1.004]	[0.283]			
NPMP	All	-0.86	3.667	-9.505**	0.408	-0.182**	0.103	3.107***
		[-1.031]	[1.248]	[-2.487]	[0.655]	[-2.130]		[0.005]
	High		0.252	8.134	0.737			
			[0.040]	[1.203]	[1.223]			
HVMLV	All	-0.555	-2.653	3.281**	-0.476		0.116	3.862***
		[-1.570]	[-1.565]	[2.137]	[-1.554]			[0.001]
	High		3.648	2.506	0.008			
			[1.393]	[1.048]	[0.026]			

Panel B: Diagnostic Checking

	Normality	LM(2)	White
r_M	11.139***	9.160***	1.079
	[0.004]	[0.000]	[0.380]
SMB	20.885***	1.748	2.017***
	[0.000]	[0.178]	[0.005]
HML	50.355***	2.824*	2.610***
	[0.000]	[0.063]	[0.000]
NPMP	14.744***	0.204	1.939***
	[0.001]	[0.816]	[0.007]
HVMLV	19.657***	0.679	1.919**
	[0.000]	[0.509]	[0.013]

Notes:

*: Significant at 10% ,
**: Significant at 5% ,
***: Significant at 1%.

5.5.2.1 Systematic Sentiment Effect

The results for r_M are consistent with ***H3*** and ***H4*** in that both normal and positive sentiment contribute separately to explaining aggregate market returns. The sentiment effects on the aggregate market are presented by turnover and advances-declines ratio, but is absent by dividend premium. Current turnover has a marginal positive symmetric effect, while lagged turnover negatively predicts future market returns. *CTURN* has a marginally significant effect on the market returns. When sentiment is positive, market turnover has an extra positive impact on the market returns, which is supported by both the level and the change of turnover. Also, *ADV/DEC* has strong affect on market returns: in general one unit imbalance between buying and selling affects 9.809 units increase of the market return; when investors are optimistic, this coefficient rises to 12.496 (9.809+2.687) times. There is no relation between the market returns and dividend premium, as the *t*-statistics for $D^{p\text{-}np}$ coefficients are never above 1.

5.5.2.2 Investor Sentiment and the Cross-section of Stock Returns

The results are also encouraging for the power of sentiment to explain the cross-sectional pattern of returns implicit in the size, distress, profitability and volatility factors. The regression for SMB suggests that small size stocks are somewhat more likely to be driven by sentiment than large stocks: recent turnover is positively correlated to the current SMB; higher current ADV/DEC leads to higher size premiums; and the decrease in current dividend premium also increases SMB. These findings are in line with Baker and Wurgler (2006) in that returns of small stocks increase further than returns of large stocks with an increase in investor sentiment and decrease further than those of large stocks with a decrease in investor sentiment, since small stocks are inherently more difficult to value and to arbitrage. Lagged ADV/DEC negatively affects SMB, suggesting that large size stocks receive higher returns subsequently.

For HML, the impact of sentiment in general is weaker in terms of significance. The only two significant determinants enter with opposite sign, and only 19.5% of HML can be explained by the sentiment proxies. ADV/DEC positively influences HML, but the dividend premium is also positively related to HML, although the coefficient is relatively small. This could be interpreted as follows: when the stock market is in an adverse state and investors become nervous about further falls, dividend-paying stocks are preferred because they have immediate payments. Meanwhile, high book to market stocks are also preferred, since they are regarded as having a higher winding-up value relative to the market than those with lower book-market ratios. This suggests that it may be reasonable to infer that sentiment effects on asset pricing are time-varying and probably regime dependent. This conjecture will be developed in the next chapter.

For profitability and volatility characterised portfolios (NPMP, HVMLV), sentiment effects are reversed. The change in buying-selling imbalance negatively explains the difference in returns between non-profitable stocks and profitable stocks, suggesting that profitable stocks have higher associated returns when there are more buying commissions than selling commissions. Dividend premium also positively determines NPMP, suggesting that NPMP increases with the decrease in investor sentiment. These findings are indicative that returns on profitable stocks are more sensitive to investor sentiment, possibly because stocks in Chinese stock markets tend to be more sentiment-driven, and profitable stocks are more attractive to the high-flying investors. For volatility characterised stocks, CADV is positively correlated with volatility premium. Dividend premium also negatively predicts HVMLV. But the positive sentiment indicated by a drop of dividend premium positively predicts subsequent HVMLV.

5.5.3. Summary

This section tries to demonstrate the approach of sentiment to the Fama-French model so as to position investor sentiment in asset pricing. In particular, the direct and indirect sentiment effects are studied. Investor sentiment has a direct effect on stock returns since it help explain the part of Chinese stock returns not explained by the FF factors.

Sentiment also impacts on the cognitive Fama-French factors. Consequently, one can be suspicious of the interpretation of the market, size and distress premiums: they may be characteristic[56] rather than fundamental risk factors. Both levels and changes in sentiment provide robust results but the levels have stronger power. The extra positive sentiment effects appear only in the excess market returns. These findings suggest that sentiment levels should be used as the sentiment measure in the sentiment-based asst pricing model, and the extra effects of positive sentiment should also be carefully considered. The significant indirect sentiment effects suggest that investor sentiment affects stock returns not only directly as omitted variables, but also indirectly via conditioning the theoretical risk factors. In principle therefore, the sentiment-based asset pricing model should account for both the direct and the indirect sentiment effects.

5.6 Results of the Sentiment-based Conditional Asset Pricing Model

5.6.1. Model Selection

Based on the preliminary findings of sentiment effects on the mis-pricing errors and Fama-French factors, we turn finally to equation 5.3, where sentiment is included in the model directly as "irrational" risk factors and indirectly as conditioning variables

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[56] The word "characteristic" comes from the Characteristic model (Daniel and Titman, 1997). See P54, 55 for the details.

for the three Fama-French factors. Since we use the individual sentiment proxies and interact with the Fama-French factor, we simplify the model first as follows.

(1) The preliminary results suggest that sentiment levels, rather than the changes are more significant in explaining both the Fama-French factors and the model residuals. Therefore only the levels of sentiment proxies are included in the conditional pricing model. The subsequent question is whether or not the sentiment effect is predictive so that lagged or current sentiment should be used in the model. To keep down the size of the model given the potential number of interaction terms, current and lagged sentiment are included in two separate models. The current sentiment model minimises the mean-square error with a smaller information criterion while the lagged sentiment measures[57] are mostly not very significant. Therefore only current sentiment will be used in the asset pricing model.

(2) The study of the systematic sentiment effect reveals no relation between the market returns and dividend premium. The $D^{p\text{-}np}$ coefficients for r_M are insignificant with *t*-statistics of smaller than 1 in the current, lagged, symmetric and positive cases. Thus the interactions between $D^{p\text{-}np}$ and r_M are excluded from the model.

To sum up, the conditional asset pricing model has 26 variables including the constant, the three Fama-French factors, the normal and positive sentiment proxies, and the 16 interactions between the Fama-French factors and sentiment proxies. The 16 interaction terms are specified as follows:

	r_M	SMB	HML
TURN	√	√	√
TURN(+)	√	√	√
ADV/DEC	√	√	√
ADV/DEC(+)	√	√	√
$D^{p\text{-}np}$		√	√
$D^{p\text{-}np}$(+)		√	√

[57] This statement is based on minimum Akaike information criteria (AIC), Schwarz information criteria (SIC), and Hannan-Quinn information criteria. Lagged sentiment measures are not significant determinants of returns, and therefore we do not report these results.

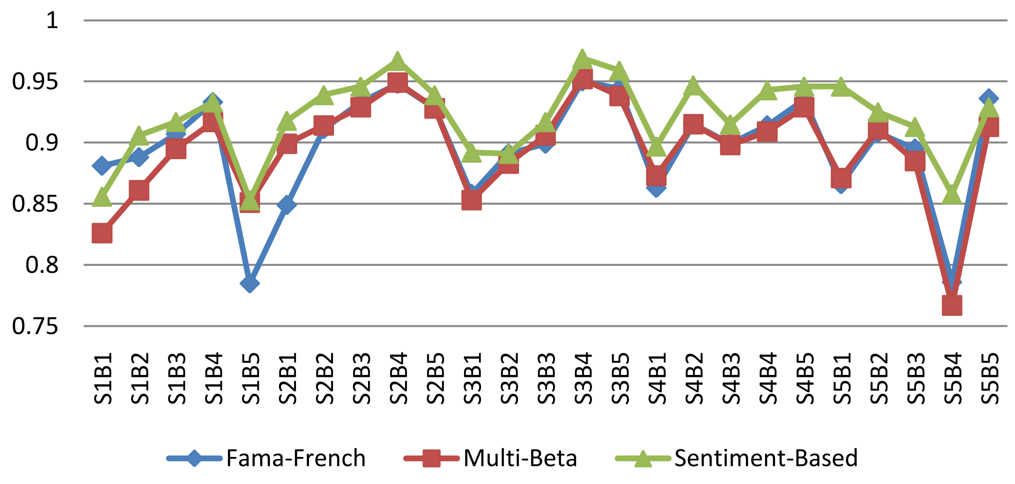
5.6.2. The Sentiment-based Conditional Asset Pricing Model

5.6.2.1 Overall Performance

We begin by comparing the adjusted R^2s from three models: the standard Fama-French model, the multi-beta pricing model with more risk factors, and the sentiment-based conditional asset pricing model (Figure 5.6). The sentiment-based conditional asset pricing model maximises the adjusted *R-squareds* for almost all portfolios. The *F*-statistics (Table 5.7) also show that all the explanatory variables are jointly significant at 99.9% confidence level. Consequently, we can conclude that adding investor sentiment into the pricing model does improve the pricing model's performance for predicting Chinese A-share stock portfolio returns.

Figure 5.6 Comparison between the Fama-French, Multi-beta, and Sentiment-based conditional asset pricing models based on Chinese A-Share stock market data, January 1997-December 2007.

This figure plots the estimated adjusted R^2s obtained from the Fama-French three factor model (r_M, SMB, and HML), the multi-beta pricing model with four more additional risk factors (MP, Inf, Ex, Rf), and the sentiment-based conditional asset pricing model with three sentiment proxies (TURN, ADV/DEC and $D^{p\text{-}np}$) into the model as the generic explanatory variables and as the conditions on the Fama-French three factors.



5.6.2.2 Loadings on the Unconditional Components of Fama-French Three Factors

The sentiment-orthogonalised excess market returns remain significant across all the portfolios, with positive sign. But in some portfolios the market betas reduce to around 0.5, such as for high book-to-market (SiB5) portfolios and size fourth big

(S4Bi) stocks. Other stock portfolios still have returns more volatile than the aggregate market return, even after eliminating the effect of conditional excess market returns.

However, after controlling for sentiment, unconditional size risk and distress risk are more or less insignificant. Only six portfolios report significant factor loadings on SMB, which tend to increase from large stocks to small ones. This is highly comparable with the significant size risks in the Fama-French model and the multi-beta pricing model, which is indicative that SMB is a characteristic factor that is driven by investor sentiment rather than a pervasive fundamental risk factor — investors evaluate stock returns not purely based upon firms' size but the characteristics represented by size that are easily influenced by investor sentiment.

Loadings on unconditional HML are insignificant. Only 10 out of 25 portfolios remain significant factor loadings on HML, which are mainly the big size and/or high book-to-market portfolios and exhibit distress effect. These findings indicate after controlling for sentiment effect, although distress effect does appear, it is relatively imprecise in magnitude.

5.6.2.3 Direct Sentiment Effects

Panel B of Table5.7 reports the direct normal and positive sentiment effects on portfolio returns (the estimated deltas in equation 5.3). 11 out of the 25 size-BE/ME portfolios report significant loadings on the normal market turnover, which locate pervasively across the portfolios. Normal turnover effects are positive, indicating stock returns rise with an increase in market activity in general. The extra effect given by positive turnover is less significant than the normal.

Table 5.7 Fama-French, Sentiment and Interaction Factors Regressions for Monthly Excess Returns on 25 Size and Book-to-Market Portfolios

$$E(r_{i,t}) = \boldsymbol{\lambda}'_i \mathbf{Char}_t + \boldsymbol{\delta}'_i \mathbf{Sent}_t + \boldsymbol{\theta}'_{1,i} \mathbf{Char}_t \mathbf{Sent}_t + \boldsymbol{\theta}'_{2,i} \mathbf{Char}_t \mathbf{Sent}_t \mathbf{D}_{\mathbf{Sent},t}$$

Regressions of 25 Size-BE/ME sorted portfolio excess returns on r_M, SMB, HML, TURN, ADV/DEC, $D^{p\text{-}np}$, and interactions among r_M and TURN, r_M and ADV/DEC, SMB and TURN, SMB and ADV/DEC, SMB and $D^{p\text{-}np}$, HML and TURN, HML and ADV/DEC, HML and $D^{p\text{-}np}$ over January 1997 and December 2007 of Chinese A-share data. OLS coefficients are corrected using Newey-West consistent covariance with 4 lages. The corresponding *t*-statistics are reported in square brackets below the coefficients. Adjusted R^2 and *F*-statistics for testing the joint significance of all the explanatory variables are reported following the coefficients.

Panel A: Constant Term and Unconditional Fama-French Factor Loadings

	Constant					***r_M***				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	-2.077	-1.082	-1.255	-4.506***	-2.042	1.542***	1.189***	0.833***	0.486**	0.413**
	[-0.760]	[-0.376]	[-0.596]	[-2.707]	[-1.203]	[4.371]	[4.375]	[3.976]	[2.419]	[2.244]
2	-3.764	-0.969	-1.421	-0.946	-0.122	1.494***	0.813***	0.991***	0.539***	0.767***
	[-1.461]	[-0.500]	[-0.765]	[-0.547]	[-0.068]	[6.548]	[3.567]	[2.960]	[2.760]	[2.689]
3	-1.619	-3.175*	-2.513	-1.740	0.464	1.188***	0.797***	1.147***	0.983***	0.919***
	[-0.645]	[-1.886]	[-1.516]	[-0.812]	[0.229]	[4.263]	[5.614]	[6.199]	[4.378]	[5.684]
4	-2.528	-2.329*	-1.632	-2.448	-0.029	0.949***	0.753***	0.811***	0.551***	1.756***
	[-1.387]	[-1.799]	[-1.352]	[-1.447]	[-0.009]	[5.481]	[7.234]	[6.872]	[2.644]	[4.220]
High	-7.575*	-1.071	-2.332	-1.554	-1.684	0.897***	0.529**	0.470***	0.535**	1.269***
	[-1.740]	[-0.568]	[-1.378]	[-1.102]	[-0.662]	[3.263]	[2.044]	[2.948]	[2.229]	[6.398]
	SMB					**HML**				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	-0.879	0.194	-0.621**	0.201	0.357	0.241	-0.578	-0.172	-0.585	-1.814***
	[-1.080]	[0.449]	[-2.209]	[0.443]	[0.979]	[0.317]	[-1.015]	[-0.498]	[-1.418]	[-7.133]
2	-0.770	0.130	0.030	-0.026	-0.624	1.184	0.131	-0.187	-0.573	0.350
	[-1.097]	[0.261]	[0.062]	[-0.072]	[-1.165]	[1.460]	[0.268]	[-0.335]	[-1.511]	[0.878]
3	-0.387	0.568	0.038	-0.183	-1.076**	-0.371	0.611*	0.301	-0.192	-0.802*
	[-0.616]	[1.367]	[0.097]	[-0.437]	[-2.496]	[-0.571]	[1.877]	[0.790]	[-0.441]	[-1.867]
4	-0.069	0.551**	0.327	-0.373	-0.774	1.904***	1.200***	0.536	0.295	-0.995
	[-0.220]	[2.083]	[1.178]	[-0.942]	[-1.335]	[6.212]	[4.335]	[1.616]	[0.651]	[-1.496]
High	1.537**	-0.057	0.000	-0.755*	0.827*	1.035*	1.406***	1.310***	0.984*	0.821*
	[2.404]	[-0.152]	[0.001]	[-1.746]	[1.701]	[1.694]	[4.054]	[4.643]	[1.869]	[1.745]

Table 5.7 (cont.)

Panel B: Direct Sentiment Effects

	TURN					***TURN(+)***				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	3.113	4.238***	1.707	0.245	0.482	-1.936	-5.346***	2.458	0.876	2.993*
	[1.342]	[3.255]	[1.367]	[0.109]	[0.297]	[-0.798]	[-3.157]	[1.402]	[0.354]	[1.766]
2	1.078	3.182*	2.625**	2.489**	5.418***	-1.722	0.539	0.503	-1.351	-1.600
	[0.720]	[1.876]	[2.072]	[2.376]	[4.443]	[-0.932]	[0.289]	[0.301]	[-1.059]	[-1.571]
3	2.791**	0.907	-0.979	-0.047	0.473	-3.446	-2.064	-1.293	-0.063	-2.071
	[2.238]	[0.652]	[-0.529]	[-0.034]	[0.309]	[-1.549]	[-1.657]	[-0.784]	[-0.045]	[-1.578]
4	2.976**	0.580	3.248***	-0.148	4.092	-0.181	2.188	-1.920	-1.231	-1.710
	[2.191]	[0.404]	[3.350]	[-0.114]	[1.272]	[-0.112]	[1.313]	[-1.400]	[-0.984]	[-0.700]
High	11.348***	2.785	3.086**	-0.507	4.202***	-4.832**	1.070	-0.960	-0.671	-1.349
	[4.470]	[1.488]	[2.208]	[-0.388]	[2.966]	[-2.057]	[0.541]	[-0.733]	[-0.308]	[-1.077]

	ADV/DEC					***ADV/DEC(+)***				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	1.747	0.480	0.703	4.090**	1.369	0.874	0.110	0.096	0.429	-0.264
	[0.533]	[0.148]	[0.277]	[2.085]	[0.702]	[0.667]	[0.137]	[0.119]	[0.499]	[-0.382]
2	4.183	1.176	1.425	0.257	-1.809	0.373	-0.661	0.614	0.523	1.016
	[1.397]	[0.498]	[0.675]	[0.114]	[-0.857]	[0.393]	[-0.849]	[0.716]	[0.675]	[1.462]
3	2.464	3.248*	3.437*	1.656	-0.168	-0.252	-0.246	-0.651	0.225	1.077
	[0.792]	[1.688]	[1.660]	[0.614]	[-0.066]	[-0.197]	[-0.375]	[-0.729]	[0.266]	[1.179]
4	2.230	2.659*	1.033	3.113	0.363	-0.134	-0.555	-0.056	0.680	-1.087
	[1.001]	[1.861]	[0.754]	[1.656]	[0.105]	[-0.174]	[-0.851]	[-0.103]	[0.999]	[-0.836]
High	5.418	-0.563	1.854	1.779	1.550	-2.196	1.444*	-0.016	1.191*	-0.215
	[1.075]	[-0.262]	[1.038]	[1.018]	[0.541]	[-1.517]	[1.845]	[-0.023]	[1.838]	[-0.257]

	D^{p-np}					$D^{p-np}(+)$				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	-1.196**	-0.694**	-0.422	-0.212	0.456	0.959	0.270	-0.434	0.534	0.332
	[-2.316]	[-2.084]	[-0.642]	[-0.405]	[1.020]	[0.933]	[0.700]	[-0.541]	[0.663]	[0.608]
2	-0.689	0.003	0.174	0.467	-1.289**	0.633	0.036	-0.547	0.045	1.197*
	[-1.568]	[0.013]	[0.204]	[1.651]	[-2.052]	[1.131]	[0.090]	[-0.474]	[0.120]	[1.838]
3	-0.506	-0.812***	-0.298	0.076	0.942	1.117**	1.870***	0.001	0.187	-0.452
	[-1.123]	[-2.836]	[-0.651]	[0.203]	[1.338]	[2.052]	[4.426]	[0.002]	[0.365]	[-0.482]
4	-0.644	-0.024	-0.072	0.212	0.373	1.363***	0.531	0.168	0.060	-1.851***
	[-1.359]	[-0.089]	[-0.408]	[0.548]	[0.595]	[2.725]	[1.468]	[0.606]	[0.115]	[-3.477]
High	-1.893**	-1.128**	-0.465*	-0.296	-0.505	2.463**	1.730*	1.274***	0.541	0.419
	[-2.214]	[-2.023]	[-1.829]	[-0.865]	[-0.788]	[2.141]	[1.891]	[3.602]	[0.803]	[0.555]

Table 5.7 (cont.)

Panel C: Conditional Effects of Investor Sentiment

	r_M*TURN*					r_M*TURN(+)*				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	-0.430	-0.456***	-0.323*	0.289	0.366	0.404	0.397***	0.313	-0.297	-0.088
	[-1.102]	[-2.767]	[-1.733]	[1.401]	[1.554]	[1.160]	[2.993]	[1.649]	[-1.633]	[-0.480]
2	-0.347*	0.254	0.057	-0.435***	0.158]	0.514***	-0.296	-0.161	0.270**	-0.007
	[-1.803]	[0.998]	[0.310]	[-3.246]	[0.922]	[3.355]	[-1.385]	[-0.857]	[2.265]	[-0.052]
3	0.168	0.021	-0.588***	-0.175	-0.029	-0.018	0.135	0.450**	0.169	0.171
	[0.735]	[0.109]	[-3.331]	[-0.784]	[-0.156]	[-0.074]	[0.762]	[2.574]	[0.901]	[1.107]
4	0.269*	-0.004	-0.004	0.244	-0.318	-0.251*	-0.058	-0.082	0.083	0.203
	[1.698]	[-0.026]	[-0.031]	[1.273]	[-1.432]	[-1.692]	[-0.433]	[-0.622]	[0.457]	[1.236]
High	1.019**	0.236	0.247	0.195	0.034	-1.045***	-0.249	-0.201	-0.031	-0.204
	[2.295]	[1.211]	[1.323]	[1.160]	[0.161]	[-2.766]	[-1.386]	[-1.073]	[-0.208]	[-1.236]

	r_M*ADV/DEC*					r_M*ADV/DEC (+)*				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	-1.008**	-0.159	0.034	0.115	0.242	0.547**	0.173	0.006	0.176	0.139
	[-2.302]	[-0.353]	[0.105]	[0.349]	[1.019]	[2.431]	[0.851]	[0.032]	[0.788]	[0.884]
2	-0.799**	0.099	-0.114	0.617**	0.092	0.189	-0.035	0.189	-0.142	-0.019
	[-2.226]	[0.294]	[-0.240]	[2.386]	[0.238]	[0.968]	[-0.197]	[0.597]	[-0.946]	[-0.099]
3	-0.323	0.041	-0.169	-0.183	0.047	0.090	0.031	0.165	0.189	-0.028
	[-0.889]	[0.172]	[-0.677]	[-0.583]	[0.206]	[0.483]	[0.185]	[0.825]	[0.985]	[-0.170]
4	-0.218	0.073	0.048	0.407	-1.082	0.078	0.086	0.220*	-0.250	0.801*
	[-0.765]	[0.355]	[0.266]	[1.149]	[-1.631]	[0.495]	[0.653]	[1.802]	[-1.226]	[1.821]
High	-0.519	0.302	0.473**	0.414	-0.578*	0.516***	-0.034	-0.191	-0.270	0.388**
	[-1.281]	[0.820]	[2.167]	[1.085]	[-1.900]	[2.673]	[-0.202]	[-1.786]	[-1.285]	[2.152]

Table 5.7 (cont.)

Panel C: Conditional Effects of Investor Sentiment

	SMB*_TURN_					**SMB*_TURN(+)_**				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	-0.315	0.484	0.850**	-0.213	0.419	-0.144	0.514	-0.449	0.601	0.038
	[-0.479]	[1.083]	[2.184]	[-0.344]	[1.032]	[-0.313]	[1.352]	[-1.194]	[1.551]	[0.135]
2	0.030	-1.029*	-0.570	0.452	-0.452	-0.004	0.944**	0.194	-0.345*	-0.018
	[0.062]	[-1.912]	[-1.331]	[1.522]	[-1.126]	[-0.013]	[2.183]	[0.646]	[-1.837]	[-0.066]
3	-0.926**	0.222	0.421	0.808**	0.543	0.742**	0.062	0.346	0.017	0.185
	[-2.078]	[0.490]	[1.050]	[2.292]	[1.110]	[2.585]	[0.184]	[1.017]	[0.058]	[0.620]
4	-0.798**	0.678*	-0.427	0.864	-1.076	0.378	-0.174	0.631**	-0.183	0.894
	[-2.224]	[1.893]	[-1.228]	[1.579]	[-1.593]	[1.323]	[-0.762]	[2.410]	[-0.514]	[1.501]
High	-0.541	-0.607	-0.273	0.591	-0.291	1.169**	0.057	0.367	-0.053	0.330
	[-0.837]	[-1.384]	[-0.990]	[1.185]	[-0.797]	[2.252]	[0.169]	[1.298]	[-0.185]	[1.287]

	SMB*_ADV/DEC_					**SMB*_ADV/DEC(+)_**				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	2.273**	-0.103	0.946**	0.007	-0.825**	-0.782**	0.069	-0.605***	-0.272	0.115
	[2.490]	[-0.180]	[2.553]	[0.013]	[-2.099]	[-2.245]	[0.324]	[-3.046]	[-0.933]	[0.636]
2	1.834**	0.770	0.261	-0.016	0.059	-0.321	-0.353	-0.195	-0.015	0.111
	[2.036]	[1.348]	[0.471]	[-0.037]	[0.095]	[-1.083]	[-1.325]	[-0.603]	[-0.086]	[0.416]
3	1.352*	-0.016	0.115	-0.031	0.325	-0.453	0.007	0.103	0.072	-0.258
	[1.714]	[-0.031]	[0.251]	[-0.065]	[0.581]	[-1.491]	[0.028]	[0.378]	[0.322]	[-0.860]
4	1.225***	-0.164	-0.003	0.158	0.784	-0.263	0.172	0.040	-0.269	-0.364
	[3.304]	[-0.587]	[-0.007]	[0.268]	[1.154]	[-1.436]	[1.166]	[0.245]	[-0.948]	[-1.284]
High	-0.968	0.962**	0.328	0.998*	0.159	0.295	-0.398**	-0.068	-0.571***	0.065
	[-1.277]	[2.161]	[1.029]	[1.780]	[0.291]	[0.787]	[-2.017]	[-0.372]	[-2.744]	[0.297]

	SMB*D^{p-np}					**SMB*$D^{p-np}(+)$**				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	0.126*	-0.115	-0.019	-0.081	0.029	-0.036	0.105	0.111	0.044	-0.014
	[1.731]	[-0.794]	[-0.201]	[-0.720]	[0.428]	[-0.241]	[0.505]	[0.716]	[0.260]	[-0.171]
2	0.161***	-0.141**	-0.161	-0.146**	0.031	-0.223*	0.189**	0.244	0.190***	-0.029
	[2.637]	[-2.534]	[-0.992]	[-2.617]	[0.282]	[-1.951]	[2.010]	[0.909]	[2.977]	[-0.202]
3	-0.024	0.109	0.098	-0.029	-0.172	0.130	-0.045	-0.173	-0.012	0.328*
	[-0.300]	[1.559]	[0.964]	[-0.363]	[-1.284]	[0.844]	[-0.349]	[-1.082]	[-0.113]	[1.732]
4	0.084*	0.132***	0.016	-0.119	-0.011	-0.057	-0.157***	0.015	0.217*	-0.028
	[1.722]	[3.973]	[0.327]	[-1.393]	[-0.113]	[-0.705]	[-2.672]	[0.215]	[1.709]	[-0.147]
High	-0.008	0.036	0.036	0.037	0.198***	-0.095	0.113	0.061	-0.007	-0.221***
	[-0.035]	[0.528]	[0.812]	[0.510]	[3.085]	[-0.391]	[1.362]	[1.015]	[-0.063]	[-3.299]

Table 5.7 (cont.)

Panel C: Conditional Effects of Investor Sentiment

	HML*$TURN$					**HML*$TURN(+)$**				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	0.616	0.122	-0.154	0.201	-0.590**	0.768*	0.369	-0.317	-0.014	-0.364*
	[0.954]	[0.368]	[-0.406]	[0.447]	[-1.939]	[1.803]	[1.551]	[-1.078]	[-0.037]	[-1.808]
2	1.314**	-0.129	0.721*	0.427	0.764**	-0.869***	-0.186	-0.193	-0.185	-0.277
	[2.382]	[-0.322]	[1.956]	[1.441]	[2.111]	[-3.185]	[-0.883]	[-0.414]	[-1.195]	[-1.220]
3	1.616***	0.730**	-0.300	-0.313	-0.398	-0.104	-0.512**	-0.440	-0.313	0.151
	[3.976]	[2.258]	[-0.944]	[-1.053]	[-1.131]	[-0.267]	[-2.573]	[-1.630]	[-1.172]	[0.521]
4	0.761**	-0.037	0.735***	-0.078	-0.407	-0.264	-0.308**	-0.494***	-0.410**	-0.106
	[2.572]	[-0.122]	[3.264]	[-0.281]	[-0.736]	[-1.577]	[-2.239]	[-2.762]	[-2.450]	[-0.206]
High	0.949**	0.743	0.791***	0.097	0.867**	-0.809**	-0.138	-0.563**	-0.017	-0.633***
	[2.032]	[1.410]	[3.000]	[0.291]	[1.976]	[-2.132]	[-0.528]	[-3.182]	[-0.087]	[-2.772]
	HML*ADV/DEC					**HML*$ADV/DEC(+)$**				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	-0.850	0.530	-0.008	0.046	1.919***	-0.260	-0.592	-0.001	0.002	-0.603***
	[-0.762]	[0.570]	[-0.014]	[0.085]	[4.870]	[-0.730]	[-1.538]	[-0.003]	[0.006]	[-3.305]
2	-1.965*	0.208	-0.035	0.246	-0.905**	0.171	-0.407	0.019	-0.284*	0.197
	[-1.702]	[0.318]	[-0.051]	[0.484]	[-2.015]	[0.558]	[-1.547]	[0.060]	[-1.722]	[0.903]
3	0.042	-0.901**	-0.019	0.495	1.206**	-0.517	0.330*	0.015	-0.205	-0.343
	[0.044]	[-2.067]	[-0.036]	[0.957]	[2.194]	[-1.626]	[1.942]	[0.059]	[-0.847]	[-1.328]
4	-2.264***	-1.261***	-0.354	0.210	3.099**	0.651***	0.471***	-0.147	-0.138	-1.931**
	[-5.337]	[-3.205]	[-0.741]	[0.342]	[2.136]	[4.378]	[3.127]	[-0.922]	[-0.579]	[-2.338]
High	-1.045	-1.186**	-0.966**	-0.598	-1.076	0.401	0.226	0.235	0.053	0.131
	[-1.186]	[-2.346]	[-2.404]	[-0.810]	[-1.599]	[1.186]	[1.250]	[1.646]	[0.231]	[0.596]
	HML*D^{p-np}					**HML*$D^{p-np}(+)$**				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	-0.052	-0.153	-0.031	0.043	-0.009	0.280	0.239***	0.126	-0.057	-0.091
	[-0.441]	[-1.615]	[-0.367]	[0.456]	[-0.143]	[2.301]	[2.100]	[1.196]	[-0.624]	[-1.470]
2	-0.037	-0.097	0.117	0.012	-0.073	0.286***	0.156*	-0.148	0.015	0.087
	[-0.376]	[-1.182]	[1.153]	[0.212]	[-0.958]	[2.837]	[1.725]	[-1.417]	[0.241]	[0.991]
3	-0.144	-0.077	0.095	0.036	0.119	0.183*	0.061	-0.051	-0.024	-0.162
	[-1.467]	[-1.179]	[0.982]	[0.360]	[1.540]	[1.802]	[0.700]	[-0.410]	[-0.253]	[-1.651]
4	-0.245***	-0.163***	-0.053	0.077	0.028	0.330***	0.222***	0.004	-0.112	-0.067
	[-3.646]	[-2.979]	[-0.854]	[0.920]	[0.322]	[4.291]	[3.611]	[0.058]	[-1.142]	[-0.539]
High	-0.474***	-0.167*	0.021	-0.093	-0.205**	0.365**	0.170*	-0.092	0.106	0.273***
	[-3.059]	[-1.883]	[0.293]	[-1.180]	[-2.326]	[2.175]	[1.827]	[-1.359]	[1.097]	[3.062]

Panel D: General Description

	***Adj.*R^2**					***F-stat.***				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	0.856	0.918	0.892	0.897	0.946	32.062***	59.688***	44.117***	46.645***	93.657***
2	0.906	0.939	0.891	0.947	0.925	51.557***	81.478***	43.843***	93.953***	65.493***
3	0.917	0.946	0.917	0.915	0.913	58.948***	93.551***	58.769***	57.768***	56.282***
4	0.933	0.967	0.969	0.943	0.858	74.106***	156.566***	166.756***	88.078***	32.702***
High	0.853	0.939	0.959	0.946	0.929	31.479***	81.389***	123.384***	92.517***	69.580***

Notes:

*: Significant at 10% ,

**: Significant at 5% ,

***: Significant at 1%.

The effect of the buying-selling imbalance is significant in only 4 out of the 25 tested portfolios (S2B3, S2B4, S3B3, and S4B1) and marginally significant from S4B4. Recalling that in the pricing errors regression ADV/DEC tends to explain the mis-pricing component of returns for mid to large stocks, this feature cannot be observed by the direct ADV/DEC, suggesting the ADV/DEC may have its main effect as a conditioning variable. Those significant loadings on ADV/DEC also have positive sign, indicating that portfolio returns are expected to be higher when investors become bullish. Positive sentiment, again, has no extra explanatory power to stock returns.

The dividend premium is likely to be significant in 7 portfolios. General dividend premium is negatively related with stock returns. This is consistent with our expectation that sentiment positively affects stock returns, and dividend premium is a negative sentiment measure. When sentiment is positive, the dividend premium positively affects portfolio returns, supported by eight portfolios. This offsets the negative effects by the symmetric dividend premium and leaves no effect by positive sentiment in total.

5.6.2.4 Effects of Conditional Sentiment on Asset Pricing

The interest here centres on the conditional factor loadings captured by the interactions between the sentiment proxies and the Fama-French factors (Panel C of Table5.7).

(i) Conditional market risk

Recalling that the unconditional market risk is highly significant, the conditional market risks are relatively minor. 7 portfolios exhibit significant factor loadings on the interaction between excess market return and turnover. The negative loadings on the conditional market risk indicate that when market liquidity increases without the corresponding increase in market returns, stock returns fall as well. This possibly describes a state in which market liquidity increases because of bearish sentiment and sentiment-driving selling. When this conditional symmetric market risk is significant, positive sentiment always gives a significant extra effect. However, the extra effects of positive sentiment have the opposite sign to the symmetric conditional effects, offsetting each other. This may reveal that when sentiment is high, stock returns increase with the market return, no matter with or without the increase in market liquidity.

The significance of returns' sensitivity to the interaction of excess market return and ADV/DEC is even weaker: 5 portfolio returns expose market risks conditioning on buying-selling imbalance; and 5 portfolios are impacted by positive sentiment in addition. When sentiment is positive as buying pressure exceeds selling pressure, the conditional market factor loadings are positive, suggesting that when the market returns increase and more investors are willing to buy, stock returns increase as well. But when selling pressure is greater, the coefficients on the conditional market returns have inconsistent signs across portfolios.

(ii) Conditional size risk

The conditional size risks vary considerably across portfolios in signs and significance. Conditioning on TURN, 6 portfolios report significant factor loadings on SMB and 3 more are marginally significant. These 9 conditional size risks provide a broad evidence of negative conditional size risk for small size portfolios but positive conditional size risk for bigger size stocks although the effect is absent for the biggest (S5Bi) portfolio group. This trend is opposite to the theoretical size effect statement that small firms expose greater size risks than big firms and reveals the particular turnover condition: when markets become more active, big size stock returns positively correlate with the conditional size premium while small size stocks reduce returns. A possible reason is that turnover is a sentiment indicator for big size stocks only. This explanation has a reasonable basis, since total market turnover is more likely to arise from the activity of large size stocks simply because they have more weights. Optimistic turnover is more likely to affect size risks positively, suggesting small stocks are more speculative when sentiment is positive.

In contradistinction to turnover, precise Fama-French-type patterns of impact on different portfolios emerge from the results of the ADV/DEC conditioning on SMB, in which loadings of the returns of small stocks are more significant and generally higher than of the returns of large stocks. However, this pattern is shown by not the unconditional size risk, but the conditional size risk. Thus the central hypothesis (***H5***) that conditioning on sentiment matters for share pricing in China is clearly established. When ADV/DEC is above 1, improvements in sentiment reduce the loadings. This suggests that even small stocks are more speculative, stock returns increase with the returns on large stocks since size character is less cared by the bullish investors.

For the dividend premium, the conditional size effect is significant in seven portfolios but the effect is less clear-cut. The conditional SMB factor loadings vary considerably across portfolios in signs and significance, leaving no conclusive finding of the effect of the interaction between size premium and dividend premium on stock returns. Again, when sentiment is positive, the statement that size character is ignored emerges from the result: positive sentiment as measured by a decrease in dividend premium always attenuates the symmetric effect.

(iii) Conditional distress risk

Comparing with the conditional market risk and size risk, conditional distress risk is more significant no matter whether it is conditioning on turnover, advances-declines ratio or dividend premium. Furthermore, the conditional distress risks are more important than the unconditional factor loadings on HML. HML is more likely to be a sentiment-driven pricing factor.

When conditioning on market turnover, 11 portfolios exhibit significant factor loadings on the interaction between HML and normal turnover and 10 portfolios show a significant conditional effect by positive turnover. Given symmetric sentiment as the condition, portfolio returns increase with the conditional HML. Loadings on positive-turnover-conditioned-HML have negative signs, which are consistent with the findings of conditional size risk and suggest that when sentiment is positive, the characteristic distress risk is less likely to be priced. No systematic pattern can be observed clearly across the 25 size-BE/ME sorted portfolios.

With normal sentiment, distress risk conditioning on advances-declines ratio is negative for small size stocks but the loadings roughly increase with the increase in firm size. This indicates returns on small and growth (low book-to-market) stocks tend to move together when buying pressure increases against selling pressures. This effect, again, is offset by the extra effect of positive sentiment, revealing that in a bull market, stock returns are not determined by firms' characteristics.

For dividend premium, the conditional factor loadings on HML are significant for 5 high book-to-market stocks with negative signs. These negative coefficients are inconsistent with the Fama-French-type pattern that high book-to-market stocks expose higher (positive) distress risk, but they are in line with the statement that dividend premium is a negative sentiment proxy as it reverses the positive correlation between HML and high book-to-market stocks. In other words, an increase in $D^{p\text{-}np}$ reflects a decrease in sentiment, which decreases the portfolio returns. The extra effect by positive sentiment has a positive sigh and attenuates the relation between the stock returns and the conditional HML, suggesting that in a bull market, distress premium cannot price the cross-sectional variation of stock returns.

5.6.3. Joint Significance of Sentiment Effects in the Conditional Asset Pricing Model

Since the individual conditional factor loadings vary across portfolios in significance and no one plays a dominant role, this section tests the collective sentiment effects. In particular, we examine the joint significance of (1) direct sentiment effects, (2) all the conditional effects as the returns' sensitivity to the interactions between the Fama-French factors and the sentiment proxies, (3) normal sentiment effects as the factor loadings on the interactions between the Fama-French factors and the symmetric sentiment, (4) high sentiment effects as the factor loadings on the interactions between the Fama-French factor and the high sentiment, (5) turnover conditional effects, (6) advances-declines conditional effects, and (7) dividend premium conditional effects. The *F*-statistics of these tests are shown in Table5.8, which show clearly that, notwithstanding some insignificant individual sentiment effects, the joint significance for each sentiment group are very strong, leading further support to the conditional sentiment effects on asset prices.

20 out of the 25 portfolios show the joint significance of direct sentiment effects, which suggests that turnover, advances-declines ratio and dividend premium are jointly important determinants to stock returns. The interactions between the Fama-French factors and the sentiment proxies (normal and positive) have substantial impacts on the pricing equation, being significant in all portfolios. The *F*-tests for symmetric sentiment show that the interactions between the Fama-French factors and the normal sentiment proxies jointly significantly explain stock returns in all but 2 portfolios. The extra effects generated by positive sentiment are jointly significant in 20 portfolios. Therefore, although the individual conditional factor loadings vary considerably across portfolios, these joint significant results are suggestive, if not decisive, evidence that the Fama-French factors conditioning on investor sentiment retain explanatory power. For individual sentiment proxies, turnover and advances-declines influence the cognitive Fama-French factors more significantly than dividend premium. 19 portfolios provide the evidence that turnover indirectly impacts on portfolio returns; 18 portfolios confirm the indirect effect of advances-declines ratio; and the indirect effect from dividend premium is shown by 13 portfolios.

Overall, this provides strong support for ***H5*** and, combined with the results from equation (5.3), clearly suggests that the influence of sentiment on asset pricing in China has come somewhat more through its indirect impact on the risk loadings of cognitive factors rather than directly through its effect as an “irrational” pricing factor.

Table 5.8 Sentiment Effects and the Conditional Asset Pricing Model in China, January 1997 – December 2007

This table reports F tests on sentimental variables in equation 5.3. The Fama-French model is augmented by including as additional variables symmetric and positive sentiment proxies and the interactions among them for each portfolio. S1 to S5 refer to size sorted portfolios from small to big; B1 to B5 refer to book-to-market sorted portfolios from low to high. The 25 size-BE/ME portfolios are the intersection of size and book-to-market sorted portfolios. Sentiment proxies consist of market turnover (TURN), buying-selling imbalance (ADV/DEC) and dividend premium ($D^{p\text{-}np}$). The dummy $D_{sent} = \{D_{TURN}, D_{ADV/DEC}, D_D^{p\text{-}np}\}$ takes the value of unity if sentiment is positive.

The F tests are carried out on different groups of sentiment variables:

DIRECT: direct sentiment: TURN, TURN*D_{turn}, ADV/DEC, ADV/DEC*$D_{ADV/DEC}$, $D^{p\text{-}np}$, $D^{p\text{-}np}$* $D_D^{p\text{-}np}$; F(6,106)

INTER: interactions between Fama-French factors and sentiment proxies: r_M*TURN, r_M*TURN*D_{TURN}, r_M*ADV/DEC, r_M*ADV/DEC*$D_{ADV/DEC}$, SMB*TURN, SMB*TURN*D_{TURN}, SMB*ADV/DEC, SMB*ADV/DEC*$D_{ADV/DEC}$, SMB*$D^{p\text{-}np}$, SMB*$D^{p\text{-}np}$*$D_D^{p\text{-}np}$ HML*TURN, HML*TURN*D_{TURN}, HML*ADV/DEC, HML*ADV/DEC*$D_{ADV/DEC}$, HML*$D^{p\text{-}np}$, HML*$D^{p\text{-}np}$*$D_D^{p\text{-}np}$, F(16, 106)

Inter. NORM: interactions between Fama-French factor and the normal sentiment: r_M*TURN, r_M*ADV/DEC, SMB*TURN, SMB*ADV/DEC, SMB*$D^{p\text{-}np}$, HML*TURN, HML*ADV/DEC, HML*$D^{p\text{-}np}$, F(8, 106)

Inter. HIGH: interactions between Fama-French factors and high sentiment: r_M*TURN*D_{TURN}, r_M*ADV/DEC*$D_{ADV/DEC}$, SMB*TURN*D_{TURN}, SMB*ADV/DEC*$D_{ADV/DEC}$, SMB*$D^{p\text{-}np}$*$D_D^{p\text{-}np}$, HML*TURN*D_{TURN}, HML*ADV/DEC*$D_{ADV/DEC}$, HML*$D^{p\text{-}np}$*$D_D^{p\text{-}np}$, F(8,106)

Inter. TURN: interactions between Fama-French factors and TURN: r_M*TURN, r_M*TURN*D_{TURN}, SMB*TURN, SMB*TURN*D_{TURN}, HML*TURN, HML*TURN*D_{TURN}, F(6,106)

Inter ADVDEC: interactions between Fama-French factors and ADV/DEC: r_M*ADV/DEC, r_M*ADV/DEC*$D_{ADV/DEC}$, SMB*ADV/DEC, SMB*ADV/DEC*$D_{ADV/DEC}$, HML*ADV/DEC, HML*ADV/DEC*$D_{ADV/DEC}$, F(6,106)

Inter DPNP: interactions between Fama-French factors and $D^{p\text{-}np}$: SMB*$D^{p\text{-}np}$, SMB*$D^{p\text{-}np}$*$D_D^{p\text{-}np}$, HML*$D^{p\text{-}np}$, HML*$D^{p\text{-}np}$*$D_D^{p\text{-}np}$, F(4,106)

Prob gives the P values of each test.

Table 5.8 (cont.)

	DIRECE		INTER		NORM		HIGH		TURN		ADVDEC		DPNP	
	F	**Prob**	**F**	**Prob**	**F**	**Prob**	**F**	**Prob**	**F**	**Prob**	**F**	**Prob**	**F**	**Prob**
S1B1	2.364**	0.035	3.857***	0.000	2.719***	0.009	3.975***	0.000	5.652***	0.000	2.117*	0.057	3.768***	0.007
S1B2	2.385**	0.034	11.557***	0.000	4.224***	0.000	5.754***	0.000	9.653***	0.000	3.747***	0.002	5.711***	0.000
S1B3	3.394***	0.004	6.695***	0.000	10.088***	0.000	3.255***	0.002	5.682***	0.000	2.292**	0.040	1.177	0.325
S1B4	4.382***	0.001	4.833***	0.000	5.330***	0.000	5.614***	0.000	2.029*	0.068	5.528***	0.000	4.903***	0.001
S1B5	5.817***	0.000	2.058**	0.016	3.039***	0.004	2.776***	0.008	2.962**	0.010	2.152*	0.053	4.697***	0.002
S2B1	5.615***	0.000	12.689***	0.000	3.423***	0.002	8.560***	0.000	7.849***	0.000	1.450	0.203	1.767	0.141
S2B2	1.933*	0.082	5.255***	0.000	3.542***	0.001	2.496**	0.016	3.259***	0.006	2.362**	0.035	2.470**	0.049
S2B3	4.181***	0.001	5.515***	0.000	1.752*	0.095	3.104***	0.004	4.117***	0.001	0.901	0.498	2.332*	0.061
S2B4	4.857***	0.000	9.759***	0.000	4.198***	0.000	3.188***	0.003	2.936**	0.011	2.926**	0.011	6.468***	0.000
S2B5	3.954***	0.001	2.463***	0.003	2.313**	0.025	2.152**	0.037	1.663	0.137	2.540**	0.025	2.205*	0.073
S3B1	2.335**	0.037	4.085***	0.000	3.096***	0.004	4.047***	0.000	1.565	0.164	1.868*	0.093	1.989	0.101
S3B2	1.301	0.263	1.857**	0.033	1.817*	0.082	1.008	0.434	2.871**	0.012	0.332	0.919	0.683	0.605
S3B3	0.818	0.558	3.438***	0.000	1.934*	0.062	3.350***	0.002	4.966***	0.000	0.903	0.496	1.030	0.396
S3B4	2.463**	0.029	12.703***	0.000	2.645**	0.011	2.745***	0.009	3.342***	0.005	3.117***	0.008	1.121	0.351
S3B5	2.926**	0.011	10.983***	0.000	4.225***	0.000	4.803***	0.000	3.919***	0.001	2.309**	0.039	3.589***	0.009
S4B1	1.893*	0.089	3.427***	0.000	0.520	0.839	1.342	0.231	1.598	0.155	2.398**	0.033	0.423	0.792
S4B2	5.150***	0.000	6.339***	0.000	9.118***	0.000	6.260***	0.000	3.837***	0.002	2.969**	0.010	2.872**	0.027
S4B3	0.427	0.859	1.889**	0.029	0.947	0.481	0.819	0.587	1.355	0.240	0.749	0.612	0.223	0.925
S4B4	1.568	0.164	16.209***	0.000	7.915***	0.000	7.644***	0.000	4.173***	0.001	2.112*	0.058	1.011	0.405
S4B5	2.865**	0.013	6.175***	0.000	5.723***	0.000	3.517***	0.001	1.255	0.285	5.109***	0.000	0.553	0.698
S5B1	4.817***	0.000	39.277***	0.000	8.687***	0.000	3.096***	0.004	19.291***	0.000	8.158***	0.000	3.674***	0.008
S5B2	4.451***	0.001	1.835**	0.036	1.762*	0.093	0.576	0.795	1.813	0.103	1.690	0.130	0.314	0.868
S5B3	1.269	0.278	8.421***	0.000	3.288***	0.002	1.484	0.172	3.099***	0.008	1.822	0.102	2.147*	0.080
S5B4	2.866**	0.013	4.589***	0.000	4.595***	0.000	2.443**	0.018	1.919*	0.084	4.574***	0.000	0.188	0.944
S5B5	2.236 **	0.045	8.181***	0.000	4.265***	0.000	6.431***	0.000	1.872*	0.092	2.502**	0.027	5.188***	0.001
Rejects		20		25		23		20		19		18		13

Notes:
*: Significant at 10% ,
**: Significant at 5% ,
***: Significant at 1%.

5.6.4. Diagnostic Tests of the Sentiment-based Asset Pricing Model

As in the traditional pricing models, residual normality from the sentiment-based conditional model is strongly rejected by 19 of the 25 test portfolios. The residuals are serially uncorrelated in 20 portfolios: this is similar to the multi-beta pricing model but superior to the standard Fama-French three factor model. Those 5 portfolios with significant residual autocorrelation still provide reliable parameter estimates since the standard errors are calculated using robust (Newey-West) methods. There are 13 portfolios with significant RESET tests compared to 18 in the standard Fama-French model and 16 in the multi-beta pricing model with additional risk factors. An important funding is that there is a substantial reduction in the number of significant Chow tests (from 19 to just 8). This is a substantial improvement in the structural stability of the parameter estimates and suggests that the apparent structural shift in the Fama-French factors maybe caused mainly by investor sentiment.

These diagnostic tests show that the sentiment-based conditional asset pricing model still cannot fully explain the variation in portfolio returns. This naturally triggers a further question: whether sentiment effects on stock returns are constant over time or alternatively, whether investors are prone to sentiment in some states but they become more rational in other states. If the latter is true, the smoothed factor loadings cannot correctly model the time-varying relations between returns, risks, and sentiment.

Table 5.9 Diagnostic Checking of the Sentiment-based Conditional Asset Pricing Model

This table reports the diagnostic tests of the sentiment-based conditional asset pricing model based on Chinese stock market data over January 1997 and December 2007. Panel A shows residual normality by Jarque-Bera test under the null hypothesis that estimated residuals distributed normally. Panel B presents serial correlation Lagrange multiplier (LM) test with two orders. Panel C reports Ramsey RESET test for omitted variables represented by the square of the predicted portfolio returns. Panel D is the Chow structure break test with June 2001 as the breaking point. Probabilities are presented below the *F*-statistics.

	Panel A: Normality (JB)					**Panel B: Serial Correlation LM(2)**				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	58.365***	52.049***	14.461***	13.263***	1.114	4.036**	1.535	1.078	1.097	1.030
	[0.000]	[0.000]	[0.001]	[0.001]	[0.573]	[0.021]	[0.220]	[0.344]	[0.338]	[0.361]
2	9.115**	49.790***	438.52***	2.168	23.940***	2.463*	2.005	2.201	0.011	3.579**
	[0.010]	[0.000]	[0.000]	[0.338]	[0.000]	[0.090]	[0.140]	[0.116]	[0.989]	[0.031]
3	5.729*	2.828	20.598***	5.754*	12.849***	1.725	1.077	0.081	0.573	0.048
	[0.057]	[0.243]	[0.000]	[0.056]	[0.002]	[0.183]	[0.344]	[0.922]	[0.566]	[0.953]
4	8.815**	5.542*	3.992	6.271**	3039.9***	1.002	0.295	1.497	0.109	0.692
	[0.012]	[0.063]	[0.136]	[0.043]	[0.000]	[0.371]	[0.745]	[0.229]	[0.897]	[0.503]
High	117.31***	16.976***	1.916	34.257***	1.514	2.952*	0.833	0.017	3.237**	0.702
	[0.000]	[0.000]	[0.384]	[0.000]	[0.469]	[0.057]	[0.438]	[0.983]	[0.043]	[0.498]

	Panel C: Omitted Variables (RESET)					**Panel D: Stability (Chow) Jun. 2001**				
	Small	2	3	4	Big	Small	2	3	4	Big
Low	0.016	4.271**	0.746	2.390	0.469	2.596***	1.596*	1.486	1.657*	0.894
	[0.899]	[0.041]	[0.841]	[0.125]	[0.495]	[0.001]	[0.086]	[0.226]	[0.070]	[0.659]
2	1.459	0.143	0.454	4.949**	21.432***	1.125	0.751	1.566*	0.917	3.135***
	[0.230]	[0.706]	[0.502]	[0.028]	[0.000]	[0.336]	[0.836]	[0.095]	[0.628]	[0.001]
3	16.222***	0.942	7.609***	2.773*	3.607*	0.513	0.427	0.909	0.812	1.809**
	[0.000]	[0.334]	[0.007]	[0.099]	[0.060]	[0.988]	[0.998]	[0.639]	[0.764]	[0.042]
4	7.667***	6.389**	0.498	3.802*	6.384**	0.355	0.745	0.912	1.140	5.161***
	[0.007]	[0.013]	[0.482]	[0.054]	[0.013]	[1.000]	[0.842]	[0.635]	[0.360]	[0.000]
High	39.085***	0.291	3.181*	2.073	0.743	2.405***	0.696	0.538	0.859	0.676
	[0.000]	[0.591]	[0.077]	[0.153]	[0.844]	[0.002]	[0.890]	[0.982]	[0.704]	[0.413]

Notes: *: Significant at 10% , **: Significant at 5% , ***: Significant at 1%.

5.7 Conclusion

Traditional asset pricing models do not allow a role for investor sentiment. This chapter relaxes the twin assumptions that investors are rational and arbitrage rules out noise trading driven by irrational investors. It considers instead the impact of sentiment on the pricing of Chinese A-shares between January 1997 and December 2007.

The Fama-French three-factor model does not provide a complete beta asset-pricing explanation of Chinese share returns. Investor sentiment, measured by turnover, the advances/declines ratio and the dividend premium, helps provide a direct explanation for mis-pricing in the Fama-French model. Sentiment also helps explain the time-series of the Fama-French factors, suggesting that these factors may be conditioning characteristics as well as fundamental factors determining stock returns. We find that sentiment affects both the time series and cross-sectional patterns of share returns. In addition, there is some evidence that positive sentiment affects the market differently from "normal" sentiment: in some cases it accentuates the impact of sentiment and leads to greater emphasis on less "fundamental" factors, but in other cases it attenuates this impact. Sentiment appears to be particularly important for smaller companies and those with "extreme" (high or low) book-to-market portfolios. This is consistent with the expectation that sentiment is more important in explaining the mis-pricing of stocks which are more difficult to value, and therefore more easily influenced by sentiment-driven demands and supplies. These results may also help explain some of the cross-sectional patterns observed by Fama-French; these patterns could be due in part to "irrational" sentiment rather than rational risk-based pricing, as suggested by Lakonishok, Shleifer and Vishny (1994), at least insofar as they apply to China.

Diagnostics suggest that the Fama-French and sentiment-based models both have shortcomings requiring further research, although an important result of the sentiment-based model is that it effectively eliminates an apparent structural break in the data when the SOEs non-tradable share reform was discussed. We conjecture that this move had a direct effect on sentiment and thus on share returns. Finally, when investor sentiment is introduced into the model as a conditioning variable for the Fama-French factors, alpha, *SMB* and *HML* all become less significant. However, the sentiment-conditioned factor loadings contribute significantly to explaining share returns. Therefore we conclude that investor sentiment tends to be both a conditional and a direct determinant of asset pricing in China.

Appendix 5.1 Closed-End Fund Discounts in China

Closed-end funds are funds issued by investment companies, with a fixed number of shares and trading on stock exchanges. Like common stocks, closed-end funds are quoted on stock markets with quoted prices. Closed-end funds hold securities as their investment and the underlying assets are also quoted on exchange, which have their net asset values (NAV). Thus the closed-end fund discount (or premium) is defined as the difference between fund's market price and the net asset value of the securities the fund holds.

Closed-end funds invariably trade at a discount or a premium to their NAV, implying that the actual values of closed-end funds always deviate from their fundamental values. Theoretical finance explains the discount as due to agency costs, and illiquidity of assets[58]. But neither of the arguments explains why the discount or premium varies over time (Dimson and Minio-Kozerski, 1999).

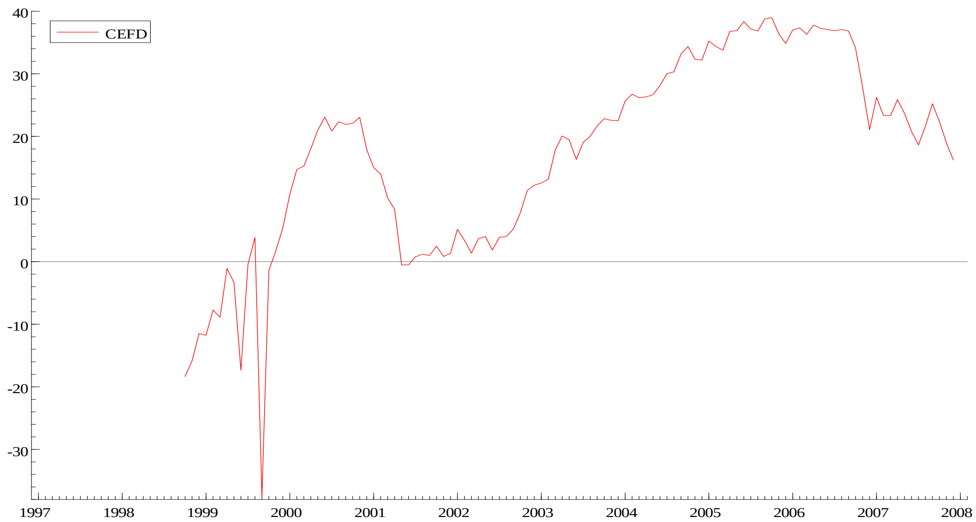
The behavioural finance literature attributes the closed-end fund discount as a proxy of individual investor sentiment. Investors lose interest in such funds when their sentiments are low, which results in the average discount widening. On the contrary, high sentiments may renew the interest in closed-end funds and narrow the discount. The early discussion was given by Zweig (1973), who suggested that discounts (or premiums) on closed-end funds reflect individual investors' expectation. Assuming that individual investors (mostly noise traders) give more interest to closed-end funds than institutional investors, the increases (decreases) in closed-end fund discounts reflect the decreases (increases) in demands for the fund share and for the underlying assets. Thus changes in the discount imply the differential effect of sentiment of the fund clientele relative to underlying asset holders. Lee *et al.*(1991) show that unpredictable individual investor sentiment explains the variation in the closed-end

[58] Agency cost theory says that the closed-end fund discount is due to the management expenses involved in running the fund. Illiquidity of assets attributes the discount of closed-end funds as the costs incurred as some securities the fund hold maybe under some trading restriction, and/or, because closed-end funds hold a large amount of securities which makes it difficult to trade on arbitrage.

fund discount to some extent.

The first two closed-end funds[59] in Chinese stock markets were introduced in March 1998. Half a year later there were five closed-end funds listed in Shanghai and Shenzhen stock exchanges. The data for closed-end funds has to begin from October 1998 to contain sufficient funds to eliminate idiosyncratic noise. There was a maximum of 54 closed-end funds listed in Chinese stock markets. After 2002 no more closed-end fund joined in, because open-ended funds became popular. At the end of 2007, 30 funds where left in Chinese stock markets.

Figure A 5.1 Time Plot of the Closed-End Fund Discount in Chinese Stock Markets



Another feature of Chinese closed-end funds is that unlike the U.S. and U.K. where the majority of closed-end fund holders are retail investors, in China institutional investors are the main closed-end fund holders, especially after 2000 when insurance companies and pension management companies were allowed to invest in closed-end funds. These institutional investors have much lower trading frequencies than individual investors, which results in the closed-end fund discount to be less

[59] There were funds in Chinese stock markets before 1998. However, they were less regulated until the China Securities Regulatory Commission launched the regulation on investment companies in November 1997. After that those old funds were transformed into new funds under the regulations.

interesting. This can be observed in Figure A 5.1, which plots the average closed-end fund discounts. This shows that the closed-end fund discount has strong trends and less variation within short periods, since institutional investors do not trade frequently. It can be argued therefore that this variable is not an appropriate measure of individual investor sentiment.

In summary, the literature argues that individual investor sentiment is an explanation for closed-end fund discounts. However, the closed-end fund discount in China does not represent the behaviour of individual investors, since the majority of fund holders are insurance and pension management companies. The data also has shorter period than the other variables which begin from January 1997. Moreover, the time-series has stronger trend and less variation, than is consistent with sentiment indicator. Therefore, the closed-end fund discount is excluded from the sentiment proxies in this study.

Appendix 5.2 Impact of Economic Factors on Investor Sentiment

Investor sentiment is defined as "not justified by the facts at hand" (Baker and Wurgler, 2007). To keep in line with this definition, a common method is to orthogonalise investor sentiment on economic factors in order to remove the common components of investor sentiment arising from economic circumstance. Before doing so, the investigation of whether sentiment is influenced by economic variables is conducted. Here the sentiment proxies (market turnover, buying-selling imbalance, and dividend premium) are regressed on the monthly industrial production growth rate, retail price inflation, bond market interest rate and return of exchange rate of Chinese RMB against US Dollar before and after the exchange rate reform[60]. The regression results are presented in TableA5.2.

Table A 5.2 Effects of Economic Factors on Sentiment Proxies

This table reports the regression results of sentiment proxies – turnover, advances-declines ratio (ADV/DEC), and dividend premium (D^{p-np}) – on constant, monthly industrial production growth rate (MP), retail price inflation (Inf), bond market interest rate (Rf) and return of exchange rate of Chinese RMB against US Dollar before the exchange rate reform (EX_I) and after the exchange rate reform (EX_II). The corresponding *t*-statistics are reported in square brackets below the coefficients. The adjusted R-square is reported followed.

	Turnover	ADV/DEC	D^{p-np}
Constant	0.444***	1.013***	0.189
	[7.633]	[29.538]	[1.114]
MP	0.012	-0.019	-0.023
	[0.882]	[-1.075]	[-0.274]
Inf	-0.033	0.002	0.750
	[-0.184]	[0.016]	[0.768]
Rf	-0.056	0.033	0.065
	[-0.913]	[0.777]	[0.239]
Ex_I	-0.717	-0.109	1.163
	[-1.084]	[-0.122]	[0.326]
EX_II	1.164*	1.118	-0.293
	[1.707]	[1.211]	[-0.072]
Adj. R^2	0.007	0.113	-0.021

The regression results show that the observed sentiment proxies have no relation with the macroeconomic factors and bond market interest rate. The adjusted R-squareds are small for all the three regressions, which indicate that the economic factors fail to

[60] See P73 for the detailed description of the RMB exchange rate reform

predict the majority of investor sentiment. Therefore, it is not necessary to orthogonalised sentiment proxies with the economic variables so as to obtain the sentiment indicators without the effects by fundamental reasons.

Only the return of exchange rate after the reform motivates market activity. However, the coefficient is not reliable due to the short data period: the reform was launched in July 2005 and the data ends in December 2007. More importantly, the reform of Chinese RMB is controlled by the Chinese government rather than oriented by market. RMB exchange rate appreciates very gradually thus implies potential further appreciation of RMB exchange rate. There is the belief that international hot money crowds in and blooms stock markets. However, the financial sector of Chinese Balance of Payment is restricted so that the power of international hot money to domestic stock markets remains questionable. Actually property attracts more hot money than stock in China. Thus the significant coefficient of exchange rate to turnover may stem from the situation that domestic investors in stock markets overvalue the role of exchange rate reform. In fact, investor sentiment is always triggered by some good information signals but goes much further. Thus the positive coefficient is not supportive to state that market activity increases because of exchange rate reform.

Chapter 6 NONLINEAR PRICE FORMATION WITH INVESTOR SENTIMENT: A MARKOV-SWITCHING ANALYSIS

6.1 Introduction

Measuring sentiment effects using the interaction terms, the previous chapter smoothly models sentiment effects on stock returns. Results revealing the direct and indirect impacts of investor sentiment on stock returns, however, also suggest the shortcomings of the sentiment-based conditional asset pricing model in terms of the pattern of sentiment effects and the diagnostics, such as the non-normally distributed residuals and the significance of the Reset tests and Chow tests. This chapter further relaxes the constant relations between returns, risks and sentiment, and allows the fundamentals and sentiment to exhibit regime shifts. This study is motivated by the fact that in some cases it accentuates the impact of sentiment on stock returns but in other cases this impact is attenuated while fundamentals are evaluated carefully.

This chapter examines regime patterns, shifts of investor sentiment and the impact of investor sentiment on returns in a Markov-switching framework (Hamilton, 1989). There appears to be little reported work on the cross-section of stock returns with multiple-regimes, except a Threshold-GARCH model with daily data (Chen, Gerlach and Lin, 2009), and there appears to be no research dealing with emerging markets. This chapter contributes to the literature in two ways. One contribution yields from the investigation of the sentiment regime-shifts: by examining the regime-shifting patterns of turnover, advances-to-declines ratio and dividend premium individually, I find the three sentiment proxies capture investor sentiment in different ways. Second, returns on the 25 size-BE/ME portfolios are used as the test assets, so that the cross-sectional variation in the time-varying loadings on fundamentals and sentiment is informative and revealing.

6.2 Literature Review

Recent literature increases interest on analysing the regime-dependent patterns in the distribution of stock markets. Stock markets appear to exhibit different states: there are bull and bear markets, and sometimes extreme manifestations of bubbles or crashes; the market is 'usual' or 'stable' in some phases but 'unusual' or 'irregular' in others. Some studies focus on the nonlinear relations between the market and other portfolio risks. Guidolin and Timmermann (2008) introduce a multivariate regime-switching process to analyse the joint distribution of the three Fama-French factors (excess market return, small-minus-big and high BE/ME-minus-low BE/ME). Using US stock market data from 1927 to 2005, they show that the joint distribution of the returns to these three portfolios can be appropriately specified in a four-regime no-lag model. The four regimes capture a moderately persistent bear market, two highly persistent bull markets with low volatility, and a highly volatile and transient market with high positive returns. The two low-volatility bull markets differ in the mean return of size tracking stocks. In one regime the SMB mean return is negative, showing the absence of size effects, but in the other a size effect is present. Similar results are reported by Chung and Yeh (2009) using US monthly data from 1928 to 2008.

Other literature takes investor sentiment into account. Karakatsani and Salmon (2007, 2008) explain the regimes of market returns, volatility, together with the changes in investor sentiment. They also adopt the Markov-switching framework and include individual and institutional investor sentiment in the explained vector. Karakatsani and Salmon (2007) specify two regimes: a dominant bear-market regime in which institutional sentiment and returns have significant interaction effects, and a less frequent bull regime in which both institutional and individual sentiment effects are absent from market returns, but where individual sentiment is significantly and positively influenced by past returns and volatility is significantly influenced by institutional sentiment. Moreover, Karakatsani and Salmon (2008) find the presence of four regimes in the stock market return, volatility, and sentiment measures. The four regimes capture two relatively prolonged regimes as the main regimes, differentiating the optimistic from pessimistic sentiment, and two more highly volatile regimes that capture temporal irregularity — adverse or reversal from adverse.

They show that institutional sentiment has significant momentum in market returns during the main and pessimistic states only, while individual sentiment has contrarian effects on market returns during the main pessimistic regime and the irregular adverse regime. On the other hand, the effect of individual sentiment is positive in the irregular state when market is in reversals after adverse events.

Nevertheless, how to model stock returns under regime shifts remains an open issue. A threshold framework (Tong, 1990) is preferred in the recent literature. Salih, Akdeniz and Caner (2003) examine a two-regime threshold CAPM. Using one month T-bill rate, dividend yield, detrended stock price level, slope of the term structure and quality-related yield spread in the corporate bond market as the threshold variables, they find that the time-varying betas produce better estimates with smaller pricing errors than those obtained from the constant-beta CAPM. Chen *et al.* (2009) propose a three-regime CAPM threshold GARCH model with the market return as the threshold variable, using data with daily frequency. They propose bear, normal and bull market conditions as the three regimes and find that the estimated thresholds roughly support their argument. Choosing daily excess returns on 16 Dow Jones industrial stocks as the dependent variables, they find that the market beta estimates differ between regimes. More specifically, the market risk is highest in bull markets, but comparable for normal and bear markets.

The Markov-switching framework is an alternative way to model stock returns in the presence of regimes. Gu (2005) examines both a conditional CAPM and a conditional Fama French three-factor model using monthly data, in which the risk factors are regime-determined. In the conditional CAPM, the instrumental variables used to specify market regimes include the one-month Treasury bill rate, the default premium, and the dividend yield. In the conditional Fama-French model, the conditional risk factors are specified by a two-regime Markov-switching mean-adjusted AR(1) process. Gu states that the two regimes reflect normal and bear market states. Using book-to-market portfolio returns as the tested asset, betas of value stocks increase significantly during bear market episodes. Lin, Wang and Tsai (2009) provide a deeper theoretical description of the estimation of the Markov-switching moving average model. They introduce both numerical and empirical evidence to argue that a hidden Markov chain is a better description of the daily stock return dynamics.

6.3 Methodology

6.3.1. From Threshold to Markov-switching Model

Regime-based non-linear models allow some or all of the estimated parameters to depend on the regime state. The regime dependence notion is implemented in different ways, including Threshold Autoregression (hereafter, TAR, Tong, 1990), Smooth transition (Chan and Tong, 1986; Terasvirta, 1994) and Markov-Switching (hereafter, MS, Hamilton, 1989). The TAR model uses threshold spaces to define regimes and allows linear approximation within regimes, where the thresholds are based on the predefined threshold variables. A criticism of this model is that the conditional mean equation is not continuous, as the thresholds are discontinuity points. The smooth transition model (STAR) solves this discontinuity problem.

However, applying the threshold framework to asset pricing faces some difficulties that arise because threshold processes are deterministic with states only determined by the unique values of parameters in the model. First, the threshold variable is unspecified. It could be any of the macroeconomic variables that capture the states of business cycle and general economy, the exogenous market returns or volatilities that capture market conditions, the measures of financial wealth tracking the time-varying loss aversion attitude of investors or the measures of investor sentiment that reflect the impact of investor psychology. Therefore a predetermined, exogenous threshold variable adds extra assumptions to the model, increasing the chance of misspecification. Second, the thresholds may not be constant over time. Both the business cycle and market volatility change over time so an appropriate reference point to measure turnings in one cycle may become a normal and unimportant point in other cycles — for example, if technological development enhances a market boom or if investors become more confident and willing to bear more risks. In such cases, adopting constant thresholds that capture the regimes in stable periods may over capture the regimes in the highly volatile periods. These limitations of Threshold models in asset pricing applications also apply to Smooth Transition models (which also use deterministic schemes to model regime transition).

The Markov-switching model provides a more flexible solution by adopting a stochastic scheme to govern regime transition. Early work on switching in Markov chains is by Goldfeld and Quandt (1973). Hamilton (1989) extends the model to the time series context and develops the Markov-switching (MS) Autoregressive model. The MS model emphasizes aperiodic transition between regimes in which the transition is driven by an unobserved Markov chain. Therefore, unlike TAR or STAR, the MS model does not require a predetermined state (threshold) variable. Rather, the transition probabilities are “the result of processes largely unrelated to past realizations of the series and are not themselves directly observable.” (Hamilton, 1993, p. 234). In addition, the MS model sheds light on the probabilities of transition between states, providing useful signals for investment opportunities and decisions.

6.3.2. The Markov-switching (Dynamic) Process

Let K be the number of feasible regimes denoted by the integer state variable s_t, so that $s_t \in \{1,...,K\}$. A K-state Markov-switching dynamic model with both autoregressive and other explanatory variables is

$$Y_t = \begin{cases} c_1 + \sum_{l=1}^{p} \phi_{1,l} Y_{t-l} + \lambda_1 \mathbf{X}_t + \varepsilon_{1,t} & \text{if } s_t = 1 \\ \vdots & \\ c_K + \sum_{l=1}^{p} \phi_{K,l} Y_{t-l} + \lambda_K \mathbf{X}_t + \varepsilon_{K,t} & \text{if } s_t = K \end{cases} \tag{6.1}$$

where c_{s_t} is the intercept in regime s_t (s_t = 1,…,K), $\phi_{s_t,l}$ is the autoregressive coefficient at lag l in regime s_t, λ_{s_t} is the vector of the coefficients on the explanatory variable $\boldsymbol{X_t}$, the residual series ε_{s_t} is a sequence of i.i.d. random variables with zero mean and finite variance, which can be regime dependent or not. If the variance is regime-dependent, residual $\varepsilon_{s_t} \sim N(0, \sigma^2_{s_t})$ where $\sigma^2_{s_t}$ varies between regimes and the Markov-switching model captures periods with high or low volatility. Further, both the autoregressive and the explanatory variables can be specified as regime changing variables if thought appropriate, so that $\phi_{s_t,l}$ and λ_{s_t} can be regime-dependent correlation coefficients.

The MS model is named 'dynamic' as the lagged dependent variable is involved. This representation is related to the MS autoregressive model of Hamilton (1989). The autoregressive form suggested by Hamilton can be specified as:

$$Y_t - \mu_{s_t} - \mathbf{X}_t{}' \gamma_{s_t} = \sum_{j=1}^{p} \rho_j \left(Y_{t-j} - \mu_{s_{t-j}} - \mathbf{X}_t{}' \lambda_{s_{t-j}} \right) + \varepsilon_{s_t,t},\ \varepsilon_{s_t t} \sim N[0, \sigma_{s_t}]$$

Since the MS model uses an unobservable and stochastic rather than a deterministic state variable, it is necessary to form probabilistic inferences of the values of the unobserved state variables. The unobserved state vector s_t evolves according to a first-order Markov chain with the transition probability matrix

$$P = \begin{bmatrix} p_{1,1} \cdots p_{1,K} \\ \vdots \quad p_{i,j} \quad \vdots \\ p_{K,1} \cdots p_{K,K} \end{bmatrix} \text{where } p_{i,j} = p(s_t = j | s_{t-1} = i), p(s_t | s_{t-1}, ..., s_1) = p(s_t | s_{t-1}) \qquad (6.2)$$

The expression $p\ (s_t = j|s_{t-1} = i) = p_{i,j}$ refers to the probability of the explained variable being in regime j given that it was in regime i in the preceding period. When i=j, $p_{i,j}$ is a diagonal element that indicates the probability of staying in the same state. When $i \neq j$, $p_{i,j}$ denotes the probability of transition from one state to another. $p_{i,j}$ is restricted so that it lies between 0 and 1 and sums to unity:

$$0 < p_{i,j} < 1, \text{ and } \sum_{i=1}^{K} p_{i,j} = \sum_{j=1}^{K} p_{i,j} = 1 \ \forall i, j \in \{1, ..., K\}$$

Therefore a large $p_{i,i}$ (and small sum of $p_{i,j}$) means that the process tends to stay in regime i. The expected duration of the stay in state i can be measured as 1/ (1 - $p_{i,i}$) = 1/$\sum p_{i,j}$. Clearly, Markov-switching and Threshold models are different: the MS model uses a stochastic hidden Markov chain to govern the transition probabilities between regimes (in which the conditional probability distribution of the state in time t depends only on its state in time t-1) whereas TAR (a deterministic model) uses unique values of parameters to govern the regime transition.

Once a Markov switching model has been estimated, linearity tests can be conducted to see whether the non-linear model outperform the associated linear model. This linearity is tested by a conventional likelihood-ratio statistic between the estimated model and the derived linear model. Setting the null hypothesis that the model can be specified into a linear formulation, let *m* be the number of coefficients that vanish under the null, *q* the number of transition probabilities that vanish under the null, and *LR* the conventional likelihood-ratio statistic, the linearity test is[61]:

$$\text{Reject the null of linear model at a level if : } \chi^2(m+q) < LR$$

A rejection of the null hypothesis indicates that parameter estimates are not constant, thus a non-linear model add something to the constant-parameter model.

6.4 Regime Classifications of Investor Sentiment

6.4.1. Theoretical Specification of Sentiment Regimes

The behavioural finance literature implies that investor sentiment shows patterns in which the sentiment shifts according to ways in which investors form beliefs change over time. These patterns can be thought of as different regimes and shifts in a pattern as a regime switch. Investors in stock markets tend to forecast a continuing trend after a string of positive or negative signals[62], thus they overreact to information and behave optimistically if the signals are positive or pessimistically if the signals are negative. Besides, they are slow to change their beliefs in the face of new evidence[63] thus they underreact to new information signals (De Bondt and Thaler, 1985, 1987; Barberis *et al.*, 1998; Shleifer, 2000b).

Barberis, Shleifer, and Vishny (hereafter BSV, 1998) develop a two-regime model of investor sentiment based on overreaction and underreaction: in regime 1, investors believe fundamentals (for example, earnings) to be mean-reverting — which implies

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[61] This procedure is applied by Garcia and Perron (1996).

[62] See Tversky and Kahneman (1974) for the representativeness heuristic.

[63] See Edwards (1968, 1982) for the conservatism.

a fundamental regime; in regime 2, they believe fundamentals to be in a trend – which is consistent with the representativeness heuristic. BSV suggest that the underlying regime-switch follows a Markov process and that the transition probabilities are small. Moreover, they specify that investors are more inclined to expect regime 1 than regime 2, especially when the next shock has an opposite sign. However, consecutive shocks of the same sign will drive investors to expect regime 2. Consequently, it is possible to suggest that investor sentiment, and therefore sentiment-driven mispricing, will stay in a mean-reverting relatively stable state for most of the time, but will shift to a mean-trending, more volatile state as the result of consecutive shocks.

6.4.2. Empirical Analysis for Sentiment Regimes

Rather than being a stationary process, investor sentiment is thought to behave as a stochastic process (Shefrin, 2008). Applying Markov-switching in investor sentiment allows nonlinear and stochastic features of investor sentiment to be captured in a regime-shifting process. Since the MS process imposes aperiodic transition between regimes, the dynamic behaviour of investor sentiment under this framework is assumed to be subject to discrete shifts in regime, which is consistent with the theoretical conjecture discussed in the previous section. The MS dynamic regressive model of investor sentiment is specified as follows:

$$Sent_{i,t} = c_{i,s_t} + \sum_{j=1}^{p} A_{ij,s_t} Sent_{i,t-j} + \varepsilon_{i,s_t,t}\ ,\ \ \varepsilon_{i,s_t,t} \sim N\left(0, \sigma^2_{i,s_t}\right),\ \forall s_t \in \{1, K\} \qquad (6.3)$$

Here $Sent_{i,t}$ denotes the three sentiment proxies: market turnover (TURN), advances-declines ratio (ADV/DEC), and dividend premium ($D^{p\text{-}np}$). c_{i,s_t} is the constant of sentiment proxy *i* in regime $s_t \in \{1,\ldots,K\}$ and K indicates the number of regimes. A_{ij,s_t} is a vector of j^{th}–order autocorrelation coefficients in regime s_t. Thus $c_{i,s_t} \Big/ \left(1 - \sum_{j=1}^{p} A_{ij,s_t}\right)$ is the estimated mean of sentiment proxy *i* in regime s_t with $\sigma^2_{s_t}$ measuring its regime dependent variance. Each sentiment proxy is used separately. The three sentiment proxies may capture investor sentiment in different ways. The separation helps to identify the different regime shifts in each variable. Equation 6.3 is not a multivariate but three univariate Markov switching regressions.

Various specifications of the models are tested for the number of regimes (K = 2, 3, or 4) and the number of lags (p = 1, 2, 3, or 4). 2, 3 or 4 regimes are all economic meaningful. When K=2, the regime specification is consistent with both the theoretical expectation of the BSV paper (with mean-trending mean- reverting regimes) and the performance of stock markets with a highly volatile irregular regime and a low volatility normal regime. K=3 may indicate two normal regimes (mean-reverting or mean-trending) and one irregular sentiment regime. K=4 may capture two low sentiment regimes with low or high volatility and two high sentiment regimes with low or high volatility. The number of regimes and number of lags are selected using the minimum information criteria and expected residual performance by testing the diagnostics. Expected residuals should be a sequence of i.i.d. random normally distributed residuals with no autocorrelation and heteroskedasticity. Since the Akaike information criterion (AIC) tends to select overparameterised models (Fenton and Gallant, 1996) while the Schwarz (SIC) and the Hannan-Quinn information criteria (HQ) are consistent, the model selection is based on minimising SIC and/or HQ[64], as well as i.i.d. normally distributed residuals and better regime performance.

6.4.2.1 Regimes of Market Activity

Table 6.1 shows the results of a MS autoregressive model selection for turnover. SIC is minimised for 2 regimes with 1 autoregressive term. However, the diagnostic tests in MS (2,1) show that the residuals are serial correlated and non-normally distributed. The autocorrelation disappears for MS (2, 4) model, which has the minimum HQ, but the residual test still strongly rejects normality. Moreover, the regime classification

[64] The Akaike Information Criteria, Schwarz Information Criteria and Hannan-Quinn information criteria formulas are $AIC = -2\ln(L_{max})/n + 2k/n$, $SIC = -2\ln(L_{max})/n + k\ln(n)/n$ and $HQ = -2\ln(L_{max})/n + 2k\ln(\ln(n))/n$.

shows rapid oscillation between the two regimes. For MS (2, 2) and MS (2, 3) that have the second minimum SIC and HQ, the diagnostic tests reject both normality and the absence of serial correlation. Thus these models are unattractive and therefore rejected. Instead, a model specification with 3 regimes and 1 autoregressive term is preferred since it has the second smallest SIC and a more interpretable regime performance.

Table 6.1 Model Selection of Turnover

This table presents the results of model selection for the sentiment regime based on the Akaike (AIC), Schwarz (SIC), and Hannan-Quinn (HQ) information criteria. In column one the first element in the parentheses is the number of regimes chosen in the Markov-switching model and the second element is the number of lags. The models with minimum SIC and/or HQ that also have interpretable regime patterns are selected with bold marking.

Model Selection	**AIC**	**SIC**	**HQ**
TURN MS(2,4)	**-0.859**	**-0.547**	**-0.732**
TURN MS(3,4)	-0.808	-0.273	-0.590
TURN MS(4,4)	-0.825	-0.045	-0.508
TURN MS(2,3)	**-0.806**	**-0.540**	**-0.698**
TURN MS(3,3)	-0.766	-0.300	-0.577
TURN MS(4,3)	-0.839	-0.174	-0.569
TURN MS(2,2)	**-0.762**	**-0.541**	**-0.672**
TURN MS(3,2)	-0.733	-0.336	-0.572
TURN MS(4,2)	-0.827	-0.297	-0.611
TURN MS(2,1)	**-0.781**	**-0.606**	**-0.710**
TURN MS(3,1)	**-0.741**	**-0.411**	**-0.607**
TURN MS(4,1)	-0.816	-0.377	-0.637

To assist in the economic interpretation of the turnover regimes, panel A of Table6.2 presents parameter estimates, while figure 6.1 shows the associated state probabilities. The three regimes of turnover capture low, normal and high activity.

Regime 1 is a relatively persistent and inactive bear market with unconditional mean return liquidity 0.150 (0.150=0.068/(1-0.546)) and average duration of 2.137 months. In this state the volatility is quite low (0.040) and past market turnover has the smallest impact on the current level. Figure 6.1 shows the bear state corresponding to the June 2001 – June 2005 pessimistic stock market in China where there was a common worry because of expected selling pressures from the non-tradable share reform of state-owned companies.

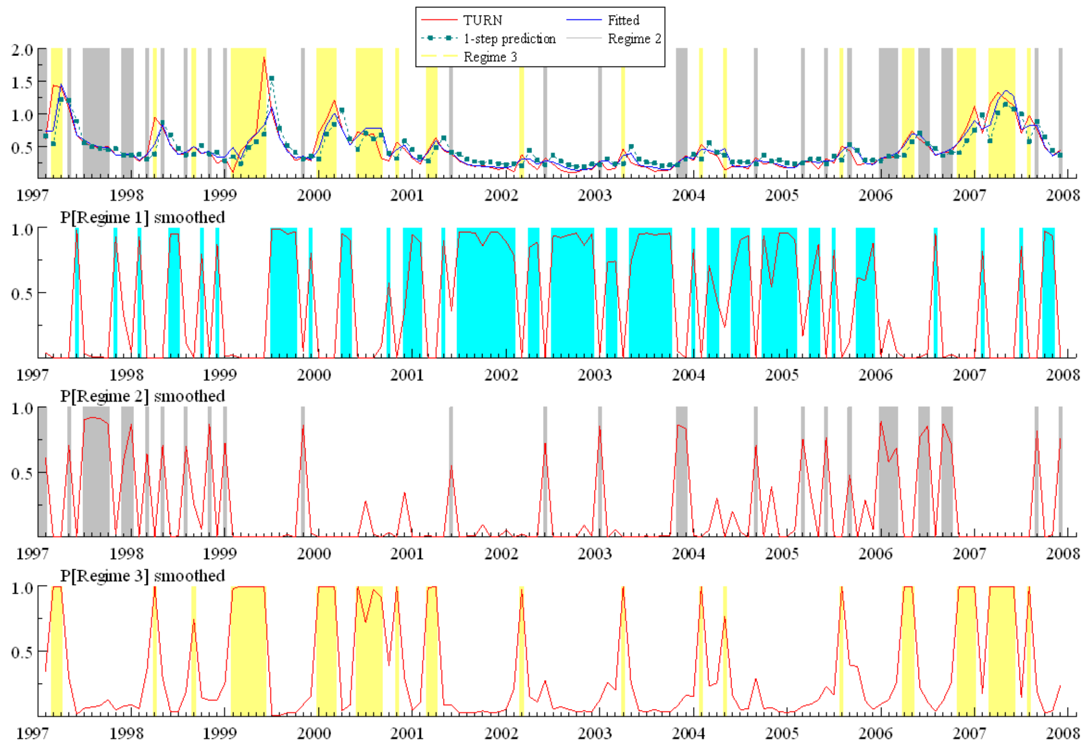
Table 6.2 Regime Performance of Turnover

	Constant	TURN(-1)	Sigma
Panel A: Regime Parameter Estimates			
Regime 1	0.068***	0.546***	0.040***
	[5.86]	[31.8]	[4.87]
Regime 2	0.164***	0. 621***	0.040***
	[5.20]	[12.3]	[3.16]
Regime 3	0.214**	0.865***	0.274***
	[2.23]	[5.47]	[8.88]
Panel B: Transition Probabilities and Linearity Test			
	Regime 1_t	Regime 2_t	Regime 3_t
Regime 1_{t+1}	0.532	0.495	0.299
Regime 2_{t+1}	0.251	0.263	0.130
Regime 3_{t+1}	0.217	0.242	0.572
Linearity test	Chi^2(12) =95.764 [0.000]***		

Notes: ***, ** and * denote significance level at the 1%, 5% and 10%, respectively. The *t*-statistics and the associated probability for the linearity Chi-square test are in the square brackets.

Figure 6.1 Smoothed Transition Probabilities of Turnover

The first panel of this figure reports the actual turnover, fitted and the 1-step prediction of turnover by the Markov-switching autoregressive model. The rest panels describe the smoothed regime probabilities.



Regime 2 shows a normal state with low volatility. The average liquidity in this regime is 0.433, which is bigger than that in regime 1. This means that 43.3% of listed shares are traded in a month on average for a period in regime 2. The volatility is as low as in the regime 1. Past liquidity has a stronger momentum effect since the serial correlation is greater than in regime 1. However, the transition probabilities in Panel B show that the normal state doesn't remain in existence for long – the average duration for regime 2 is 1.35 months, which is the shortest among the three regimes. Turnover tends to shift to regime 1 (with transition probability 49.5%) rather than stay in the original regime (with stay probability 26.3%).

Regime 3 clearly captures a highly liquid and fluctuating market with regime mean of 1.585 and variance of 0.274. The mean indicates that in this highly active state average shares are traded 1.5 times in a month. This regime has an average duration of 2.34 months, which is the longest among the three regimes and shows that the highly active turnover has a strong momentum effect. This finding is also supported by the large regime 3 autoregressive coefficient of 0.865 (significant at 99% confidence level). This highly active regime captures phases that are consistent with the corresponding market performance. Shown in Figure 6.1, this regime captures the periods of '5.19' 1999 market booms, and of the market bubbles in June 2005 - October 2007 stimulated by the potential appreciation of the Chinese RMB and the worldwide boom in emerging markets.

The LR test of linearity clearly rejects the linear model. Transition probabilities (panel B of Table 6.2) show that when turnover is low and high, the same regime is maintained: there is a 53.2% probability of staying in regime 1 and a 57.2% probability of staying in regime 3. However, market liquidity rarely remains in a normal regime. There is a 49.5% probability of moving from normal liquidity (regime 2) to low activity but only a 26.3% probability of staying. When past liquidity is very high in regime 3, there is a 29.9% probability of moving from high into low activity, while only a 13.0% chance of moving into normal liquidity. Together with the relative short state duration, the regime performance of turnover indicates that Chinese stock markets exhibit high, unstable and volatile market liquidity.

6.4.2.2 Regimes of Buying-selling Imbalance

For the advances-declines proxy for sentiment, only 2 regimes are revealed by the information criteria and residual performance. For ADV/DEC, SIC is minimised with the model specified with 2 regimes and 1 autoregressive term and HQ is minimised with 2 regimes and 2 lags, but in both cases the residuals suffer from significant ARCH effects. MS (2, 3) is selected since the residual test shows a normally distributed i.i.d. residual series. The linearity LR test has a chi-square statistic of 43.581, which significantly rejects the linear model.

Table 6.3 Model Selection of Advances-declines Ratio

This table presents the results of sentiment ADV/DEC MS model specification based on the Akaike (AIC), Schwarz (SIC), and Hannan-Quinn (HQ) information criteria. For the first column of model specification, the first element in the parenthesis is the number of regimes chosen in the Markov-switching model and the second element indicates lags. The models with the minimum SIC and/or HQ and interpretable regime patterns are selected with bold marking.

Model Specification	AIC	SIC	HQ
ADVDEC MS(2,4)	0.349	0.661	0.475
ADVDEC MS(3,4)	0.309	0.799	0.508
ADVDEC MS(4,4)	0.387	1.145	0.695
ADVDEC MS(2,3)	**0.324**	**0.590**	**0.432**
ADVDEC MS(3,3)	0.312	0.733	0.483
ADVDEC MS(4,3)	0.275	0.918	0.536
ADVDEC MS(2,2)	**0.338**	**0.559**	**0.428**
ADVDEC MS(3,2)	0.342	0.717	0.495
ADVDEC MS(4,2)	0.341	0.936	0.583
ADVDEC MS(2,1)	**0.363**	**0.539**	**0.434**
ADVDEC MS(3,1)	0.389	0.697	0.514
ADVDEC MS(4,1)	0.377	0.859	0.573

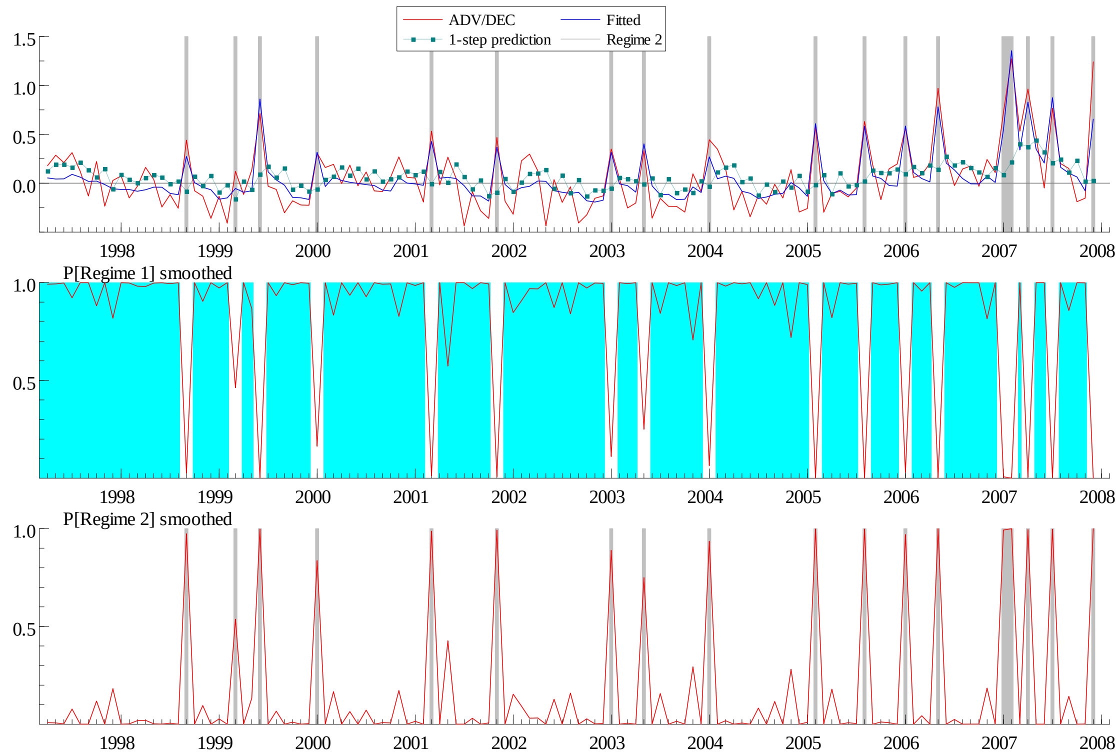
Table 6.4 reports the parameter estimates of the MS model for the advances-declines ratio in panel A and the transition probabilities between regimes in panel B. Regime 1 can be interpreted as a persistent bear state with lower volatility whose average duration is 5.525 months. There is a high 81.9% probability of staying in this regime. The unconditional mean in regime 1 is -0.087. Since the ADV/DEC data were adjusted to obtain a zero mean by subtracting 1 from the original value, the actual advances-declines ratio is 0.913, which is slightly less than 1 indicating that selling pressure slightly exceeds buying pressure in this market. Past sentiment has less effect on the current level: only the first-order lag of ADV/DEC has a significant momentum effect. Volatility in this pessimistic regime is lower.

Table 6.4 Parameter Estimates of MS (2, 3) model for ADV/DEC

Panel A: Regime Parameter Estimates					
	Constant	ADV/DEC(-1)	ADV/DEC(-2)	ADV/DEC(-3)	Sigma
Regime 1	-0.065***	0.249***	0.109	0.091	0.184***
	[-2.98]	[3.58]	[1.66]	[1.43]	[12.7]
Regime 2	0.603***	0.919***	-0.546**	0.601***	0.211***
	[7.29]	[3.58]	[-2.47]	[2.71]	[3.70]
Panel B: Transition Probabilities and Linearity Test					
	Regime 1_t		Regime 2_t		
Regime 1_{t+1}	0.819		0.943		
Regime 2_{t+1}	0.181		0.057		
Linearity test	Chi^2(7) =43.581 [0.000]***				

Notes: (***), (**) and (*) denote significance at 1%, 5% and 10%, respectively. The *t*-statistics are in square brackets.

Figure 6.2 Smoothed Regime Classification for ADV/DEC



In regime 2, investor sentiment is extremely optimistic. The unconditional mean in this state is 23.192, which indicates that the number of stocks closing at higher prices (usually through buying commissions) is over 24 times the number of stocks closing at lower prices (selling commissions). Figure 6.2 shows that regime 2 captures almost every high ADV/DEC ratio phase, including the '5.19' bubble in 1999 and the recent bull market of early 2007, which is in line with the third active regime classification for turnover. In addition, the third panel of Figure 6.2 suggests that regime 2 appears in January, which supports the January effect (Keim, 1983) that investor sentiment and stock prices increase in the month of January. The coefficients of the lags are strong and significant, but with opposite signs over months. These results suggest that highly optimistic sentiment oscillates rather than lasts – average duration is short at 1.06 months, with a staying probability of only 0.057.

6.4.2.3 Regimes of Dividend Premium

Dividend premium is a negative sentiment indicator and reflects investor sentiment in terms of time preference. A larger dividend premium implies that investors have shorter time allowance: they prefer instant dividend payments to deferred payments from capital gain.

Table 6.5 Model Selection of Dividend Premium

This table presents the results of sentiment $D^{p\text{-}np}$ MS model specification based on the Akaike (AIC), Schwarz (SIC), and Hannan-Quinn (HQ) information criteria. In the first column, the first element in parentheses is the number of regimes chosen in the Markov-switching model and the second element indicates the number of lags. The models with the minimum SIC and/or HQ that also have interpretable regime patterns are selected with bold marking.

Model Selection	AIC	SIC	HQ
$D^{p\text{-}np}$ MS(2,4)	**3.558**	**3.870**	**3.685**
$D^{p\text{-}np}$ MS(3,4)	3.654	4.144	3.853
$D^{p\text{-}np}$ MS(4,4)	3.502	4.215	3.791
$D^{p\text{-}np}$ MS(2,3)	3.624	3.890	3.732
$D^{p\text{-}np}$ MS(3,3)	3.694	4.116	3.865
$D^{p\text{-}np}$ MS(4,3)	3.642	4.219	3.877
$D^{p\text{-}np}$ MS(2,2)	3.788	4.009	3.878
$D^{p\text{-}np}$ MS(3,2)	3.699	4.052	3.842
$D^{p\text{-}np}$ MS(4,2)	3.556	4.041	3.753
$D^{p\text{-}np}$ MS(2,1)	**3.665**	**3.840**	**3.736**
$D^{p\text{-}np}$ MS(3,1)	3.687	3.972	3.803
$D^{p\text{-}np}$ MS(4,1)	3.613	4.008	3.773

As shown in Table 6.5, information criteria select the models with only two regimes, since SIC is minimised for MS (2, 1) and HQ is the smallest for MS (2, 4). Both models satisfy the residual assumptions in diagnostic checking but the regime classification is not good in the MS (2, 1) model, as the regime duration is too long and there is only one transition between the two states. Hence a model with 2 regimes and 4 lags is specified.

Table 6.6 Parameter Estimates of the MS (2, 4) for Dividend Premium

Panel A: Regime Parameter Estimates						
	constant	$D^{p\text{-}np}(-1)$	$D^{p\text{-}np}(-2)$	$D^{p\text{-}np}(-3)$	$D^{p\text{-}np}(-4)$	Sigma
Regime 1	0.039	-0.105	0.040	-0.192***	-0.102	1.178***
	[0.337]	[-1.31]	[0.504]	[-2.18]	[-1.35]	[14.7]
Regime 2	2.185***	0.565***	-0.818***	1.729***	-0.760***	0.374***
	[13.9]	[12.5]	[-16.5]	[17.7]	[-13.0]	[4.40]
Panel B: Transition Probabilities and Linearity Test						
	Regime 1_t			Regime 2_t		
Regime 1_{t+1}	0.927			0.663		
Regime 2_{t+1}	0.073			0.337		
Linearity Test	Chi^2(8)= 53.014 [0.000]***					

Notes: (***), (**) and (*) denote significance at 1%, 5% and 10%, respectively. The *t*-statistics are in the square brackets.

Figure 6.3 Smoothed Regime Classification for Dividend Premium

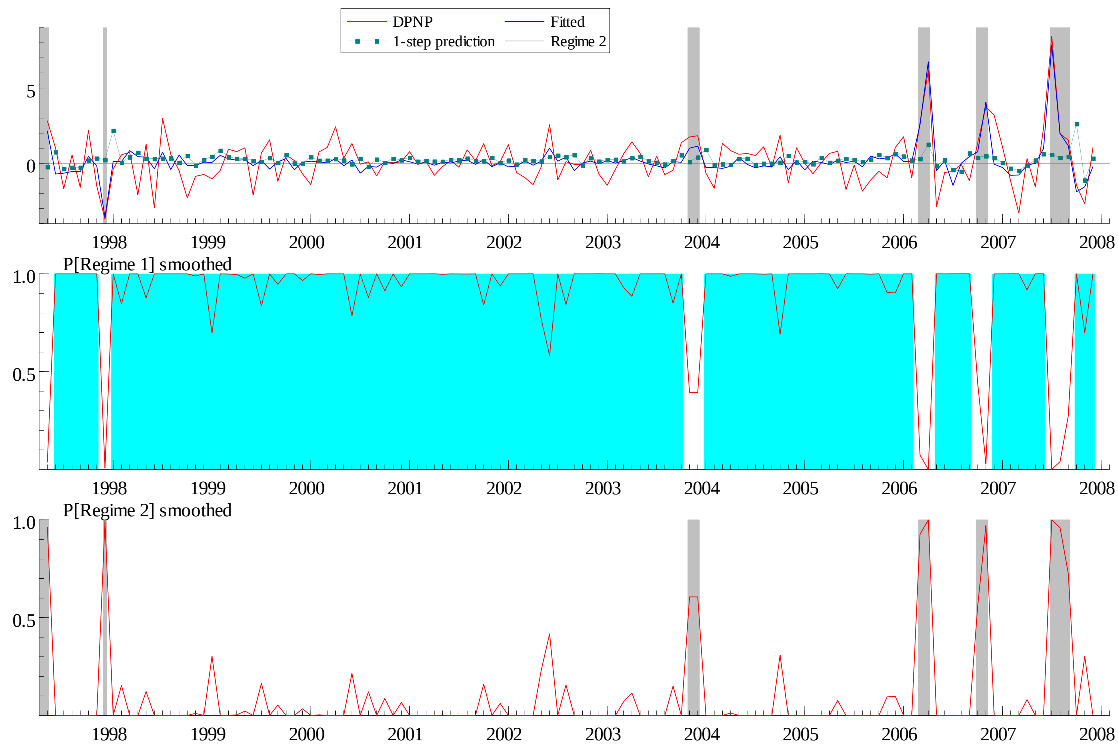


Table 6.6 reports the estimated regime dependent parameters and the transition probabilities for the dividend premium. In regime 1 the constant is insignificantly different from zero, leading to a regime-dependent mean of zero. This indicates that

there is no preference difference between time-instant and time-delayed payments in regime 1. The variance in this regime is relatively high at 117.8%. On the other hand, regime 2 has an unconditional mean of 7.694. Since higher dividend premium refers to shorter time allowance, and hence greater anxiety about the future, the positive regime mean and the low volatility are informative, suggesting that regime 2 represents a state with extreme low sentiment.

The probability of transition from regime 1 to regime 2 is only 7.3% but the reverse probability is 66.3%. Thus the regime 1 is prolonged-period with regime duration of 13.7 months, whereas the duration of regime 2 is only 1.5 months, which shows that extreme bear sentiment is infrequent. This result confirms the argument from the previous chapter: firms do not care about their dividend policies and investors pay similarly little attention. Most of the time the dividend premium does not exist – it is high only during the middle of bear market states (for example, end of 1997 and end of 2003) and during some highly volatile states, for example, March-April, and October-November of 2006, and July-September of 2007).

6.4.3. Summary

Overall, investor sentiment may not be consistent over time. Investors are optimistic sometimes but pessimistic at other times; their emotions may trend or change rapidly. The regime performance and classification of the three sentiment proxies show that the Markov-switching autoregressive process captures sentiment dynamics with different regime performances.

Measured by turnover and ADV/DEC, negative sentiment is relatively long-lasting in Chinese stock markets. The turnover regime-shifting model separates the low volatile phase into a state with persistent low sentiment and a state with transient neutral sentiment. But the advances-declines ratio exhibits only one persistent low volatile state. Unlike turnover and ADV/DEC, dividend premium selects the main positive state apart from a strong anxiety state.

The high sentiment periods that are selected by turnover and ADV/DEC are robust: they both cover the “5.19” bubble in 1999 and the rapid growth in 2006 to middle

2007 and are with high volatility. The difference between the turnover selected high sentiment state and ADV/DEC selected one is that when measured by turnover, the highly liquid market is persistent but when measured by ADV/DEC, this state has a short duration. This suggests that the stock market in China is highly volatile in general, even without supports from long positions. The regime shifts in dividend premium show that there is no premium given to dividend-paying stocks except in an extreme low sentiment state. These reflect, again, that the three sentiment proxies capture investor sentiment from different senses, which leads further support that they should be applied separately in an asset pricing model.

6.5 Sentiment, Returns and Regime Shifts

The basic idea behind the Markov-switching asset pricing model is that the sensitivities of stock returns to the fundamental risk and/or sentiment factors may be inconsistent over time: rather, the dominating factor may change in different market phases. At first glance, stock markets themselves may exhibit four regimes – low volatility bear or bull states, and high volatility bear or bull states. However, the previous analysis of sentiment regime shifting suggests that sentiment exhibits less regime patterns. Moreover, the regime performance of sentiment proxies has two further applications to the asset pricing model. First, the sentiment regime analysis suggests that the number of regimes varies across the three sentiment proxies: turnover shows three different regimes while advances-declines ratio and dividend premium show only two. Thus combining the three proxies in one pricing model makes it difficult to specify the appropriate model. Second, since the regime classifications of TURN, ADV/DEC and $D^{p\text{-}np}$ have different interpretations, it is hard to find a consistent sentiment state for all three proxies in any one regime. For example, both ADV/DEC and $D^{p\text{-}np}$ entail two regimes. But, while for ADV/DEC the two regimes separate bull sentiment from bear and normal markets, for $D^{p\text{-}np}$ the two regimes separate bear from normal and bull markets. These show that it is better to study the impacts of each sentiment proxy respectively. This section concerns the construction and tests of three Markov-switching asset pricing models with turnover (TURN), advances-declines ratio (ADV/DEC) and dividend premium ($D^{p\text{-}np}$), respectively.

The previous chapter suggests that the Fama-French factors (r_M, SMB and HML) are themselves significantly influenced by investor sentiment and analyses the decomposed factor loadings of the Fama-French factors both with and without the sentiment interactions. In this chapter the interaction terms are excluded, since the regime switching model cannot include too many regime-dependent variables. In order to test the market, size and book-to-market risks without the effect of investor sentiment, the Fama-French three factors are orthogonalised on the sentiment proxies (TURN, ADV/DEC and $D^{p\text{-}np}$). The residuals from the orthogonalisation are used in the pricing models to capture the market, size and book-to-market risks without the influence of investor sentiment.

No previous work seems to have attempted to identify variation in the sensitivity of portfolio returns to Fama-French and sentiment factors under a Markov-switching process. The literature provides little guidance on how to select the number of states and lags for the Markov-switching process in asset pricing models. Hence, the number of regimes for each sentiment based model is chosen so as to be consistent with the regime classification in the sentiment regime analysis. This classification helps to identify the behaviour of regimes for portfolio returns with clarified sentiment meanings[65].

6.5.1. Asset Pricing Model with Regime Dependent Turnover

6.5.1.1 The MS model with Turnover

The 25 size and book-to-market sorted portfolios are modelled on the state varying constant, the first-order autoregression of portfolio return, the state varying orthogonalised market excess return, small-minus-big, high-minus-low book to

[65] We also test the Akaike (AIC), Schwarz (SIC), and Hannan-Quinn (HQ) information criteria for randomly selected portfolio returns with one of the sentiment proxies. The models with smaller information criteria are then checked for regime classification and residual diagnostics. However, the model selection results are not consistent across selected portfolios.

market ratio, the state varying turnover with one lag, and the state varying error term. Three regimes are specified in the model with turnover, as indicated by most of the model selections and consistent with the regime classification of turnover in previous section. The asset pricing model under the Markov-switching process with regime dependent turnover and volatility is specified as:

$$r_{i,t} = c_{i,s_t} + \rho_{i,s_t} r_{i,t-1} + \beta_{M,i,s_t} r_{Mt} + \beta_{SMB,i,s_t} SMB_t + \beta_{HML,i,s_t} HML_t$$
$$+ \kappa_{TURN,i,s_t} TURN_t + \kappa_{TURN(-1),i,s_t} TURN_{t-1} + \varepsilon_{i,s_t,t} \, , \qquad (6.4)$$
$$\text{where } \varepsilon_{i,s_t,t} \sim N\left(0, \sigma_{s_t}^2\right), \forall s_t \in \{1, K\}$$

r_M, *SMB* and *HML* are the sentiment orthogonalised excess market return, small-minus-big, and high-minus-low book-to-market (respectively used to measure market, size and book-to-market risks). *TURN* is the level of market turnover, which represents investor sentiment in terms of market activity. s_t is a regime indicator with an integer value between 1 and K, where K is the number of regimes. Thus the lowercase s_t represents the parameter estimate for regime s_t. c_{i,s_t} is the model intercept of portfolio *i* in regime s_t. Betas and kappas are the state determined fundamental and sentiment risk measures. The coefficients β_{M,i,s_t}, β_{SMB,i,s_t} and β_{HML,i,s_t} are regime-dependent factor loadings on market, size and book-to-market risks without sentiment impact while κ_{TURN,i,s_t} and $\kappa_{TURN(-1),i,s_t}$ show the impact of contemporaneous and one-period lagged market activity on asset pricing in state s_t. The residual variance represents regime dependent volatility.

It should be noticed that the one-period lag of the portfolio returns appears in the MS model with turnover although the lag variable is excluded in the models in Chapter 4 and 5, and in the MS model with ADV/DEC and $D^{p\text{-}np}$. This specification is based on the result of model selection: without the first-order lag portfolio returns, estimated residuals exhibit autocorrelation, which disappears when the lag variable is introduced, while the models in Chapter 4, and 5, and the MS models with ADV/DEC and $D^{p\text{-}np}$ do not have this issue. Also, the information criteria suggest

Markov-switching models with one lag[66].

6.5.1.2 Empirical Results: Regime Behaviour

Across all 25 size and book-to-market sorted portfolios, the three-regime nonlinear pricing formations provide consistent state behaviour that is clearly different between states. The Markov-switching estimation results are reported in Table 6.7 and the smoothed regime classifications are demonstrated in Figure 6.4. The transition probabilities are presented in Table 6.8.

Comparing between the three states, regime 1 appears to be a moderate, low frequency and high volatility state that captures the market cycle period when market is forming or lessening speculative trading. In other words, regime 1 tends to be a transition state between a fundamentals-driven regime and a sentiment-driven regime. The probabilities of staying in a regime are inconsistent across portfolios. As shown in Figure 6.4 of the smoothed regime probabilities, the moderate period may last between one and a few months. The probabilities of staying are greater than the transition probabilities for 14 out of a total of 25 portfolios. In this regime, portfolio returns may also shift to regime 3, which is a highly speculative state that will be discussed later. There is little transition probability from regime 1 to regime 2. As shown in Table 6.7, the regime-dependent variances are much greater than in regime 2. Also shown in Figure 6.4, regime 1 corresponds to some periods during early 1997 to early 1999 and late 2005 to 2007, when both market and portfolio returns fluctuate to a greater extent.

[66] Not all the portfolios are tested for model selection. Here seven portfolios are chosen randomly from the 25 size and book-to-market sorted portfolios, and are regressed with 2 to 4 number of regimes, 0 or 1 autoregressive term of the portfolio returns.

Table 6.7 Factor Loadings of Regime switching model for orthogonalised Market, SMB, HML and Turnover

This table reports the estimated factor loading parameters from the three-regime Markov-switching pricing model with turnover as the proxy of investor sentiment. The 25 size-BE/ME sorted portfolio excess returns are regressed on a constant, lagged portfolio returns, sentiment-orthogonalised excess market return, SMB and HML, current and one-lag market turnover, and regime-dependent variance.

Panel A: Regime 1										
	Small	2	3	4	Large	Small	2	3	4	Large
			constant					**r(-1)**		
Low	-2.045***	-3.665***	-3.582	-1.695***	-2.604**	0.234***	0.179***	-0.168	-0.266***	-0.007
	[-112]	[-3.34]	[-1.43]	[-3.94]	[-2.35]	[387]	[3.39]	[-0.956]	[-7.30]	[-0.067]
2	-0.818	-1.998	-2.167**	-11.111***	-3.116***	-0.029	0.015	-0.316***	0.333***	-0.363***
	[-0.411]	[-1.59]	[-2.40]	[-20.9]	[-5.67]	[-0.324]	[0.224]	[-4.99]	[12.7]	[-9.69]
3	-1.957	-1.338	0.54	-2.283***	-2.086	-0.14	0.006	0.089	0.281***	0.076
	[-1.46]	[-0.851]	[0.239]	[-5.28]	[-0.982]	[-1.33]	[0.07]	[0.627]	[10.4]	[0.422]
4	-4.487***	-1.727	-3.260***	-1.481	-2.578***	-0.138*	-0.272***	-0.043	0.001	-0.262***
	[-2.68]	[-1.23]	[-3.48]	[-1.08]	[-13.1]	[-1.71]	[-2.67]	[-0.701]	[0.007]	[-31.1]
High	-2.022*	0.312	-2.346	-2.845**	-0.418	-0.091	-0.098*	-0.123	-0.122	-0.074
	[-1.89]	[0.269]	[-0.602]	[-2.07]	[-0.303]	[-1.60]	[-1.78]	[-1.42]	[-1.35]	[-1.14]
			R_M					**SMB**		
Low	0.377***	0.480***	0.619***	0.882***	0.594***	0.629***	0.399***	0.777***	0.322***	-0.472***
	[541]	[7.23]	[4.88]	[16.9]	[7.92]	[319]	[3.05]	[4.14]	[4.24]	[-3.24]
2	0.530***	0.685***	1.059***	0.583***	0.559***	0.942***	0.830***	0.267	1.393***	-0.569***
	[5.16]	[10.8]	[14.5]	[16.6]	[17.8]	[4.12]	[5.76]	[1.54]	[13.7]	[-5.66]
3	0.778***	0.665***	0.444***	0.236***	0.592***	0.963***	1.074***	0.408**	-0.141***	0.06
	[6.96]	[7.51]	[2.96]	[8.42]	[4.23]	[4.88]	[4.02]	[2.44]	[-2.86]	[0.368]
4	0.587***	0.586***	0.638***	0.847***	1.178***	0.669***	0.658***	0.588***	0.192	0.209***
	[7.24]	[8.57]	[8.50]	[9.31]	[88.2]	[4.44]	[4.04]	[4.39]	[0.718]	[6.36]
High	0.804***	0.818***	0.757***	0.828***	0.610***	1.321***	1.086***	0.590**	0.422*	1.162***
	[10.1]	[10.1]	[4.31]	[8.43]	[6.12]	[7.18]	[6.39]	[2.58]	[1.97]	[6.94]
			HML					**TURN**		
Low	0.880***	0.276**	0.073	-0.956***	-0.669***	15.435***	15.655***	7.726***	12.555***	16.811***
	[668]	[2.37]	[0.244]	[-9.97]	[-3.68]	[409]	[8.69]	[2.74]	[10.5]	[5.07]
2	0.716***	0.14	-0.219	-0.662***	-0.247***	5.721	6.237**	4.271**	16.478***	30.469***
	[4.61]	[1.42]	[-1.41]	[-11.6]	[-3.86]	[1.10]	[2.45]	[2.02]	[8.74]	[20.7]
3	0.237	-0.339*	-0.347*	-0.246***	-0.866***	16.061***	12.643***	16.050***	14.073***	22.898***
	[1.42]	[-1.70]	[-1.69]	[-4.11]	[-4.32]	[6.02]	[3.70]	[5.47]	[11.7]	[3.85]
4	0.732***	-0.148	0.232**	-0.014	-0.075***	16.356***	22.466***	13.557***	14.931***	7.872***
	[6.59]	[-1.00]	[1.99]	[-0.059]	[-3.92]	[7.34]	[7.61]	[4.93]	[3.53]	[14.6]
High	0.325**	0.488***	0.347*	0.329**	0.290**	8.964***	10.257***	14.965***	12.721***	13.193***
	[2.34]	[4.21]	[1.72]	[2.00]	[2.33]	[2.90]	[3.56]	[4.54]	[3.43]	[4.07]
			TURN(-1)					**Sigma**		
Low	-15.599***	-7.804***	-1.872	-6.694***	-13.115***	0.017***	2.968***	2.379***	1.379***	2.361***
	[-460]	[-3.45]	[-0.642]	[-5.41]	[-3.05]	[3.75]	[8.21]	[2.93]	[8.03]	[8.20]
2	-0.61	2.379	5.101**	-8.676***	-26.194***	3.926***	2.959***	2.121***	0.741***	0.621***
	[-0.128]	[1.05]	[2.20]	[-4.40]	[-12.4]	[6.03]	[7.50]	[6.30]	[4.92]	[4.10]
3	-9.454***	-10.748**	-16.766***	-11.406***	-13.685***	3.652***	2.749***	2.732***	0.690***	3.593***
	[-2.82]	[-2.48]	[-3.56]	[-9.05]	[-2.82]	[7.40]	[5.63]	[5.78]	[5.34]	[6.46]
4	-5.254**	-19.081***	-4.197*	-13.985**	-0.508	2.437***	2.235***	3.094***	3.177***	0.303***
	[-2.55]	[-7.10]	[-1.76]	[-2.17]	[-0.861]	[4.63]	[5.60]	[9.35]	[7.10]	[4.42]
High	2.191	-7.200***	-7.71	-6.67	-6.106**	4.396***	3.634***	3.912***	3.997***	3.976***
	[0.783]	[-2.81]	[-1.54]	[-1.63]	[-2.09]	[12.7]	[9.10]	[8.34]	[7.25]	[8.43]

Table 6.7 (cont.)

Panel B: Regime 2										
	Small	2	3	4	Large	Small	2	3	4	Large
	constant					**r(-1)**				
Low	-1.122	-4.657***	-1.942***	-2.524***	-2.294***	-0.126**	-0.228***	-0.138***	0.033	-0.066***
	[-1.66]	[-6.26]	[-4.37]	[-7.09]	[-5.15]	[-2.40]	[-4.62]	[-2.83]	[1.53]	[-3.17]
2	-1.726**	-2.284***	-2.165***	-3.408***	-3.686***	-0.079*	-0.061***	-0.149***	-0.196***	-0.078**
	[-2.52]	[-18.0]	[-4.94]	[-7.18]	[-9.39]	[-1.96]	[-6.49]	[-4.02]	[-5.12]	[-2.41]
3	-1.116**	-1.913***	-2.396***	-3.317***	-3.870***	-0.112***	-0.067***	-0.102***	-0.162***	-0.285***
	[-2.36]	[-7.31]	[-4.83]	[-6.87]	[-9.47]	[-6.41]	[-3.83]	[-3.10]	[-5.16]	[-10.4]
4	-2.557***	-2.873***	-2.754***	-3.424***	-1.133	-0.168***	-0.324***	-0.196***	-0.163***	-0.058
	[-10.6]	[-6.13]	[-13.0]	[-9.14]	[-1.30]	[-11.9]	[-11.5]	[-14.8]	[-7.47]	[-1.10]
High	-2.637***	-2.495***	-3.163***	-2.382***	-2.253***	0.001	-0.066***	-0.212***	-0.165***	-0.161***
	[-7.17]	[-14.9]	[-6.40]	[-7.45]	[-3.54]	[0.057]	[-4.85]	[-2.78]	[-6.29]	[-3.14]
	R_M					**SMB**				
Low	0.900***	1.276***	0.554***	0.644***	0.819***	1.336***	0.587***	0.454***	0.420***	-0.155*
	[13.8]	[19.6]	[22.0]	[31.8]	[25.5]	[11.3]	[4.40]	[9.07]	[11.7]	[-1.82]
2	1.104***	0.916***	1.059***	0.964***	0.858***	1.083***	0.606***	0.370***	0.068	-0.440***
	[17.7]	[69.5]	[24.5]	[21.0]	[23.7]	[9.02]	[32.5]	[5.16]	[0.860]	[-6.53]
3	0.896***	0.976***	1.134***	0.996***	1.048***	1.329***	1.061***	0.389***	0.170**	-0.642***
	[24.4]	[46.7]	[26.0]	[26.8]	[31.7]	[19.5]	[27.3]	[5.15]	[2.34]	[-8.98]
4	0.739***	0.964***	1.195***	1.040***	1.110***	1.259***	0.926***	0.535***	0.349***	-0.585***
	[45.6]	[25.2]	[61.5]	[34.6]	[13.4]	[37.6]	[13.4]	[21.5]	[7.81]	[-6.17]
High	0.843***	0.918***	1.051***	0.982***	1.183***	0.705***	0.491***	0.338***	0.461***	1.335***
	[21.7]	[47.4]	[7.60]	[22.5]	[16.3]	[11.9]	[20.8]	[4.62]	[8.06]	[11.3]
	HML					**TURN**				
Low	-0.333***	-0.260**	-0.150***	-0.696***	-0.864***	11.392***	16.625***	16.638***	22.913***	21.722***
	[-3.15]	[-2.13]	[-2.80]	[-17.9]	[-19.8]	[6.74]	[7.87]	[12.4]	[49.9]	[28.4]
2	-0.382***	-0.240***	-0.254***	-0.527***	-0.276***	6.414***	15.400***	14.886***	13.789***	15.021***
	[-3.06]	[-9.90]	[-4.11]	[-7.38]	[-4.87]	[2.91]	[35.8]	[13.9]	[11.1]	[12.9]
3	-0.057	-0.132***	-0.078	0.135**	0.195***	6.450***	10.959***	10.718***	14.188***	15.183***
	[-1.00]	[-4.58]	[-1.29]	[2.48]	[4.35]	[6.02]	[14.9]	[9.87]	[13.6]	[18.7]
4	0.325***	-0.058	0.096***	0.338***	0.342***	13.674***	17.782***	17.595***	15.287***	13.646***
	[13.5]	[-1.07]	[4.26]	[8.89]	[3.85]	[24.7]	[19.2]	[39.5]	[15.0]	[7.42]
High	0.631***	0.510***	0.600***	0.422***	-0.310***	15.873***	16.591***	15.365***	15.760***	7.667***
	[18.5]	[24.5]	[3.36]	[7.07]	[-2.78]	[23.7]	[47.4]	[11.0]	[16.9]	[5.14]
	TURN(-1)					**Sigma**				
Low	-1.348	2.877	-7.552***	-13.566***	-12.538***	3.339***	2.370***	0.610***	0.508***	0.781***
	[-0.678]	[1.64]	[-7.71]	[-19.4]	[-12.5]	[13.5]	[10.6]	[3.22]	[4.77]	[6.11]
2	3.302*	-3.040***	-2.350***	-1.078	-3.582***	1.415***	0.246***	1.255***	2.294***	1.836***
	[1.92]	[-9.21]	[-2.49]	[-0.857]	[-3.18]	[4.64]	[6.58]	[8.45]	[14.3]	[14.4]
3	3.853***	-0.205	1.718*	-2.569**	-3.985***	0.972***	0.486***	1.544***	1.751***	1.357***
	[4.43]	[-0.300]	[1.77]	[-2.57]	[-4.47]	[3.37]	[5.19]	[8.25]	[10.2]	[9.45]
4	0.554	-1.840*	-5.130***	-1.214*	-5.060***	0.406***	1.316***	0.414***	0.625***	2.402***
	[1.41]	[-1.90]	[-6.79]	[-1.78]	[-3.54]	[5.46]	[7.86]	[6.03]	[3.72]	[11.1]
High	-3.567***	-3.857***	1.585	-3.563***	7.346***	0.754***	0.284***	1.304***	0.971***	1.958***
	[-4.64]	[-7.62]	[0.605]	[-3.94]	[5.53]	[4.88]	[5.49]	[5.86]	[5.39]	[7.13]

Table 6.7 (cont.)

Panel C: Regime 3

	Small	2	3	4	Large	Small	2	3	4	Large
			constant					**r(-1)**		
Low	-6.642***	-0.962	-5.413***	-2.285	-2.251**	-0.697***	-0.037	-0.118*	0.125**	-0.039
	[-3.59]	[-0.455]	[-5.09]	[-1.86]	[-2.31]	[8.09]	[-0.406]	[-1.86]	[2.00]	[-0.801]
2	-5.541***	-3.947***	-7.295***	12.909***	2.184***	-0.442***	-0.161**	0.11	0.389***	-0.183***
	[-3.53}	[-3.83]	[-2.73]	[12.5]	[2.89]	[-2.98]	[-2.61]	[0.974]	[8.67]	[-5.60]
3	-5.704***	-3.867***	-8.055***	-2.401**	0.357	-0.165*	-0.204**	-0.235***	-0.270***	0.114**
	[-3.51]	[-3.49]	[-6.81]	[-2.09]	[0.598]	[-1.89]	[-2.54]	[-3.70]	[-3.80]	[2.31]
4	-4.326***	-4.086***	-1.632***	1.118	-2.576	-0.242***	-0.189***	-0.099**	0.127	-0.058
	[-3.12]	[-2.94]	[-2.75]	[0.593]	[0.706]	[-3.33]	[-2.93]	[-2.38]	[1.42]	[-0.371]
High	-9.735***	-5.393***	-0.568	0.985	-7.248***	-0.690***	-0.368***	-0.038	-0.005	-0.354***
	[-3475]	[-3.25]	[-0.277]	[1.26]	[-16.8]	[-4037]	[-3.38]	[-0.554]	[-0.103]	[-10.9]
			R_M					**SMB**		
Low	0.175	0.669***	0.984***	1.142***	1.109***	1.251***	0.249	0.111	-0.543***	-0.117
	[1.45]	[4.68]	[11.9]	[12.6]	[13.1]	[7.58]	[1.18]	[0.867]	[-3.03]	[-0.634]
2	0.942***	1.207***	0.801***	1.438***	-0.033	0.942***	0.310**	-0.283	-0.401***	-1.379***
	[4.35]	[12.3]	[3.81]	[16.9]	[-0.577]	[3.51]	[2.11]	[-0.965]	[-4.53]	[-18.5]
3	1.190***	0.965***	1.603***	1.173***	0.931***	0.162	0.384**	-0.637**	0.067	-0.962***
	[9.79]	[11.1]	[7.53]	[12.0]	[21.4]	[0.782]	[2.53]	[-2.63]	[0.418]	[-11.2]
4	0.937***	1.169***	1.223***	1.203***	0.301	0.758***	0.009	-0.404***	-0.302	-0.378
	[6.88]	[9.45]	[24.5]	[11.9]	[1.51]	[4.01]	[0.049]	[-3.26]	[-1.42]	[-1.17]
High	0.523***	0.966***	1.125***	1.114***	1.241***	-0.599***	0.19	-0.723***	-0.736***	-0.295***
	[3337]	[8.44]	[5.97]	[27.4]	[25.1]	[-2168]	[0.784]	[-3.47]	[-8.37]	[-5.89]
			HML					**TURN**		
Low	-1.111***	0.314	-0.454***	-0.125	-0.598***	51.591***	36.822***	20.542***	27.856***	30.674***
	[-6.18]	[1.28]	[-3.68]	[-1.16]	[-4.59]	[9.80]	[6.46]	[9.97]	[9.35]	[15.9]
2	-0.777***	-0.203	0.024	-0.012	0.838***	19.918***	17.410***	41.004***	7.329***	27.943***
	[-3.21]	[-1.22]	[0.095]	[-0.131]	[10.0]	[4.62]	[7.53]	[6.83]	[4.43]	[26.6]
3	0.333	0.283*	0.548***	-0.112	0.716***	31.730***	18.041***	21.404***	20.699***	34.406***
	[1.25]	[1.72]	[2.84]	[-0.788]	[7.19]	[6.50]	[8.44]	[4.67]	[6.77]	[20.1]
4	-0.09	0.504*	0.567***	0.306*	1.089***	17.550***	24.100***	19.730***	19.356***	37.736***
	[-0.401]	[1.78]	[5.26]	[1.69]	[3.21]	[3.57]	[7.70]	[11.6]	[9.20]	[3.93]
High	2.613***	1.229***	1.404***	1.187***	0.503***	70.116***	27.630***	20.969***	17.110***	17.097***
	[5948]	[4.49]	[11.5]	[13.3]	[6.29]	[9778]	[5.53]	[7.12]	[9.29]	[15.0]
			TURN(-1)					**Sigma**		
Low	-5.407*	-7.902	0.457	-14.051***	-14.522***	0.126***	1.542***	3.219***	2.843***	2.290***
	[-1.81]	[-1.64]	[0.194]	[-6.08]	[-7.76]	[4.99]	[3.88]	[10.7]	[8.02]	[6.51]
2	5.791	1.101	-14.651***	-15.241***	-17.095***	4.287***	3.463***	5.254***	1.237***	1.217***
	[1.42]	[0.401]	[-2.65]	[-10.6]	[-15.6]	[8.55]	[10.5]	[7.05]	[5.26]	[5.74]
3	-1.94	2.178	13.249**	0.737	-19.722***	3.330***	3.415***	2.013***	2.119***	1.215***
	[-0.492]	[0.766]	[2.57]	[0.281]	[-10.8]	[8.06]	[10.0]	[5.08]	[6.57]	[5.71]
4	4.295	0.205	-4.039**	-10.194***	-18.820**	4.388***	2.168***	1.581***	2.416***	7.029***
	[1.11]	[0.085]	[-2.51]	[-3.46]	[-2.18]	[10.2]	[6.83]	[7.79]	[5.71]	[6.48]
High	-14.896***	-0.596	-5.237**	-6.269***	15.415***	0.003***	3.661***	1.127***	1.241***	0.621***
	[-3026]	[-0.177]	[-2.48]	[-4.11]	[11.8]	[4.02]	[8.06]	[4.72]	[5.94]	[5.28]

Notes: (***), (**) and (*) denote significance at the 1%, 5% and 10% levels respectively. The *t*-statistics are in the square brackets[67].

[67] The *t*-statistics estimators for regime 1 of S1B1 and regime 3 of S1B5 are extremely high but the numbers of observations in these two states are very small, therefore the parameter estimators are not reliable.

The constant and the lagged portfolio returns are insignificant. Market risk is always significant. However, compared to the other two regimes, in regime 1 portfolios are less exposed to market risk. Accordingly, it is possible to deduce that, in regime 1, investors tend to have heterogeneous opinions and investment decisions, resulting in zero mean excess portfolio returns that are less influenced by the aggregate market.

Loadings on sentiment-corrected SMB are significant in most of the portfolios, but there is no systematic pattern of size risk across portfolios and no clear evidence that small stocks are exposed to greater risk than large stocks. Loadings on HML show book-to-market effects for large stocks only, as the coefficients on HML increase from -0.956 for S4B1 and -0.669 for S5B1 to the positive values of 0.329 for S4B5 and 0.290 for S5B5. Small size stocks do not reveal this effect – the HML coefficients are even insignificant for some portfolios.

Current turnover has a positive impact on portfolio returns. Comparing among the three regimes, the turnover effects in regime 1 are small or similar to those in regime 2, but always smaller than those in regime 3. Again this reflects the heterogeneous beliefs resulted heterogeneous trading, which reduces the sentiment effect in total. Lagged turnover, on the other hand, has negative factor loadings. This shows that there is no momentum effect from market liquidity beyond one month, probably also because any concerted aggregate investor sentiment cannot last for long. The regime-dependent variances appear to be greater than those in regime 2, but smaller than those in regime 3.

Regime 2 appears to be a persistent rational and fundamental-driven regime with low sentiment, low return and low volatility. As shown in Table 6.8 and Figure 6.4, portfolio returns tend to stay in regime 2 rather than shift to other regimes. There are only 4 cases where portfolio returns shift from regime 2 to regime 1 (mainly small size stocks) and there are 7 cases where portfolio returns shift from regime 2 to regime 3.

The constant terms in regime 2 are significant and negative, although they are smaller in absolute value than those in regime 3. However, because the estimated sentiment loadings are smaller than those in the other two regimes, the negative intercepts indicate that the mean portfolio returns in regime 2 are negative rather than the effect from a large sentiment slope. For most portfolios regime 2 covers the period from June 2001 to May 2005, when Chinese stock markets had suffered from pessimism because of the hang SOEs' nontradable share reform. The lagged portfolio returns have a negative and significant impact on current returns, suggesting that portfolio returns show mean-reversion in regime 2.

The portfolio returns are exposed to greater market risk than in regime 1, which demonstrates relatively homogeneous investor beliefs and therefore investment decisions so that portfolio returns co-move with the aggregate market. The sentiment-corrected market beta is close to 1. Comparing portfolios, the middle to big size portfolios tend to have market betas that are above 1.

The systematic size risk and book-to-market distress risk are informative and revealing in regime 2, which strongly suggests that regime 2 is fundamentals-driven. In this regime, loadings on SMB increase as stock size increases, from negative to positive values. This systematic pattern is consistent across all portfolios except S5B5, the outlier shown in the traditional applications (Chapter 4) as well. Similarly, loadings on HML range from low negative for low book-to-market portfolios to high positive for high book-to-market portfolios, which is consistent with the statement of Fama and French (1993, 1996) that high book-to-market stocks have greater distress probabilities than low book-to-market stocks.

Loadings on market turnover are consistently significant across portfolios, although the coefficients are smaller than those in regime 3. An increase in turnover will raise portfolio returns even in the bear state. For middle book-to-market portfolios (the third book-to-market sorted group), turnover effects on portfolio returns increase from small size stocks to big size stocks, partially suggesting that returns of large companies are more sensitive to aggregate market activity. Lagged turnover has an inconsistent impact on portfolio returns.

Regime 2 is a low-volatility regime. The regime-dependent variances are much lower than those of the other two regimes, consistent across almost all portfolios. Taking into account the negative intercepts, greater market beta, systematic size risk and distress risk pattern, these results reveal an inactive bear market where investors are more rational and fundamental risks are more likely to be considered.

Highly distinct from the first two regimes, regime 3 suggests a highly speculative and volatile state with low frequency but high staying probability. Figure 6.9 shows that, for most of the tested portfolios, the third regime captures the dramatic increase in return of 19 May 1999 and the bubble starting in mid-2005 that initially arose from the implementation of SOEs non-tradable share reform, which eliminated uncertainty, and from exchange rate reform, which allowed the possibility of RMB appreciation.

As shown in the third results column of Table 6.8, the staying durations are inconsistent across portfolios: returns tend to stay in regime 3 for 11 of the 25 tested portfolios and shift to regime 1 for a further 11 of the 25. The high staying probability is consistent with the regime pattern of turnover[68] Taking into account the probability of transition from regime 1 to regime 3, the inter-shifts between regime 1 and 3 lead further support that regime 1 is a transition state for the highly irrational market. The middle book-to-market portfolios are composed of the most normally and rationally behaved stocks. They could shift directly from the sentiment-driven state to the fundamentals-driven state.

[68] See the description of regime 3 of turnover (P236).

Table 6.8 Transition Probabilities of the Markov-switching pricing model with turnover

This table presents the transition probabilities of the three-regime MS asset pricing model with turnover. In the first column the 25 size and book-to-market sorted portfolios are ordered from the smallest size portfolios (S1) with low to high book-to-market ratios (B1 to B5) to the biggest size portfolios (S5) with low to high book-to-market ratios (B1 to B5).

		Regime 1_t	Regime 2_t	Regime 3_t
S1B1	Regime 1_{t+1}	0.000	0.039	0.207
	Regime 2_{t+1}	0.126	0.938	0.344
	Regime 3_{t+1}	0.874	0.022	0.449
S1B2	Regime 1_{t+1}	0.730	0.149	0.000
	Regime 2_{t+1}	0.197	0.456	0.467
	Regime 3_{t+1}	0.073	0.395	0.533
S1B3	Regime 1_{t+1}	0.000	0.482	0.599
	Regime 2_{t+1}	0.443	0.303	0.192
	Regime 3_{t+1}	0.557	0.215	0.209
S1B4	Regime 1_{t+1}	0.163	0.443	0.198
	Regime 2_{t+1}	0.687	0.204	0.036
	Regime 3_{t+1}	0.150	0.353	0.767
S1B5	Regime 1_{t+1}	0.582	0.873	1.000
	Regime 2_{t+1}	0.367	0.025	0.000
	Regime 3_{t+1}	0.051	0.025	0.000
S2B1	Regime 1_{t+1}	0.691	0.058	0.886
	Regime 2_{t+1}	0.129	0.932	0.000
	Regime 3_{t+1}	0.180	0.009	0.114
S2B2	Regime 1_{t+1}	0.878	0.111	0.000
	Regime 2_{t+1}	0.000	0.413	0.288
	Regime 3_{t+1}	0.122	0.476	0.712
S2B3	Regime 1_{t+1}	0.129	0.325	0.277
	Regime 2_{t+1}	0.543	0.000	0.239
	Regime 3_{t+1}	0.328	0.675	0.484
S2B4	Regime 1_{t+1}	0.000	0.315	0.282
	Regime 2_{t+1}	0.596	0.507	0.326
	Regime 3_{t+1}	0.404	0.179	0.392
S2B5	Regime 1_{t+1}	0.452	0.053	0.685
	Regime 2_{t+1}	0.182	0.000	0.259
	Regime 3_{t+1}	0.366	0.947	0.057
S3B1	Regime 1_{t+1}	0.205	0.670	0.077
	Regime 2_{t+1}	0.216	0.330	0.161
	Regime 3_{t+1}	0.578	0.000	0.763
S3B2	Regime 1_{t+1}	0.661	0.078	0.245
	Regime 2_{t+1}	0.012	0.888	0.189
	Regime 3_{t+1}	0.327	0.033	0.565
S3B3	Regime 1_{t+1}	0.521	0.160	0.218
	Regime 2_{t+1}	0.238	0.738	0.435
	Regime 3_{t+1}	0.242	0.102	0.347
S3B4	Regime 1_{t+1}	0.534	0.000	0.587
	Regime 2_{t+1}	0.103	0.302	0.413
	Regime 3_{t+1}	0.362	0.698	0.000
S3B5	Regime 1_{t+1}	0.419	0.296	0.563
	Regime 2_{t+1}	0.355	0.704	0.000
	Regime 3_{t+1}	0.226	0.000	0.437

Table 6. 8 (cont.)

		Regime 1_t	Regime 2_t	Regime 3_t
S4B1	Regime 1 $_{t+1}$	0.624	0.335	0.343
	Regime 2 $_{t+1}$	0.196	0.000	0.322
	Regime 3 $_{t+1}$	0.179	0.665	0.336
S4B2	Regime 1 $_{t+1}$	0.000	0.042	0.617
	Regime 2 $_{t+1}$	0.287	0.959	0.000
	Regime 3 $_{t+1}$	0.713	0.000	0.383
S4B3	Regime 1 $_{t+1}$	0.280	0.000	0.475
	Regime 2 $_{t+1}$	0.488	0.688	0.525
	Regime 3 $_{t+1}$	0.232	0.312	0.000
S4B4	Regime 1 $_{t+1}$	0.182	0.297	0.429
	Regime 2 $_{t+1}$	0.332	0.258	0.341
	Regime 3 $_{t+1}$	0.486	0.445	0.230
S4B5	Regime 1 $_{t+1}$	0.500	0.076	0.598
	Regime 2 $_{t+1}$	0.244	0.694	0.202
	Regime 3 $_{t+1}$	0.256	0.230	0.200
S5B1	Regime 1 $_{t+1}$	0.520	0.217	0.397
	Regime 2 $_{t+1}$	0.384	0.000	0.371
	Regime 3 $_{t+1}$	0.096	0.783	0.233
S5B2	Regime 1 $_{t+1}$	0.000	0.030	0.339
	Regime 2 $_{t+1}$	0.000	0.970	0.161
	Regime 3 $_{t+1}$	1.000	0.000	0.499
S5B3	Regime 1 $_{t+1}$	0.803	0.102	0.000
	Regime 2 $_{t+1}$	0.000	0.657	0.953
	Regime 3 $_{t+1}$	0.197	0.241	0.047
S5B4	Regime 1 $_{t+1}$	0.367	0.123	0.143
	Regime 2 $_{t+1}$	0.633	0.823	0.000
	Regime 3 $_{t+1}$	0.000	0.053	0.857
S5B5	Regime 1 $_{t+1}$	0.864	0.037	0.183
	Regime 2 $_{t+1}$	0.037	0.874	0.330
	Regime 3 $_{t+1}$	0.099	0.089	0.487

The intercept terms in regime 3 are highly significant and negative for small size stocks but become insignificant or even positive for big size stocks, shedding light on that small size stocks have lower return than large size stocks in a highly speculative market. From another point of view, in this sentiment-driven regime, returns of big size stocks can be more successfully and fully captured by the Fama-French three factors and aggregate market activity while returns of small size stocks are less affected by market activity, since aggregate market activity mainly comprises the activity of stocks with large market capitalisation. This is consistent with the discussion in the previous chapter, where it is found that market activity is more likely to be a sentiment proxy for big size stocks only.

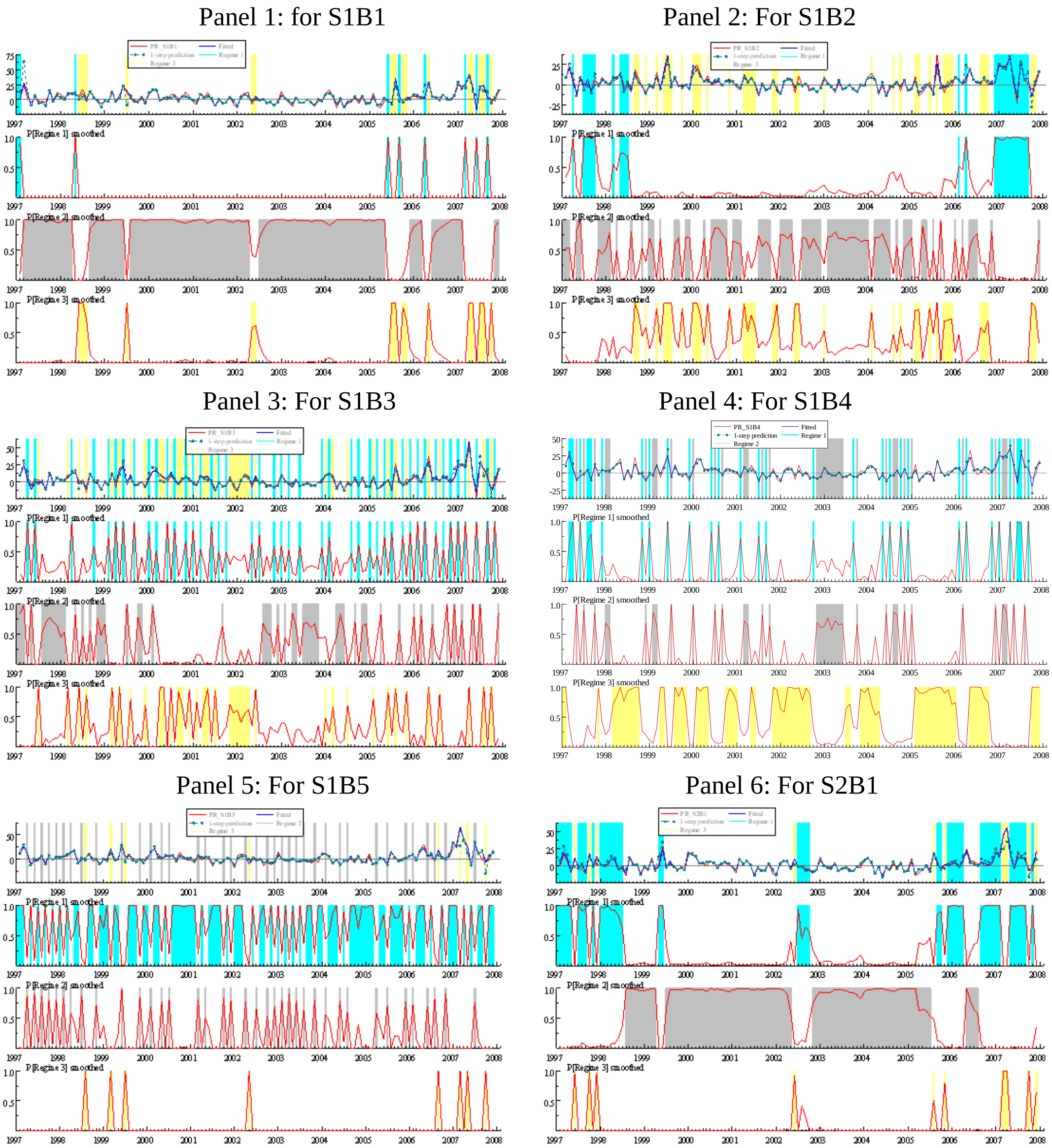
Loadings on the Fama-French three factors also suggest that regime 3 is a non-fundamental regime. Loadings on the excess market return reveal that portfolios in this regime are exposed to greater market risks, as most of the market betas (especially for middle size stocks) are greater than 1, even though the market returns are orthogonalised by investor sentiment. The high market risk factor loadings in the strong sentiment-driven periods are consistent with Chen, *et al.* (2009), who state that market beta estimates are higher in bull markets than in stable and bear markets. There are only 3 portfolios (S1B1, S5B2 and S5B4) for which the market betas are insignificant. This suggests that the smallest and biggest size stocks may behave independently from the aggregate market in sentiment-driven conditions. Loadings on SMB and HML become less significant in regime 3, as there are 10 portfolios not exposed to size risk and 8 portfolios not exposed to distress risk.

The major difference between regime 3 and the other two regimes is the strong sentiment effect. For almost all portfolios, market activity has the greatest impact on portfolio returns in regime 3. In about half of the cases, the impact is double or more than in the first two regimes. This strongly supports the view that regime 3 is sentiment-driven. Comparing portfolios, the smallest size stocks seem more likely to be driven by investor sentiment. The lagged market activity has no effect on small size stock returns but does have a significant effect on the returns of big size stocks (where it is usually negative).

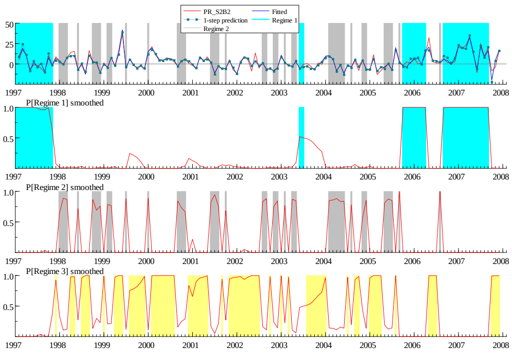
Finally, the regime dependent variances are greater than those in regime 2 but more or less the same as those in regime 1. This shows that sentiment-driven returns are highly volatile. This is in line with the natural conjecture that asset returns fluctuate more in speculative markets.

Figure 6.4 Smoothed Regime Probabilities: Three-State MS Pricing Model with Turnover

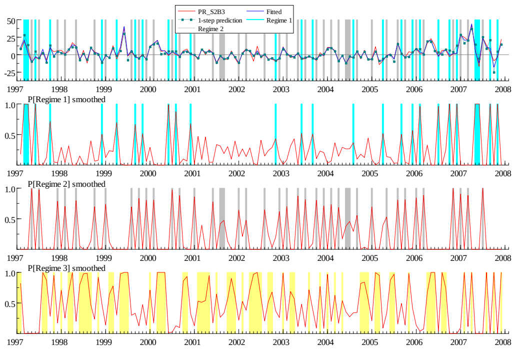
This figure describes the actual, fitted and forecasted portfolio returns and smoothed regime probabilities for the two-regime MS model with turnover for the 25 size and book-to-market sorted portfolio returns. Results of each portfolio are presented separately in panels 1 to 25. For each portfolio, the first resulting panel plots the actual, fitted and one-step ahead forecasted portfolio returns. The next two panels plot the smoothed regime probabilities. The dependent variables are the constant, the sentiment-orthogonalised excess market return (r_M), SMB and HML, market activity (TURN), and residual variance.



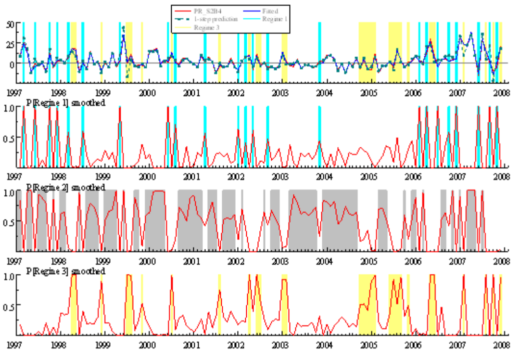
Panel 7: For S2B2



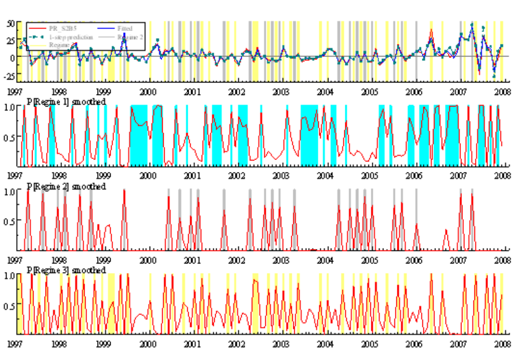
Panel 8: For S2B3



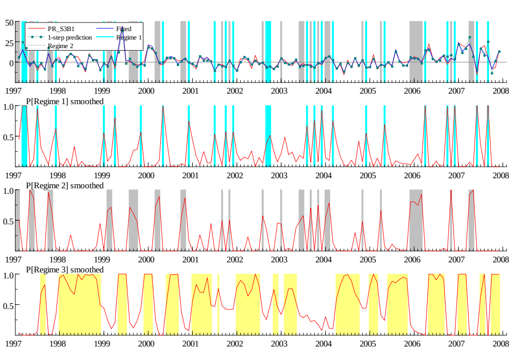
Panel 9: For S2B4



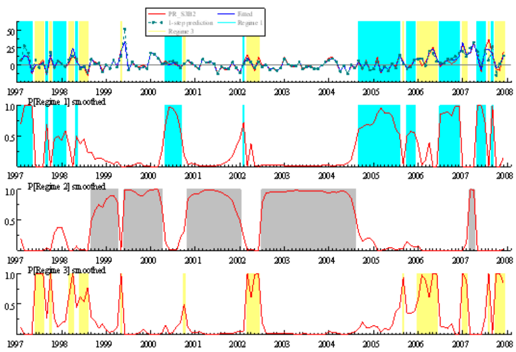
Panel 10: For S2B5



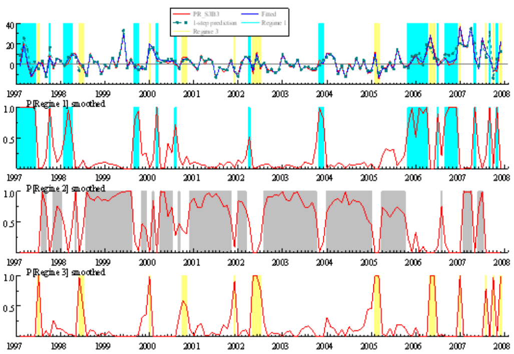
Panel 11: For S3B1



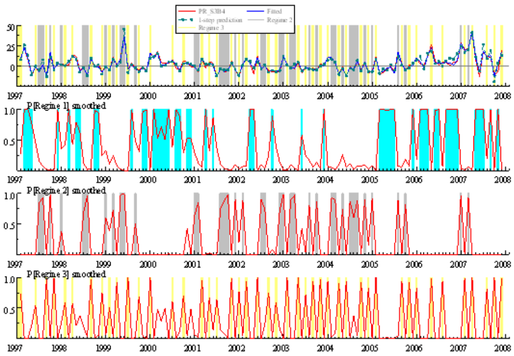
Panel 12: For S3B2



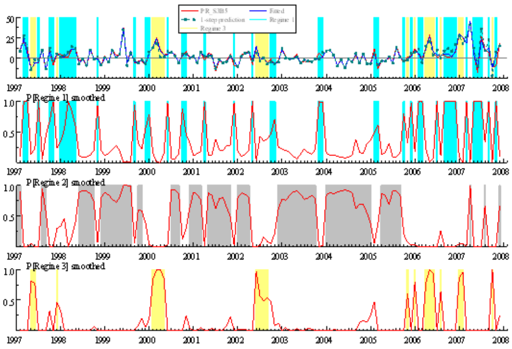
Panel 13: For S3B3



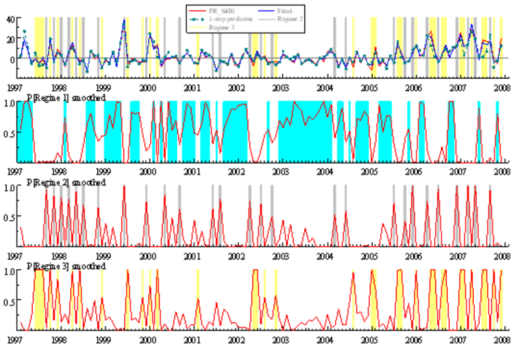
Panel 14: For S3B4



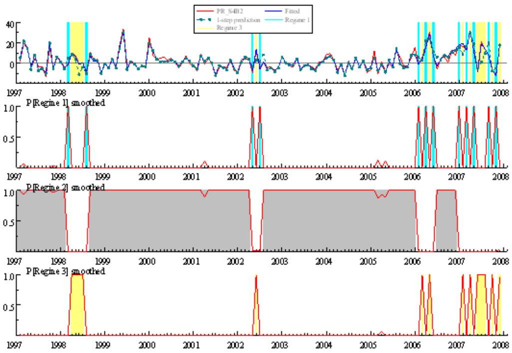
Panel 15: For S3B5



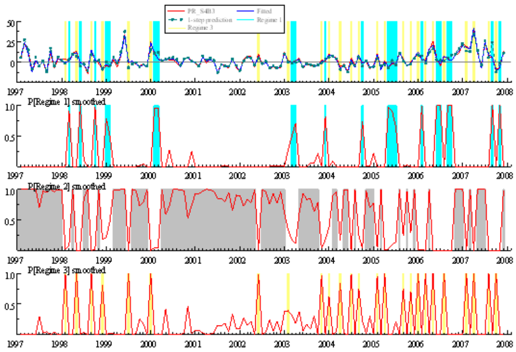
Panel 16: For S4B1



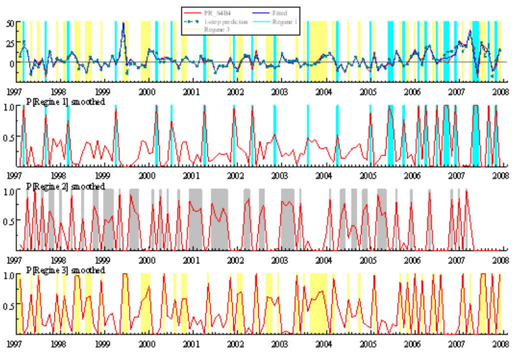
Panel 17: For S4B2



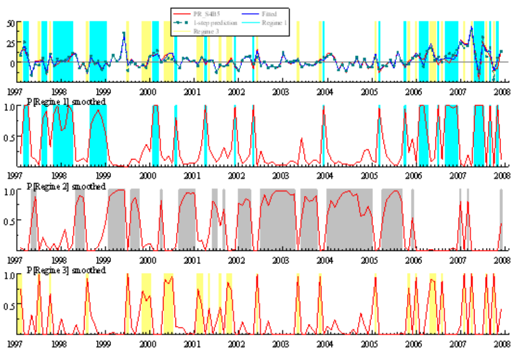
Panel 18: For S4B3



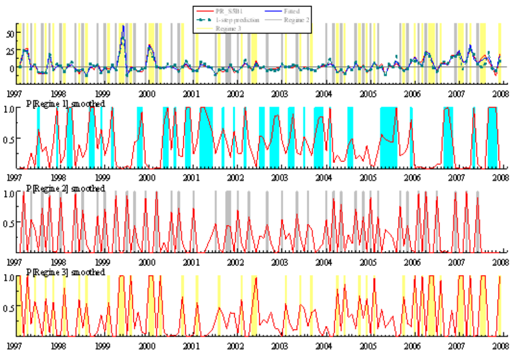
Panel 19: For S4B4



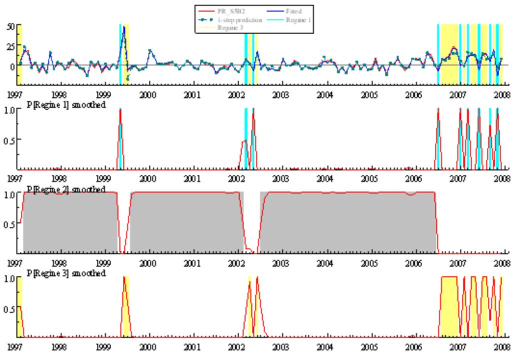
Panel 20: For S4B5



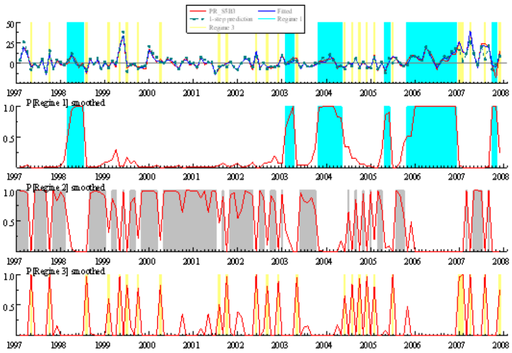
Panel 21: For S5B1



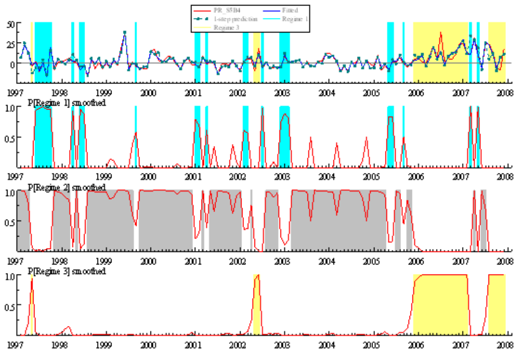
Panel 22: For S5B2



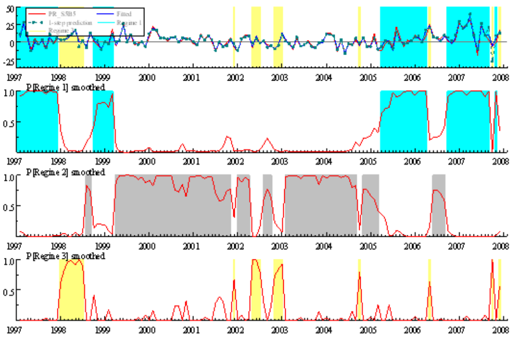
Panel 23: For S5B3



Panel 24: For S5B4



Panel 25: For S5B5



6.5.1.3 Diagnostic Checking

Three diagnostic tests are reported in Table 6.9 for the Markov-switching asset pricing model with market liquidity (turnover) as the proxy of investor sentiment. The results show that, for most of portfolios, the scaled residuals have no serial correlations. The only exceptions are for S1B2 and S3B3, where zero autocorrelation is rejected at the 95% confidence level. 5 of the 25 tested portfolios show significant ARCH (1, 1) effects, and most of these are for small size stocks. In 9 cases, the normal distribution is rejected for the residuals. Nevertheless, for most of the portfolios, the diagnostic checks suggest that the scaled residuals are independent and identically distributed random variables that are normally distributed and that the three-regime Markov-switching asset pricing model with turnover successfully fits the data. These residual descriptions are much improved than then sentiment-based conditional asset pricing model with time-invariant factor loadings.

Table 6.9 Diagnostic Checking for the Markov-switching Pricing Model with Turnover

This table reports the descriptive statistics for scaled residuals from the three-regime MS model with turnover as the proxy of investor sentiment. The three results columns present the scaled residual diagnostic test results: normality Jarque-Bera test, ARCH 1-1 Engle test and Ljung-Box serial correlation test with 12 lags. The Chi-square statistics are reported with the corresponding probabilities in the square brackets.

	JB	**ARCH**	**LB**
S1B1	2.483	0.456	34.603
	[0.289]	[0.501]	[0.535]
S1B2	0.077	1.238	55.97**
	[0.962]	[0.269]	[0.018]
S1B3	1.229	3.131*	22.38
	[0.541]	[0.080]	[0.963]
S1B4	0.689	7.377***	29.207
	[0.709]	[0.008]	[0.782]
S1B5	12.077***	0.566	36.857
	[0.002]	[0.454]	[0.429]
S2B1	2.091	0.988	37.064
	[0.352]	[0.323]	[0.420]
S2B2	7.889**	2.158	32.344
	[0.019]	[0.145]	[0.643]
S2B3	3.237	1.934	37.594
	[0.198]	[0.168]	[0.396]
S2B4	0.622	5.168**	30.410
	[0.733]	[0.019]	[0.731]
S2B5	14.373***	6.635**	43.993
	[0.001]	[0.012]	[0.169]
S3B1	12.698***	0.557	[26.516
	[0.002]	[0.457]	[0.876]
S3B2	1.977	0.004	33.283
	[0.372]	[0.951]	[0.599]
S3B3	1.753	2.415	53.474**
	[0.416]	[0.123]	[0.031]
S3B4	5.571*	1.449	46.387
	[0.062]	[0.232]	[0.115]
S3B5	5.705*	0.068	43.929
	[0.058]	[0.795]	[0.171]

	JB	**ARCH**	**LB**
S4B1	1.354	0.059	37.934
	[0.508]	[0.809]	[0.381]
S4B2	4.159	0.093	35.273
	[0.125]	[0.761]	[0.503]
S4B3	2.291	0.221	24.048
	[0.318]	[0.641]	[0.936]
S4B4	6.692**	4.072**	30.543
	[0.035]	[0.046]	[0.726]
S4B5	0.526	0.000	31.203
	[0.769]	[0.998]	[0.696]
S5B1	2.030	1.306	34.199
	[0.362]	[0.256]	[0.555]
S5B2	2.011	0.023	37.083
	[0.366]	[0.880]	[0.419]
S5B3	8.304**	0.462	24.337
	[0.016]	[0.498]	[0.930]
S5B4	6.779**	0.064	31.772
	[0.034]	[0.801]	[0.670]
S5B5	0.661	1.173	25.164
	[0.718]	[0.282]	[0.912]

Notes: (***), (**) and (*) denote significance at the 1%, 5% and 10% levels, respectively.

JB: Jarque-Bera normality test,
ARCH: ARCH (1-1) test (Engle, 1982),
LB: Ljung-Box serial correlation test.

6.5.2. Asset Pricing Model with Regime Dependent ADV/DEC

6.5.2.1 The Nonlinear Pricing Model with Advances-declines Ratio

In this section the buying-selling imbalance (ADV/DEC) proxy for sentiment is specified in the model. 10 randomly selected portfolios[69] show that the MS model with ADV/DEC is preferred without lags in both the sentiment proxy and the portfolio return. Two regimes are used, based on the results of the regime performance estimation of ADV/DEC. The Markov-switching asset pricing model with ADV/DEC is specified as

$$r_{i,t} = c_{i,s_t} + \beta_{M,i,s_t} r_{M,t} + \beta_{SMB,i,s_t} SMB_t + \beta_{HML,i,s_t} HML_t + \kappa_{ADV/DEC,i,s_t} ADVDEC_t + \varepsilon_{i,s_t,t}, \quad (6.5)$$
$$\varepsilon_{i,s_t,t} \sim N\left(0, \sigma^2_{s_t}\right), \forall s_t \in \{1, K\}$$

Here the tested asset returns r_i are the excess returns of the size and book-to market sorted portfolio *i*. r_M, SMB and HML are the sentiment- orthogonalised excess market return, size and value factors, as before. *ADVDEC* is the ratio of advancing issues to declining issues. c_{i,s_t} is the model intercept of portfolio *i* in regime s_t. β_M, β_{SMB}, and β_{HML} stand for the fundamental FF risk factor loadings. $\kappa_{ADV/DEC}$ indicated the sensitivity of portfolio returns to the current buying-selling imbalance. β_i and κ_i are regime-dependent. The residual ε is assumed to be iid normal with zero mean and finite regime-dependent variance.

6.5.2.2 Empirical Results: Regime Behaviour

Table 6.10 reports the time-series factor loadings of the Markov-switching asset pricing model with ADV/DEC as the sentiment proxy. Table 6.11 presents the transition probabilities of portfolio returns shifting between regimes. The actual and fitted portfolio returns and the smoothed regime probability classification are shown in Figure 6.5. All the estimated results across all 25 portfolios seem robust: there is a prolonged fundamentals-driven regime with both relatively small sentiment effects and low volatility,

[69] The ten randomly selected portfolios are S1B1, S1B2, S1B5, S2B2, S3B3, S3B5, S4B2, S4B4, S5B1 and S5B5.

and an infrequent, relatively transient regime with a strong sentiment effect and high volatility. The fundamentals-driven regime covers the early data period from mid-1997 to late 1998, and the long period from mid-2001 to mid-2005 (when investor sentiment is pessimistic). The sentiment-driven regime is very transient and covers periods of highly-volatility and booming markets, such as the dramatic increase in the market index from 2006.

Regime 1 is a persistent fundamentals-driven low-volatility state whose duration ranges between 3.13 months (for portfolios S3B5 and S4B5) and 17.86 months (for S1B2). Portfolio returns are more likely to stay in regime 1 rather than shift to the other regime. As shown in Table 6.11, the smallest probability of staying is 68.1% across all the tested portfolios and most probabilities of staying are over 80%. Regime 1 captures the moderate bull market from mid-2000 to early 2001 and the period with sustained bear market between mid-2001 and mid-2005, These periods in regime 1 are also captured by the low sentiment regime (regime 1) of ADV/DEC[70], which therefore provides robustness of the model.

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[70] See Figure 6.2 (p238).

Table 6.10 Factor Loadings of the Regime-switching model for orthogonalised Market, SMB, HML and ADV/DEC

This table reports the estimated factor loading parameters from the nonlinear Markov-switching pricing model, of which the 25 size-BE/ME sorted portfolio excess returns are regressed on a constant term, sentiment-corrected (orthogonalised) excess market return, SMB and HML, advances-declines ratio, and regime-dependent variance over the period January 1997 to December 2007, using 11 years monthly data from Chinese A-Share stock markets.

			Panel A: Regime 1							
	Small	2	3	4	Large	Small	2	3	4	Large
			constant					**R_M**		
Low	-6.795***	-8.897***	-11.788***	-8.734***	-7.964***	0.703***	0.783***	0.401***	0.643***	0.477***
	[-3.18]	[-5.22]	[-9.13]	[-5.02]	[-5.60]	[8.23]	[9.52]	[6.95]	[7.27]	[6.36]
2	-10.065***	-9.655***	-6.198***	-13.408***	-3.428**	0.512***	0.564***	0.902***	0.486***	0.850***
	[-5.64]	[-6.42]	[-5.39]	[-7.36]	[-2.62]	[6.98]	[8.93]	[14.9]	[4.83]	[13.8]
3	-9.991***	-9.379***	-11.129***	-11.338***	-8.588***	0.560***	0.668***	0.614***	0.551***	0.630***
	[-6.01]	[-6.16]	[-7.08]	[-10.3]	[-6.77]	[7.87]	[9.96]	[7.99]	[10.5]	[10.5]
4	-9.064***	-8.002***	-10.178***	-11.899***	-11.138***	0.607***	0.707***	0.651***	0.549***	0.497***
	[-4.93]	[-7.78]	[-9.18]	[-9.30]	[-7.78]	[6.83]	[13.7]	[13.0]	[9.84]	[8.08]
High	-9.365***	-9.315***	-9.369***	-13.422***	-7.974***	0.620***	0.678***	0.648***	0.433***	0.729***
	[-5.15]	[-6.46]	[-6.59]	[-9.40]	[-5.43]	[7.65]	[10.6]	[9.52]	[6.10]	[10.6]
			SMB					**HML**		
Low	1.249***	0.718***	0.253**	-0.04	-0.373***	-0.263**	-0.543***	-0.138*	-0.559***	-0.168
	[9.04]	[5.28]	[2.63]	[-0.148]	[-3.12]	[-2.45]	[-5.15]	[-1.87]	[-4.67]	[-1.10]
2	0.916***	0.572***	0.075	-0.048	-0.423***	0.275***	-0.118	-0.049	-0.415***	-0.254***
	[6.79]	[5.33]	[0.720]	[-0.336]	[-4.47]	[2.64]	[-1.34]	[-0.672]	[-3.34]	[-3.65]
3	0.751***	0.900***	0.321**	-0.012	-0.515***	0.11	0.123	0.144	-0.177**	0.226**
	[5.91]	[8.49]	[2.53]	[-0.158]	[-4.86]	[1.21]	[1.52]	[1.61]	[-2.26]	[2.36]
4	0.697***	0.450***	0.426***	0.008	-0.357***	0.339***	0.116*	0.065	0.053	0.370***
	[5.77]	[5.98]	[5.19]	[0.099]	[-3.69]	[3.09]	[1.78]	[1.06]	[0.689]	[3.87]
High	0.955***	0.706***	0.453***	0.108	0.989***	0.412***	0.547***	0.468***	0.168*	-0.024
	[7.59]	[6.81]	[3.97]	[1.03]	[9.25]	[4.53]	[6.87]	[5.49]	[1.97]	[-0.261]
			ADVDEC					**Sigma**		
Low	8.822***	10.038***	11.655***	8.849***	7.340***	3.536***	3.397***	2.521***	2.283***	2.194***
	[5.24]	[6.57]	[9.59]	[5.67]	[5.20]	[12.7]	[12.2]	[9.06]	[8.93]	[6.34]
2	10.823***	10.009***	7.259***	12.851***	3.314***	3.587***	2.366***	1.897***	2.470***	2.312***
	[6.73]	[7.65]	[7.10]	[8.32]	[2.76]	[12.3]	[11.7]	[9.05]	[8.17]	[12.7]
3	10.899***	10.634***	11.629***	11.571***	8.796***	2.712***	2.984***	2.739***	2.306***	2.489***
	[7.35]	[7.83]	[8.40]	[11.1]	[7.87]	[9.84]	[13.4]	[9.44]	[13.2]	[10.7]
4	10.334***	9.149***	10.553***	12.529***	11.468***	2.543***	1.752***	2.026***	2.297***	2.296***
	[6.36]	[10.1]	[10.9]	[11.0]	[8.80]	[6.89]	[10.4]	[12.0]	[11.6]	[9.41]
High	11.032***	10.257***	10.564***	13.796***	9.320***	3.558***	2.587***	2.696***	2.545***	2.690***
	[6.78]	[8.05]	[8.32]	[10.9]	[7.11]	[12.8]	[12.5]	[9.90]	[11.4]	[11.3]

Table 6.10 (cont.)

Panel B: Regime 2										
	Small	2	3	4	Large	Small	2	3	4	Large
	constant					**R_M**				
Low	-33.579***	-37.925***	-2.92	-23.179***	-8.288	-0.661***	0.052	1.425***	0.463	1.159***
	[-7.23]	[-5.60]	[-0.296]	[-2.74]	[-1.21]	[-3.75]	[0.294]	[4.40]	[1.10]	[4.57]
2	-24.871***	-15.076***	-22.824***	-14.078***	-27.543***	0.489***	0.692***	0.25	0.821***	0.29
	[-6.46]	[-4.31]	[-4.44]	[-3.81]	[-3.17]	[2.82]	[5.29]	[1.36]	[5.19]	[1.47]
3	-14.711***	-40.056***	-32.952***	8.050**	-29.865***	0.868***	-0.079	-0.026	1.557***	0.341
	[-2.64]	[-7.55]	[-7.87]	[2.64]	[-3.47]	[4.39]	[-0.535]	[-0.161]	[15.9]	[0.958]
4	-24.009***	-24.960***	-26.219***	-15.374***	6.17	0.138	0.077	0.329**	1.269***	1.520***
	[-5.35]	[-5.93]	[-7.50]	[-3.40]	[0.738]	[0.784]	[0.460]	[2.22]	[8.07]	[4.61]
High	-48.390***	-27.763***	-31.867***	-10.797***	-23.492***	-0.590**	0.115	0.08	1.021***	-0.072
	[-5.49]	[-8.04]	[-4.74]	[-3.38]	[-3.53]	[-2.52]	[0.847]	[0.366]	[8.98]	[-0.356]
	SMB					**HML**				
Low	0.535**	-0.216	-0.444	0.176	-0.186	-0.195	1.032***	0.251	-0.581**	-0.882***
	[2.22]	[-0.911]	[-1.11]	[0.437]	[-0.542]	[-0.756]	[3.76]	[0.638]	[-2.62]	[-3.43]
2	0.381**	0.105	0.173	-0.227	-1.308***	-0.398*	0.042	-0.281	-0.202	0.317
	[2.02]	[0.581]	[0.720]	[-1.22]	[-3.91]	[-1.77]	[0.236]	[-1.22]	[-1.40]	[0.873]
3	0.11	0.313	0.481**	0.364**	-0.287	0.740***	0.332	-0.440*	-0.523***	-0.248
	[0.418]	[1.32]	[2.16]	[2.44]	[-0.871]	[2.62]	[1.29]	[-1.88]	[-4.75]	[-0.829]
4	0.607***	0.511**	0.096	-0.790***	-0.438	0.191	-0.027	0.158	0.680***	0.412
	[2.70]	[2.31]	[0.486]	[-2.67]	[-1.03]	[0.782]	[-0.125]	[0.787]	[2.87]	[1.15]
High	0.367	0.325*	0.165	-0.432*	0.670**	1.770**	0.480**	0.486	1.080***	0.002
	[0.676]	[1.67]	[0.575]	[-1.89]	[2.51]	[2.21]	[2.19]	[1.53]	[6.14]	[0.007]
	ADVDEC					**Sigma**				
Low	41.182***	40.564***	9.434	26.442***	12.343**	4.164***	3.932***	5.809***	4.946***	8.318***
	[9.66]	[6.62]	[1.09]	[2.81]	[2.16]	[5.44]	[5.89]	[6.61]	[6.14]	[6.61]
2	31.341***	19.696***	27.058***	18.288***	30.778***	3.321***	4.047***	6.165***	3.565***	6.651***
	[8.58]	[6.05]	[5.56]	[5.29]	[3.83]	[6.56]	[8.23]	[8.46]	[8.02]	[6.38]
3	20.459***	45.716***	37.701***	1.776	33.817***	4.690***	3.266***	3.715***	2.216***	6.296***
	[4.43]	[9.15]	[9.29]	[0.751]	[3.97]	[6.57]	[4.87]	[5.89]	[5.27]	[6.57]
4	27.669***	29.427***	31.014***	19.837***	-0.075	5.006***	5.157***	3.556***	4.326***	8.302***
	[6.47]	[7.31	[9.09]	[5.05]	[-0.010]	[8.27]	[8.29]	[7.87]	[6.34]	[6.76]
High	58.075***	32.959***	36.393***	14.761***	29.191***	4.492***	3.675***	4.732***	3.057***	4.845***
	[7.15]	[10.3]	[5.41]	[5.29]	[4.32]	[4.85]	[7.43]	[6.08]	[7.06]	[6.66]

Notes: (***), (**) and (*) denote significance at the 1%, 5% and 10% levels respectively. The *t*-statistics are in the square brackets.

The regime-dependent model intercepts are significant and negative. Since the mean ADV/DEC ratio in regime 1 is -0.087, the negative intercepts indicate that the zero-beta excess rate of return in the bear market phase is negative. The negative intercepts may also come from the large loadings on ADV/DEC, which give the sentiment risk factor a steep effect on portfolio returns. In regime 1 the estimated market risks are significant, although none of the market betas is greater than 1. That the market beta is smaller than 1 is not a surprise, because the market excess return is orthogonalised with respect to the sentiment proxies to rule out sentiment effects. All the estimated market betas are significant at the 99% confidence level, showing that portfolio returns are sensitive to the aggregate market return in the fundamentals-driven regime.

Size risk in regime 1 seems to be important, as loadings on SMB provide a systematic pattern of sustained increase from big size stocks to small size stocks. The biggest size stocks (S5Bi) have negative factor loadings on SMB. The next biggest size (S4Bi) has insignificant size risks; while the next has positive SMB factor loadings. This trend continues and the smallest portfolios (S1Bi) have the greatest and significant factor loadings on SMB. Loadings on HML indicate distress risk after controlling for sentiment. Although the coefficients are insignificant for some portfolios, especially middle size, the significant factor loadings always show an increase from low to high book-to-market portfolios (SiB1 to SiB5). These results are informative and support the view that fundamental risks are priced in regime 1.

The coefficients on the advances-declines ratio are significant and positive, indicating that portfolio returns increase with the increase of buying over selling commissions, even in a fundamentals-driven state. The estimated factor loadings on ADV/DEC are generally greater than 5 and less than 15 with an average of 10. This reveals that a 1% increase in the advances-declines ratio should trigger a 10% increase in portfolio returns. There is no systematic pattern for the loadings on ADV/DEC across the 25 size and book-to-market sorted portfolios, suggesting that sentiment effects are aggregated rather than cross-sectional different. The estimated regime-dependent variances are significant and smaller in regime 1 than in regime 2, which indicates that regime 1 is a low-volatility state.

Overall, portfolio returns in regime 1 are exposed to significant market, size and distress risks. This regime captures low-volatility and bear sentiment states, with small but significant sentiment effects. Portfolio returns have high probabilities of staying and this regime is highly persistent. Therefore, regime 1 is found to be a prolonged-period, fundamentals-driven, low-volatility and moderately bear state.

Regime 2 in this model is an infrequent sentiment-driven regime with relatively short duration. 11 out of 25 portfolio returns tend to shift from regime 2 to regime 1 over time. For the other 14 portfolios, returns remain in regime 2. This highly-volatile and sentiment-driven state may persist for one and six months. The longest staying duration is 6.13 months for portfolio S2B2. The second smallest size and low book-to-market stocks have returns that are most likely to stay rather than shift. The shortest staying duration is 1.33 months for portfolio S1B5. Low book-to-market stocks seem to have stronger sentiment-driven momentum.

This regime is characterised as a sentiment-driven regime mainly because portfolio returns are significantly and highly positive correlated with the sentiment proxy of ADV/DEC. 22 estimated loadings are significant. In most portfolios, loadings on ADV/DEC in regime 2 are between 3 and 9 times greater than the equivalent estimators in regime 1. The most extreme case is for portfolio S1B5, the smallest size stocks with the highest book-to-market ratios, where the sentiment loading is 58.075. This regime captures most periods that are also covered by the second regime of ADV/DEC estimation in section 6.3.2 (where the regime is found to be a high-sentiment state with 23.192 as the unconditional mean of ADV/DEC). Hence the high estimated coefficients on ADV/DEC support the view that asset returns are largely driven by investor sentiment when such sentiment is extremely high.

Table 6.11 Transition Probabilities of the Markov-switching pricing model with ADV/DEC

This table presents the transition probabilities of the two-regime MS pricing model with advances-declines ratio. In the first column the 25 size and book-to-market sorted portfolios are ordered from the smallest size portfolios (S1) with low to high book-to-market ratios (B1 to B5) to the biggest size portfolios (S5) with low to high book-to-market ratios (B1 to B5).

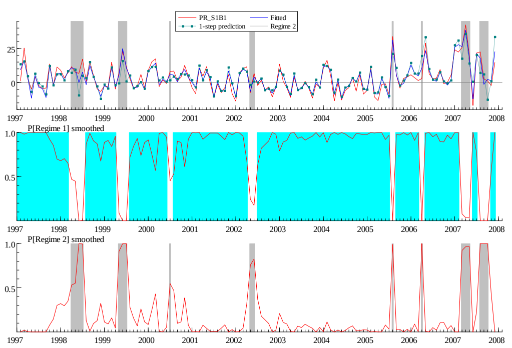
		Regime 1_t	Regime 2_t
S1B1	Regime 1_{t+1}	0.888	0.471
	Regime 2_{t+1}	0.112	0.529
S1B2	Regime 1_{t+1}	0.944	0.196
	Regime 2_{t+1}	0.056	0.804
S1B3	Regime 1_{t+1}	0.711	0.572
	Regime 2_{t+1}	0.289	0.428
S1B4	Regime 1_{t+1}	0.840	0.309
	Regime 2_{t+1}	0.160	0.691
S1B5	Regime 1_{t+1}	0.874	0.750
	Regime 2_{t+1}	0.126	0.250
S2B1	Regime 1_{t+1}	0.851	0.550
	Regime 2_{t+1}	0.149	0.450
S2B2	Regime 1_{t+1}	0.908	0.163
	Regime 2_{t+1}	0.092	0.837
S2B3	Regime 1_{t+1}	0.944	0.274
	Regime 2_{t+1}	0.057	0.726
S2B4	Regime 1_{t+1}	0.815	0.393
	Regime 2_{t+1}	0.185	0.607
S2B5	Regime 1_{t+1}	0.928	0.198
	Regime 2_{t+1}	0.072	0.802
S3B1	Regime 1_{t+1}	0.810	0.498
	Regime 2_{t+1}	0.190	0.502
S3B2	Regime 1_{t+1}	0.838	0.274
	Regime 2_{t+1}	0.162	0.726
S3B3	Regime 1_{t+1}	0.858	0.693
	Regime 2_{t+1}	0.142	0.307
S3B4	Regime 1_{t+1}	0.801	0.620
	Regime 2_{t+1}	0.199	0.380
S3B5	Regime 1_{t+1}	0.681	0.733
	Regime 2_{t+1}	0.319	0.267
S4B1	Regime 1_{t+1}	0.810	0.498
	Regime 2_{t+1}	0.190	0.502
S4B2	Regime 1_{t+1}	0.838	0.274
	Regime 2_{t+1}	0.162	0.726
S4B3	Regime 1_{t+1}	0.858	0.693
	Regime 2_{t+1}	0.142	0.307
S4B4	Regime 1_{t+1}	0.801	0.620
	Regime 2_{t+1}	0.199	0.380
S4B5	Regime 1_{t+1}	0.681	0.733
	Regime 2_{t+1}	0.319	0.267
S5B1	Regime 1_{t+1}	0.887	0.252
	Regime 2_{t+1}	0.113	0.748
S5B2	Regime 1_{t+1}	0.894	0.427
	Regime 2_{t+1}	0.106	0.573
S5B3	Regime 1_{t+1}	0.795	0.726
	Regime 2_{t+1}	0.205	0.274
S5B4	Regime 1_{t+1}	0.819	0.547
	Regime 2_{t+1}	0.181	0.453
S5B5	Regime 1_{t+1}	0.883	0.358
	Regime 2_{t+1}	0.117	0.642

The estimated market risks exhibit a heterogeneous pattern across portfolios. 6 of the 25 portfolio returns show an aggregate market risk greater than 1, even after controlling for sentiment effects. All 6 portfolios contain middle or big size stocks, providing further evidence that returns of large size stocks are more sensitive to excess market returns. On the other hand small stocks have lower factor loadings on excess market returns and, of the smallest size group, two portfolios (S1B1 and S1B5) actually show significantly negative market risk. In many cases market risk is largely absent from the data as 12 of the 25 portfolios have returns uncorrelated with the excess market returns. As was the case for the turnover, size and distress risks are not significant in most of cases. 14 out of 25 portfolios have insignificant size or distress risks. These insignificant betas provide robustness in support of the statement that fundamental risks are absent from the data in highly-volatile and sentiment-driven states.

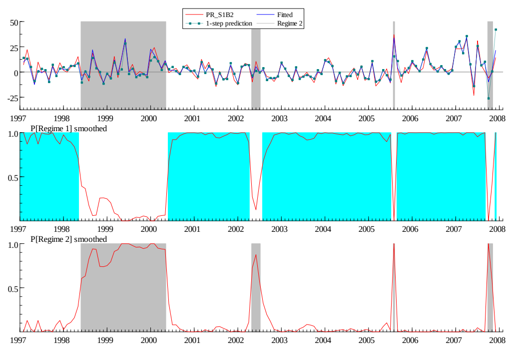
Figure 6.5 Smoothed Regime Probabilities: Two-State MS Pricing Model with ADV/DEC

This figure describes the actual, fitted and forecasted portfolio returns and smoothed regime probabilities for the two-regime MS model with advances-declines ratio for the 25 size and book-to-market sorted portfolio returns. Results of each portfolio are presented separately in panels 1 to 25. For each portfolio, the first row plots the actual, fitted and one-step ahead forecasted portfolio returns. The next two rows plot the smoothed regime probabilities. The dependent variables are a constant term, the sentiment-corrected (orthogonalised) excess market return (r_M), SMB and HML, the buying-selling imbalance (ADV/DEC), and residual variance.

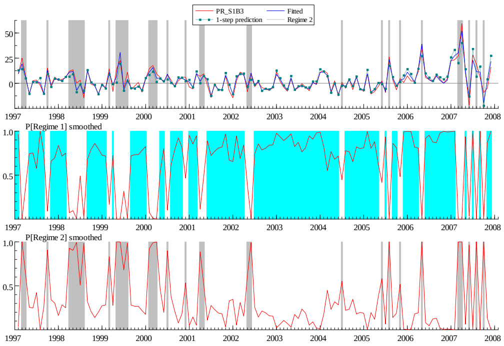
Panel 1: For S1B1



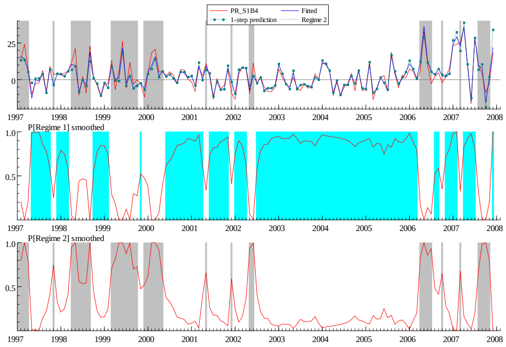
Panel 2: For S1B2



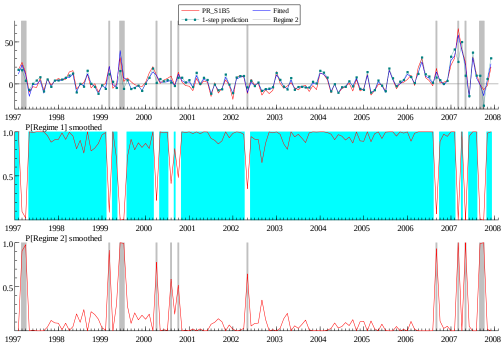
Panel 3: For S1B3



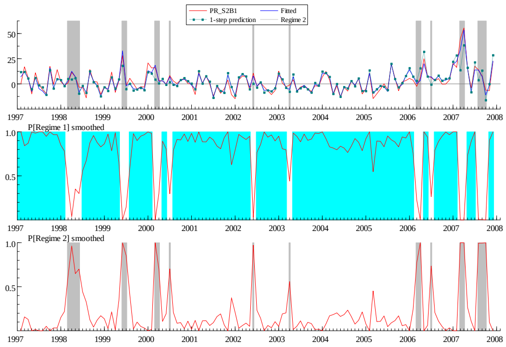
Panel 4: For S1B



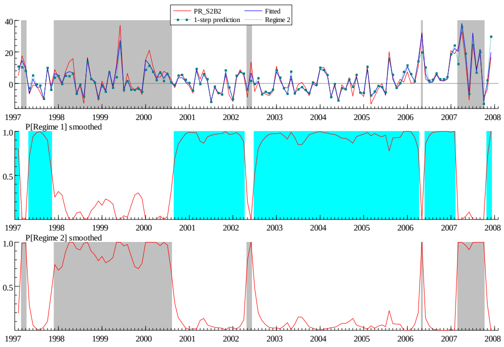
Panel 5: For S1B5



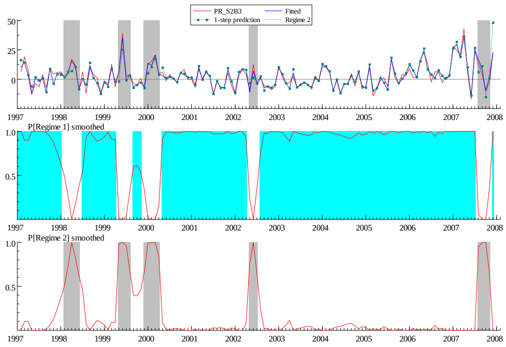
Panel 6: For S2B1



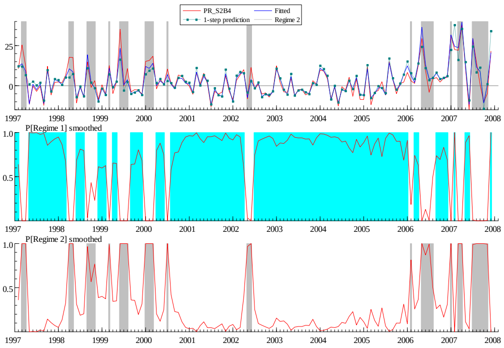
Panel 7: For S2B2



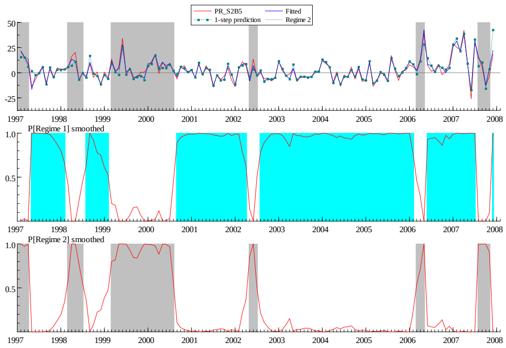
Panel 8: For S2B3



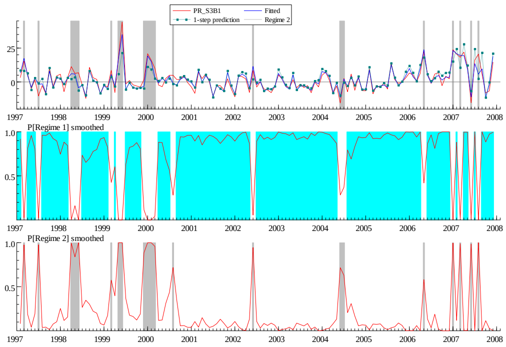
Panel 9: For S2B4



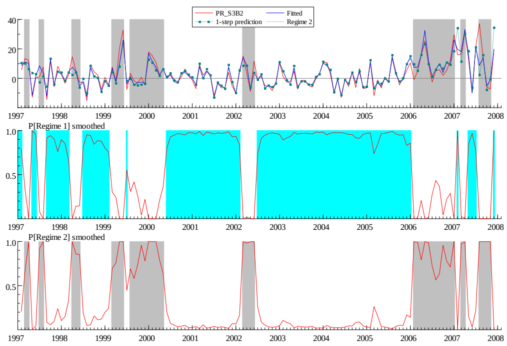
Panel 10: For S2B5



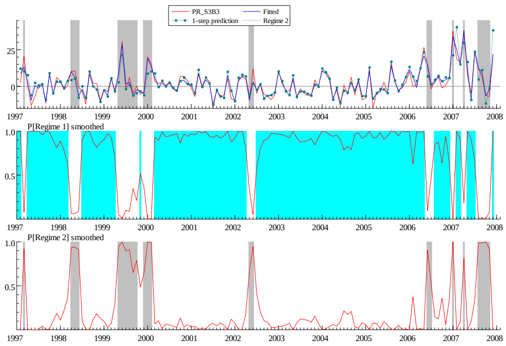
Panel 11: For S3B1



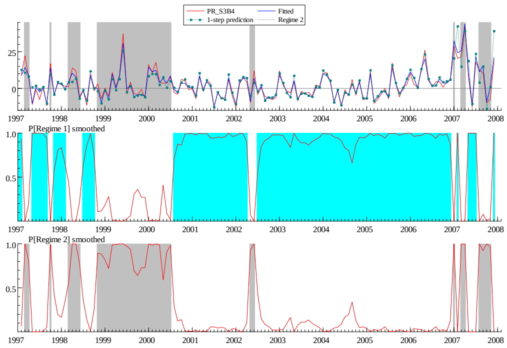
Panel 12: For S3B2



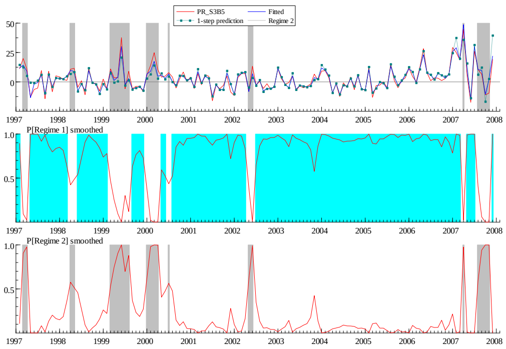
Panel 13: For S3B3



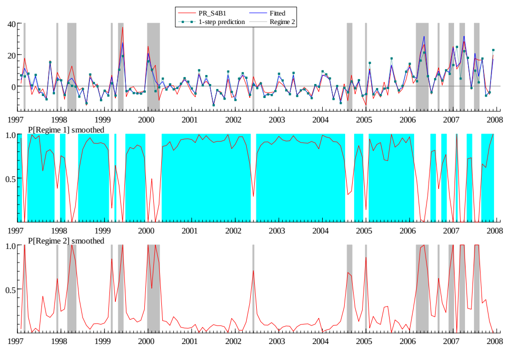
Panel 14: For S3B4



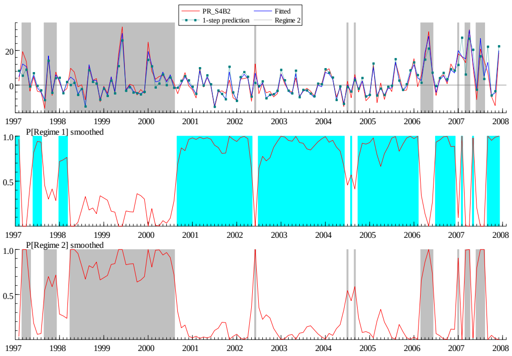
Panel 15: For S3B5



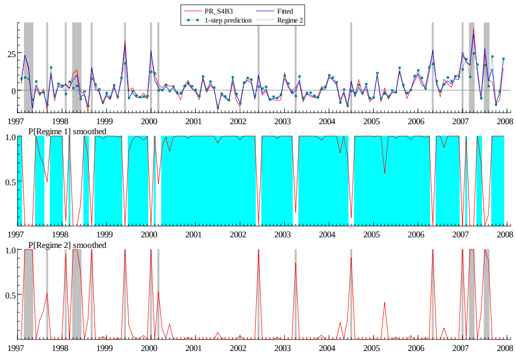
Panel 16: For S4B1



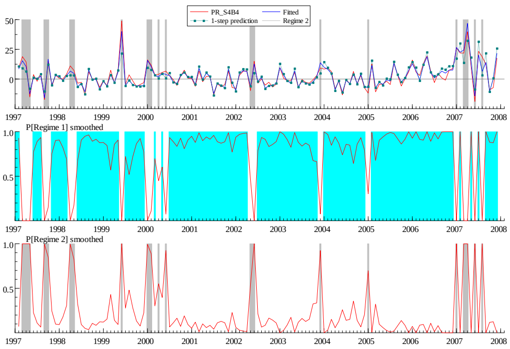
Panel 15: For S3B5



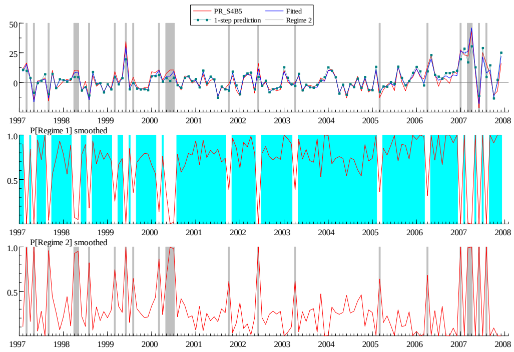
Panel 16: For S4B1



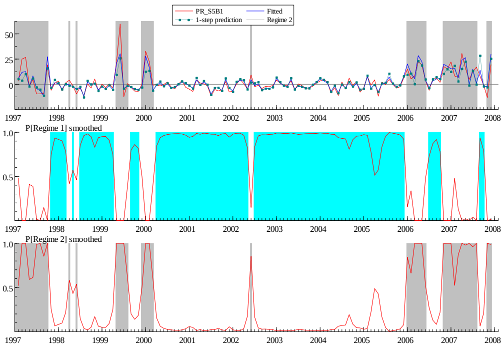
Panel 19: For S4B4



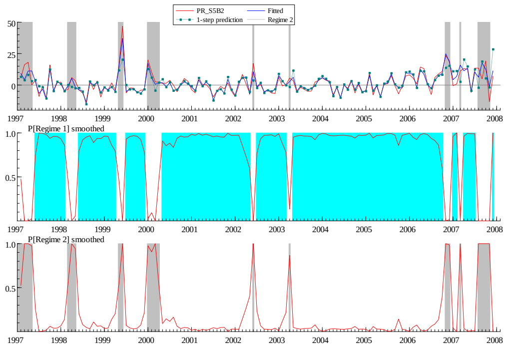
Panel 20: For S4B5



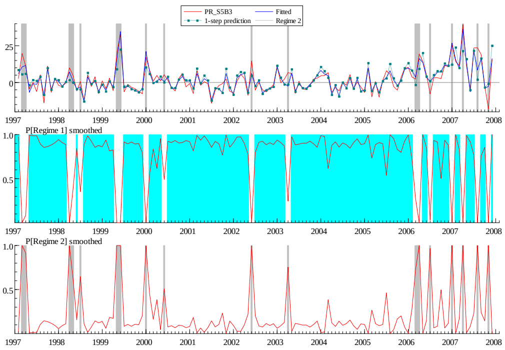
Panel 21: For S5B1



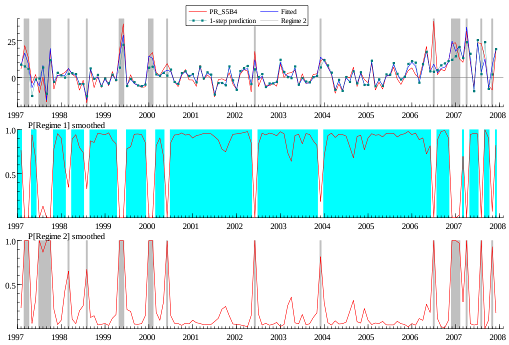
Panel 22: For S5B2



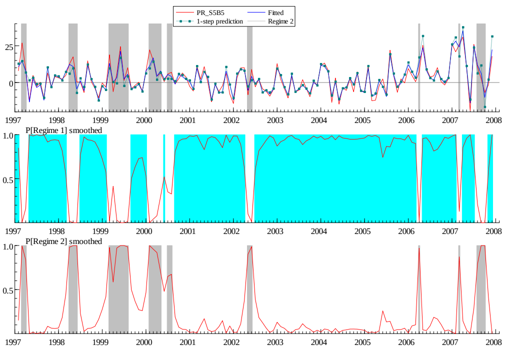
Panel 23: For S5B3



Panel 24: For S5B4



Panel 25: For S5B5



Regime 2 captures the ‘5.19’ substantial increase in returns in May 1999 for all portfolios and periods around the ‘5.19’ boom. This regime also appears from early 2006 to the end of the data period. Taking into account the higher regime-dependent variances, these findings suggest that this sentiment-driven regime is a highly volatile and bullish.

6.5.2.3 Diagnostic Checking

Across the 25 size and book-to-market sorted portfolios, there are four portfolios (S3B2, S4B3, S4B4 and S5B4) for which residual normality is significantly rejected. 7 portfolios (S1B1, S1B3, S1B4, S2B1, S4B2, S4B4 and S4B5) show ARCH (1, 1) effects in the scaled residuals. Residual serial correlation is shown only in 1 portfolio (S2B4). Nevertheless, the assumption of independent and identically distributed residuals with zero mean and finite variances (that may differ between regimes) is accepted for most portfolios, which supports the MS pricing model specification.

Table 6.12 Diagnostic Checking for the Markov-switching Pricing Model with ADV/DEC

This table reports descriptive statistics for the scaled residuals from the two-regime MS model with advances-declines ratio as the proxy of investor sentiment. The results columns show diagnostic results: Jarque-Bera normality test, ARCH (1-1) Engle test and Ljung-Box serial correlation test with 12 lags. Chi-squared statistics are reported with the corresponding probabilities in the square brackets.

	Jarque-Bera	ARCH (1-1)	Ljung-Box
S1B1	1.842	2.899*	36.667
	[0.398]	[0.091]	[0.438]
S1B2	0.356	0.015	37.226
	[0.837]	[0.904]	[0.412]
S1B3	3.798	50.654***	19.340
	[0.150]	[0.000]	[0.990]
S1B4	0.648	4.310**	25.117
	[0.723]	[0.040]	[0.913]
S1B5	2.493	0.256	33.426
	[0.288]	[0.614]	[0.592]
S2B1	2.398	3.205*	32.240
	[0.301]	[0.076]	[0.648]
S2B2	0.324	0.000	20.123
	[0.850]	[0.984]	[0.985]
S2B3	0.898	0.397	33.710
	[0.638]	[0.530]	[0.578]
S2B4	0.779	0.328	64.035 ***
	[0.678]	[0.568]	[0.003]
S2B5	3.911	0.099	37.539
	[0.142]	[0.753]	[0.399]
S3B1	0.958	1.612	36.110
	[0.619]	[0.207]	[0.464]
S3B2	27.632***	0.409	35.534
	[0.000]	[0.524]	[0.491]
S3B3	3.904	0.098	32.254
	[0.142]	[0.754]	[0.647]
S3B4	1.590	2.729	24.535
	[0.452]	[0.101]	[0.926]
S3B5	2.563	0.072	36.311
	[0.278]	[0.789]	[0.454]
S4B1	2.044	0.448	34.132
	[0.360]	[0.505]	[0.558]
S4B2	3.176	6.794**	28.906
	[0.204]	[0.010]	[0.793]
S4B3	6.363**	0.000	21.216
	[0.042]	[0.983]	[0.976]
S4B4	4.974*	4.197**	35.170
	[0.083]	[0.043]	[0.508]
S4B5	3.155	8.681***	33.857
	[0.207]	[0.004]	[0.571]
S5B1	3.873	0.047	39.290
	[0.144]	[0.830]	[0.325]
S5B2	3.625	0.989	16.810
	[0.163]	[0.322]	[0.997]
S5B3	1.131	0.333	35.786
	[0.568]	[0.565]	[0.479]
S5B4	5.467*	0.507	26.488
	[0.065]	[0.478]	[0.877]
S5B5	1.428	0.689	32.344
	[0.490]	[0.408]	[0.643]

Notes: (***), (**) and (*) denote significance at the 1%, 5% and 10% levels respectively. The *t*-statistics are in the square brackets.

6.5.3. Asset Pricing Model with Regime Dependent Dividend Premium

6.5.3.1 The Markov-switching Pricing Model with Dividend Premium

The MS pricing model with dividend premium ($D^{P\text{-}NP}$) is specified as the previous two models with turnover and ADV/DEC. The constant term, the sentiment-orthogonalised fundamental factors and the sentiment proxy $D^{P\text{-}NP}$ are made regime dependent. The estimated residual variance is also allowed to vary between regimes. The appropriate number of regimes in the MS pricing model with $D^{P\text{-}NP}$ is 2, based on model selection results from 10 randomly selected portfolio returns[71] using the minimum Schwarz Information Criteria (SIC) and Hannan-Quinn information criteria (HQ). This is in line with the number of regimes defined by the dividend premium regime estimation in section 6.3.2. In addition, the results show that the pricing model is better specified without including lags as explanatory variables for either portfolio return or sentiment proxy. This specification is the same as the model with advances-declines ratio as the proxy of investor sentiment. The Markov-switching asset pricing model with dividend premium is as follows:

$$r_{i,t} = c_{i,s_t} + \beta_{M,i,s_t} r_{M,t} + \beta_{SMB,i,s_t} SMB_t + \beta_{HML,i,s_t} HML_t + \kappa_{D^{P-NP},i,s_t} D^{P-NP}{}_t + \varepsilon_{i,s_t,t}, \quad \varepsilon_{i,s_t,t} \sim N\left(0, \sigma^2_{s_t}\right), \forall s_t \in \{1, K\} \tag{6.6}$$

Here c_{i,s_t} captures the intercept in each regime for portfolio *i*, β_i captures the sensitivity of portfolio returns to the fundamental risk measured by the aggregate market, SMB and HML, corrected for sentiment effects by orthogonalisation. κ_i estimates the regime-dependent sentiment effect and $\varepsilon_{i,s_t,t}$ should be iid normal with zero mean and finite regime-dependent variance.

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[71] The 10 randomly selected portfolios are S1B1, S1B2, S1B5, S2B2, S3B3, S3B5, S4B2, S4B5, S5B1 and S5B5.

6.5.3.2 Empirical Results: Regime Behaviour

The parameter estimates of the two-regime Markov-switching pricing model with dividend premium are reported in Table 6.13. The regime transition probabilities are presented in Table 6.14 and the smoothed regime probabilities are shown in Figure 6.6.

The estimates in Table 6.13 suggest that this model identifies two regimes: a persistent bear state (regime 1) and an infrequent bull market (regime 2). This classification is consistent with the patterns of the pricing model with ADV/DEC as sentiment proxy, but it is different from the state performance in dividend premium itself.

Regime 1 is found to be a persistent, fundamentals-driven and low-volatility state with an average duration of 14.15 months. Table 6.14 shows that for most portfolios, returns have a higher probability of staying in regime 1 than shifting, except for portfolio S2B3, where the estimates suggest rapid oscillation between the two regimes. This is reflected in Figure 6.6: there is a multi-month staying duration and the state corresponds roughly to low-volatility and bearish market phases, such as mid-1997 to early 1999 and mid-2001 to early 2005.

Loadings on dividend premium are significant for 14 of the 25 portfolios and it seems that the dividend premium effect is more significant for small size stocks than big size stocks. Also, there is a roughly systematic pattern in that, for each size group, low book-to-market stocks have smaller loadings on dividend premium than high book-to-market stocks, which reveals that the latter stocks are more sensitive to firms' dividend policies and therefore the premium on dividend. This is consistent with the general view that investors take dividends into consideration when evaluating 'value' stocks (stocks with high book-to-market ratios) but expect profits from capital gains of 'growth' stocks (those with low book-to-market ratios).

Volatilities in regime 1 are lower than those in regime 2. All the parameter estimates suggest that stock returns in this persistent and low-volatility regime are likely to be fundamentals-driven. Dividend premium works to explain the cross-sectional variation of stock returns.

Table 6.13 Factor Loadings of the Regime-switching model for orthogonalised Market, SMB, HML and $D^{P\text{-}NP}$.

This table reports the estimated factor loading parameters from the nonlinear Markov-switching pricing model, of which the 25 size-BE/ME sorted portfolio excess returns are regressed on a constant term, sentiment-corrected (orthogonalised) excess market return, SMB and HML, dividend premium, and regime-dependent variance over the period of January 1997 to December 2007, using 11 years monthly data for Chinese A-Share stock markets.

Panel A: Regime 1

	Small	2	3	4	Large	Small	2	3	4	Large
			constant					$\mathbf{R_M}$		
Low	3.232***	1.247***	-0.273	0.243	-0.156	1.235***	1.088***	0.720***	0.849***	0.909***
	[7.73]	[3.23]	[-0.633]	[0.683]	[-0.579]	[12.4]	[16.4]	[11.6]	[14.3]	[19.7]
2	1.261***	1.465***	1.439***	-0.481	0.144	0.808***	1.045***	1.178***	0.747***	0.958***
	[3.02]	[4.65]	[4.60]	[-0.747]	[0.532]	[7.70]	[17.2]	[21.7]	[7.75]	[22.1]
3	1.860***	-0.445	-0.741	0.777**	0.313	1.177***	0.603***	0.624***	0.888***	0.836***
	[5.09]	[-0.579]	[-0.802]	[2.29]	[0.805]	[17.4]	[8.20]	[7.34]	[16.2]	[16.5]
4	0.993**	-0.316	-0.54	1.219***	1.393***	0.927***	0.582***	0.709***	1.001***	1.209***
	[2.15]	[-0.301]	[-0.600]	[2.99]	[5.11]	[9.96]	[3.71]	[8.37]	[16.6]	[23.0]
High	2.343***	1.884***	-0.891	0.609	2.036***	1.062***	1.247***	0.654***	0.900***	1.099***
	[5.63]	[5.64]	[-0.830]	[1.39]	[5.47]	[14.1]	[16.7]	[6.40]	[13.5]	[17.0]
			SMB					**HML**		
Low	1.440***	0.774***	0.276**	0.125	-0.381***	-0.217*	-0.079	-0.221***	-1.068***	-0.640***
	[9.57]	[6.56]	[2.29]	[1.21]	[-3.99]	[-1.74]	[-0.575]	[-4.11]	[-6.67]	[-6.81]
2	1.268***	0.811***	0.221**	0.072	-0.298***	0.234*	-0.104	-0.018	-0.644***	-0.232***
	[5.33]	[7.86]	[2.06]	[0.527]	[-2.74]	[1.81]	[-0.930]	[-0.132]	[-4.24]	[-3.05]
3	1.033***	0.974***	0.116	0.095	-0.320***	-0.06	-0.426***	-0.347	-0.028	-0.045
	[8.05]	[3.88]	[0.684]	[-0.876]	[-2.68]	[-0.462]	[-3.02]	[-1.55]	[-0.312]	[-0.416]
4	1.259***	0.304*	0.15	0.323**	-0.352***	0.627*	-0.2	0.022	0.099	0.252**
	[5.21]	[1.93]	[1.03]	[2.34]	[-3.88]	[1.94]	[-1.19]	[0.204]	[0.943]	[2.41]
High	1.239***	0.943***	0.1	0.499***	1.136***	0.474***	0.537***	0.251*	0.072	-0.096
	[9.15]	[8.15]	[0.595]	[3.31]	[10.0]	[3.72]	[3.79]	[1.84]	[0.639]	[-0.774]
			$\mathbf{D^{p\text{-}np}}$					**Sigma**		
Low	-1.101***	-1.511***	-0.664**	-0.345	0.934***	3.736***	3.520***	2.961***	2.441***	2.430***
	[-2.69]	[-5.56]	[-2.23]	[-1.13]	[4.11]	[11.3]	[12.6]	[9.79]	[8.62]	[12.8]
2	-1.347***	-0.815***	-0.736***	0.303	0.382**	3.222***	2.440***	2.204***	3.266***	2.237***
	[-3.51]	[-3.03]	[-3.07]	[0.790]	[2.02]	[6.16]	[10.3]	[11.4]	[8.37]	[10.6]
3	-0.203	0.035	-0.289	0.665***	1.112***	2.568***	2.394***	3.342***	3.414***	2.871***
	[-0.583]	[0.097]	[-0.760]	[3.16]	[5.61]	[8.01]	[5.34]	[9.67]	[14.8]	[10.2]
4	0.222	0.212	0.426	0.377	1.203***	1.986***	3.162***	2.947***	3.462***	2.193***
	[0.453]	[0.436]	[1.51]	[1.51]	[5.56]	[7.34]	[6.47]	[6.74]	[11.4]	[12.1]
High	-0.274	0.231	0.859**	0.809***	-1.600***	4.401***	2.464***	3.295***	3.421***	3.016***
	[-0.930]	[0.727]	[2.18]	[2.98]	[-5.75]	[15.1]	[9.12]	[5.79]	[11.5]	[11.6]

Table 6.13 (cont.)

Panel B: Regime 2										
	Small	2	3	4	Large	Small	2	3	4	Large
			constant					$\mathbf{R_M}$		
Low	5.567***	9.382***	6.992***	3.233***	8.414***	0.222	0.907***	1.266***	1.442***	1.221***
	[2.78]	[3.87]	[3.95]	[2.87]	[3.29]	[1.07]	[4.01]	[5.91]	[7.77]	[4.39]
2	6.284***	5.811***	5.782***	5.081***	6.074***	1.361***	1.047***	0.919***	1.528***	0.682***
	[3.26]	[4.81]	[4.67]	[3.29]	[2.79]	[6.21]	[7.38]	[6.12]	[11.0]	[2.93]
3	6.039***	4.264***	3.391***	11.206***	4.304**	0.952***	0.603***	1.436***	1.594***	1.746***
	[4.58]	[6.37]	[4.92]	[13.1]	[2.44]	[5.90]	[12.5]	[9.94]	[16.6]	[6.49]
4	4.038***	4.431***	4.094***	7.192***	6.105***	0.906***	1.318***	1.555***	1.945***	0.779***
	[5.93]	[4.92]	[6.13]	[3.35]	[3.57]	[9.81]	[11.6]	[12.7]	[7.54]	[4.05]
High	19.296***	4.837***	4.422***	5.739***	4.650***	0.196	0.814***	1.421***	1.371***	0.792***
	[7.55]	[4.44]	[6.91]	[4.89]	[5.17]	[0.936]	[6.09]	[11.7]	[11.4]	[6.19]
			SMB					**HML**		
Low	-0.16	0.828*	-0.221	0.291	0.082	0.479	0.073	0.115	-0.032	-0.802*
	[-0.371]	[1.73]	[-0.582]	[1.17]	[0.150]	[1.16]	[0.190]	[0.3]53	[-0.127]	[-1.71]
2	0.564	0.106	0.378	0.022	-1.168***	-0.454	0.288	0.02	-0.166	0.149
	[1.31]	[0.364]	[1.36]	[0.081]	[-2.86]	[-1.46]	[1.22]	[0.087]	[-0.700]	[0.352]
3	0.733**	0.475***	0.558***	-0.177	-0.471	0.498*	0.350**	0.131	-0.073	0.281
	[2.37]	[2.67]	[2.77]	[-0.691]	[-1.00]	[1.88]	[2.24]	[0.652]	[-0.323]	[0.660]
4	0.760***	0.774***	0.341	-1.297***	-0.178	0.396**	0.263	0.485**	1.089**	0.462
	[4.34]	[3.96]	[1.41]	[-2.69]	[-0.526]	[2.59]	[1.52]	[2.42]	[2.24]	[1.56]
High	0.36	0.459*	0.279	-0.981***	0.517**	1.924***	0.579***	0.872***	1.751***	0.181
	[0.764]	[1.73]	[1.33]	[-4.00]	[2.12]	[4.74]	[2.81]	[5.59]	[6.01]	[0.886]
			$\mathbf{D^{p\text{-}np}}$					**Sigma**		
Low	0.458	-1.322	-1.435**	-0.844*	-0.206	7.391***	9.252***	6.423***	5.623***	11.172***
	[0.603]	[-1.59]	[-2.29]	[-1.77]	[-0.226]	[6.27]	[7.30]	[6.72]	[7.90]	[7.03]
2	0.091	-0.362	-0.018	-0.361	0.055	7.036***	6.854***	7.960***	4.522***	8.858***
	[0.127]	[-0.763]	[-0.035]	[-0.800]	[0.066]	[7.78]	[9.14]	[9.83]	[7.81]	[7.27]
3	-0.497	-0.552	-0.447	0.265	2.536***	7.931***	5.246***	4.569***	2.355***	6.981***
	[-0.939]	[-1.54]	[-0.947]	[0.642]	[2.76]	[9.55]	[12.9]	[6.48]	[4.25]	[5.90]
4	-0.277	-0.065	0.296	0.427	0.357	5.997***	4.802***	4.052***	5.974***	8.983***
	[-0.797]	[-0.171]	[0.697]	[0.431]	[0.579]	[13.1]	[8.74]	[9.36]	[4.27]	[9.09]
High	-3.849***	-0.064	0.782*	0.656	0.44	7.187***	7.100***	4.093***	3.492***	6.138***
	[-5.10]	[-0.130]	[1.90]	[1.26]	[0.877]	[5.16]	[9.98]	[10.5]	[4.77]	[10.0]

Notes: (***), (**) and (*) denote significance at the 1%, 5% and 10% levels respectively. The *t*-statistics are in the square brackets.

Table 6.14 Transition Probabilities of the Markov-switching pricing model with $D^{P\text{-}NP}$

This table presents the transition probabilities of the two-regime MS pricing model with dividend premium. In the first column the 25 size and book-to-market sorted portfolios are ordered from the smallest size portfolios (S1) with low to high book-to-market ratios (B1 to B5) to the biggest size portfolios (S5) with low to high book-to-market ratios (B1 to B5).

		Regime 1_t	Regime 2_t
S1B1	Regime 1_{t+1}	0.912	0.335
	Regime 2_{t+1}	0.088	0.666
S1B2	Regime 1_{t+1}	0.849	0.338
	Regime 2_{t+1}	0.151	0.662
S1B3	Regime 1_{t+1}	0.886	0.166
	Regime 2_{t+1}	0.114	0.834
S1B4	Regime 1_{t+1}	0.908	0.035
	Regime 2_{t+1}	0.092	0.965
S1B5	Regime 1_{t+1}	0.980	0.200
	Regime 2_{t+1}	0.020	0.800
S2B1	Regime 1_{t+1}	0.952	0.154
	Regime 2_{t+1}	0.048	0.846
S2B2	Regime 1_{t+1}	0.899	0.179
	Regime 2_{t+1}	0.101	0.821
S2B3	Regime 1_{t+1}	0.017	0.427
	Regime 2_{t+1}	0.983	0.573
S2B4	Regime 1_{t+1}	0.555	0.283
	Regime 2_{t+1}	0.445	0.717
S2B5	Regime 1_{t+1}	0.911	0.115
	Regime 2_{t+1}	0.089	0.885
S3B1	Regime 1_{t+1}	0.894	0.265
	Regime 2_{t+1}	0.106	0.735
S3B2	Regime 1_{t+1}	0.933	0.092
	Regime 2_{t+1}	0.067	0.908
S3B3	Regime 1_{t+1}	0.472	0.359
	Regime 2_{t+1}	0.528	0.641
S3B4	Regime 1_{t+1}	0.538	0.407
	Regime 2_{t+1}	0.462	0.593
S3B5	Regime 1_{t+1}	0.371	0.422
	Regime 2_{t+1}	0.629	0.578
S4B1	Regime 1_{t+1}	0.746	0.428
	Regime 2_{t+1}	0.254	0.572
S4B2	Regime 1_{t+1}	0.696	0.457
	Regime 2_{t+1}	0.304	0.543
S4B3	Regime 1_{t+1}	0.939	0.478
	Regime 2_{t+1}	0.061	0.522
S4B4	Regime 1_{t+1}	0.889	0.571
	Regime 2_{t+1}	0.111	0.429
S4B5	Regime 1_{t+1}	0.790	0.608
	Regime 2_{t+1}	0.210	0.392
S5B1	Regime 1_{t+1}	0.939	0.220
	Regime 2_{t+1}	0.061	0.780
S5B2	Regime 1_{t+1}	0.912	0.311
	Regime 2_{t+1}	0.088	0.689
S5B3	Regime 1_{t+1}	0.830	0.575
	Regime 2_{t+1}	0.170	0.425
S5B4	Regime 1_{t+1}	0.945	0.110
	Regime 2_{t+1}	0.055	0.890
S5B5	Regime 1_{t+1}	0.964	0.051
	Regime 2_{t+1}	0.036	0.949

The estimated constants are noticeably different from those of the turnover and buying-selling imbalance models: here the regime-dependent intercepts are positive. This finding lends further support to the suggestion that the negative constants in the turnover and buying-selling imbalance models are driven by the large coefficients on the sentiment proxies of turnover and ADV/DEC, as the slopes are very steep. Because the kappa loadings on dividend premium are smaller and sometimes insignificant, the zero-beta excess returns become positive. The constant terms in regime 1 are much smaller than those in regime 2 and the estimated constants are insignificant for 12 of 25 portfolios, which sheds light on that portfolio returns in regime 1 are lower. Regime 1 is a bear or normal market state, as measured by the portfolio returns data.

In regime 1, portfolio returns increase as returns of the aggregate market increase. Some portfolios are more volatile than the market, even after correction for sentiment. There is no clear systematic pattern of market risk exposure across portfolios but, loosely speaking, the smallest and biggest size stocks show greater market risk than the middle size stocks.

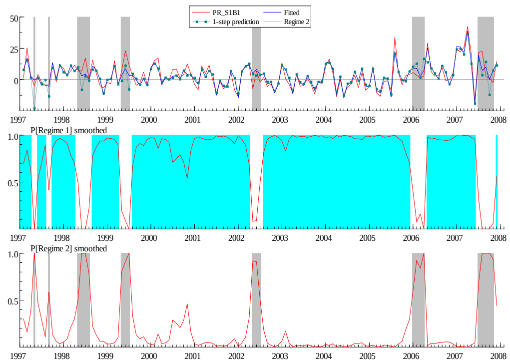
Regime 1 seems to be a fundamentals-driven state. Factor loadings on SMB are more significant than those in regime 2 and are insignificant only for some middle size stock portfolios. More important, the significant factor loadings on SMB show a systematic pattern of size risk effects: small size stocks are exposed to greater size risks, with SMB betas that are bigger for small size stocks than for big size stocks. S5B5, the biggest size and highest book-to-market ratio portfolio, again shows inconsistent results.

However, HML is slightly unimportant as a risk factor in this model. Only in half of the portfolios returns are significantly correlated with HML. To the extent that they are significant, the factor loadings on HML reveal patterns that are in line with the distress risk expectation as for each size group, low book-to-market stocks are less exposed to distress risks than high book-to-market stocks.

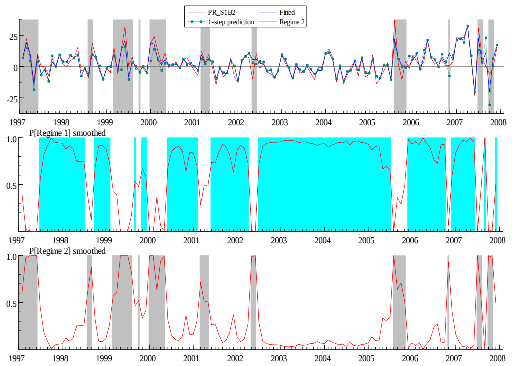
Figure 6.6 Smoothed Regime Probabilities for the two-regime MS model with dividend premium.

This figure describes the actual, fitted and forecasted portfolio returns and smoothed regime probabilities for the two-regime MS model with dividend premium for the 25 size and book-to-market sorted portfolio returns. Results of each portfolio are presented separately in panels 1 to 25. For each portfolio, the first row plots the actual, fitted and one-step ahead forecasted portfolio returns. The next two rows plot the smoothed regime probabilities. The dependent variables are a constant term, sentiment-corrected (orthogonalised) excess market return (r_M), SMB and HML, dividend premium ($D^{P\text{-}NP}$), and residual variance.

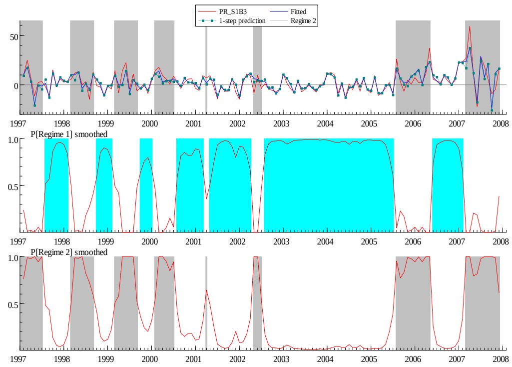
Panel 1: For S1B1



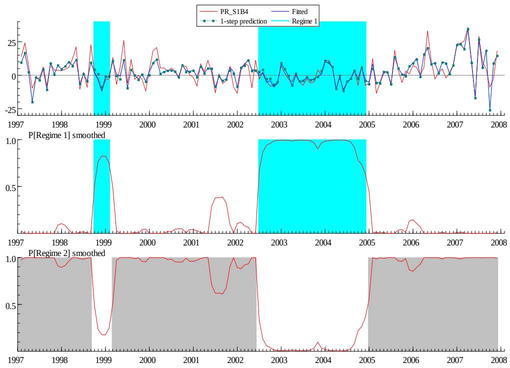
Panel 2: For S1B2



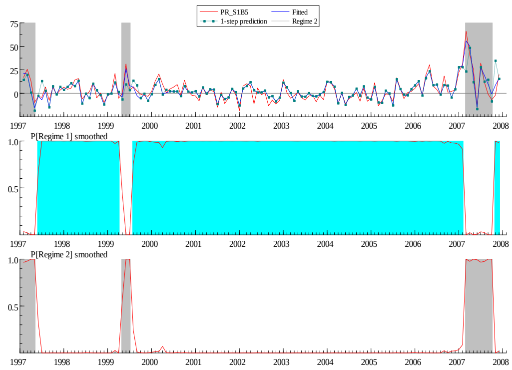
Panel 3: For S1B3



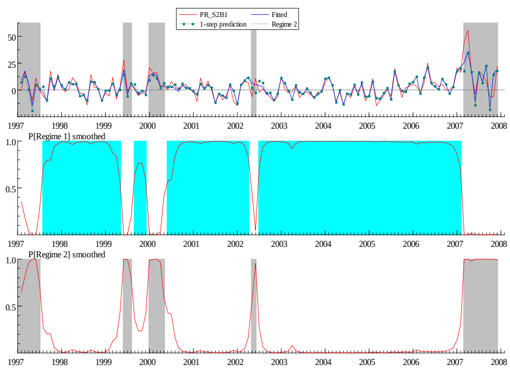
Panel 4: For S1B



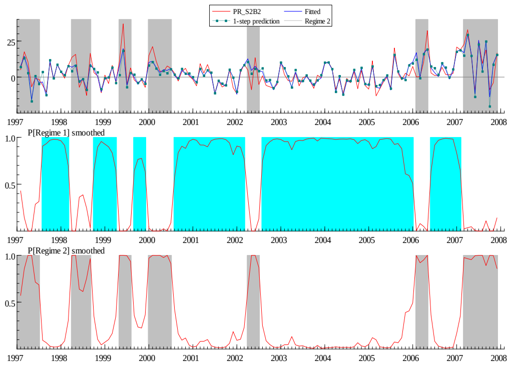
Panel 5: For S1B5



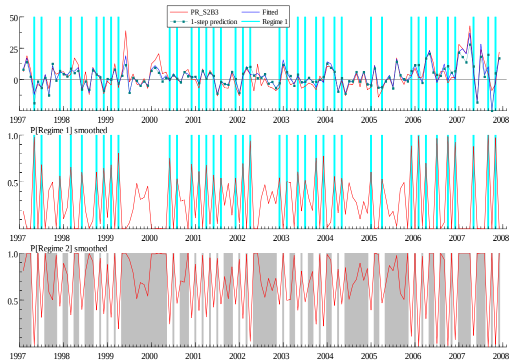
Panel 6: For S2B1



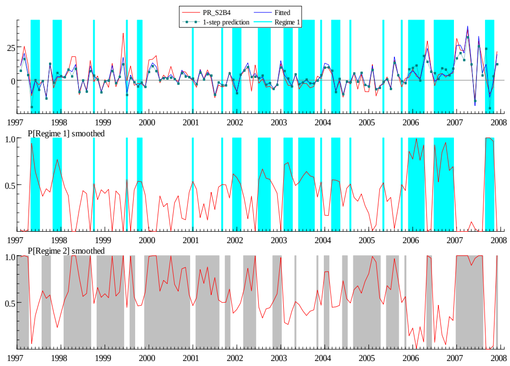
Panel 7: For S2B2



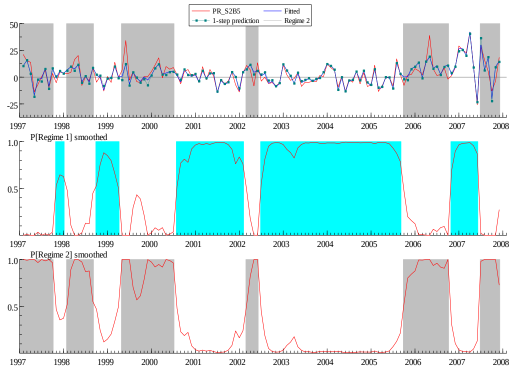
Panel 8: For S2B3



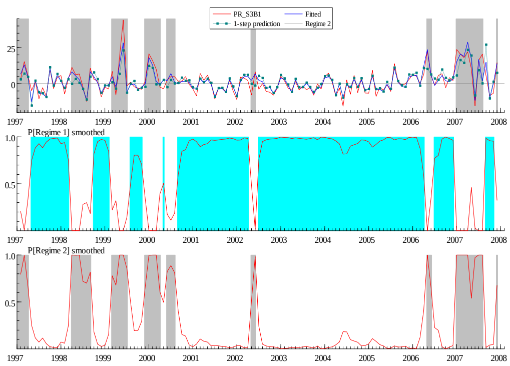
Panel 9: For S2B4



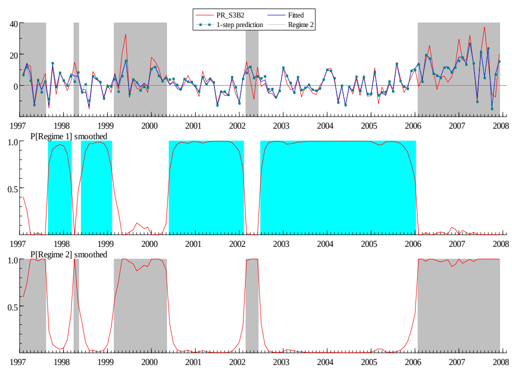
Panel 10: For S2B5



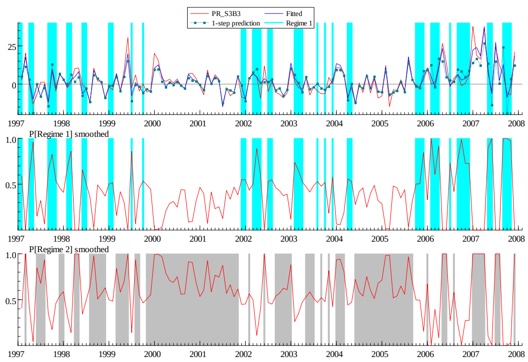
Panel 11: For S3B1



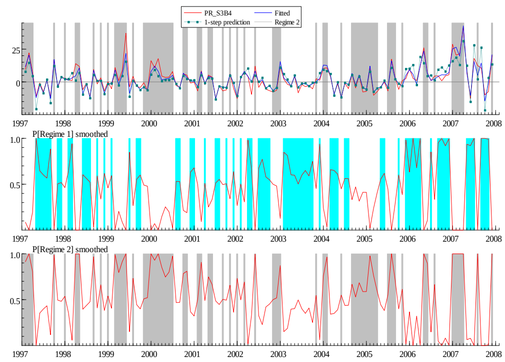
Panel 12: For S3B2



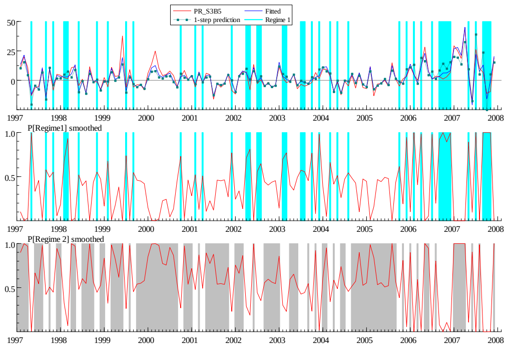
Panel 13: For S3B3



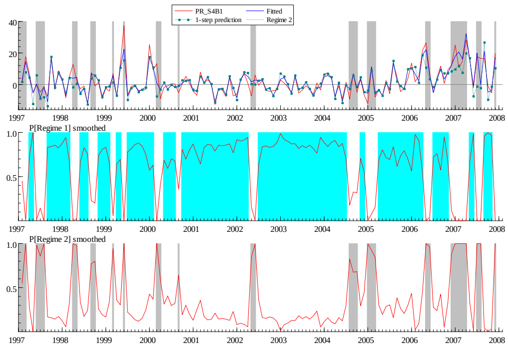
Panel 14: For S3B4



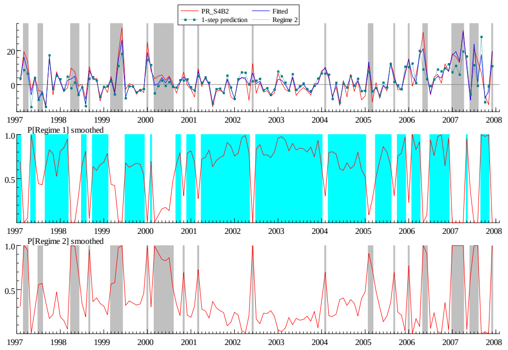
Panel 15: For S3B5



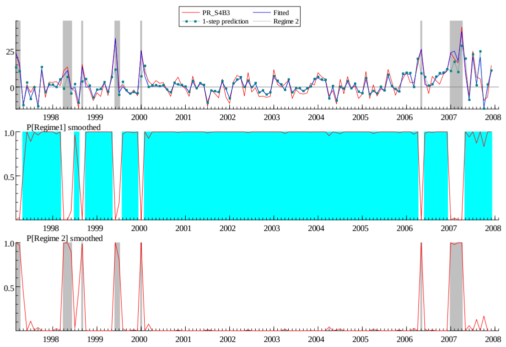
Panel 16: For S4B1



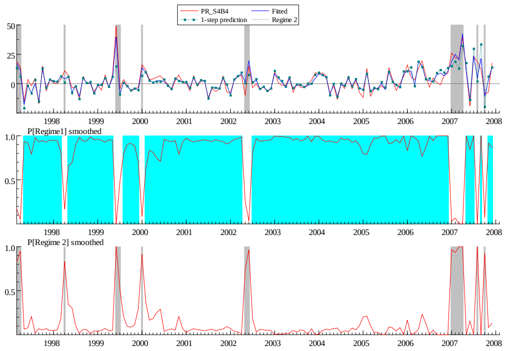
Panel 17: For S4B2



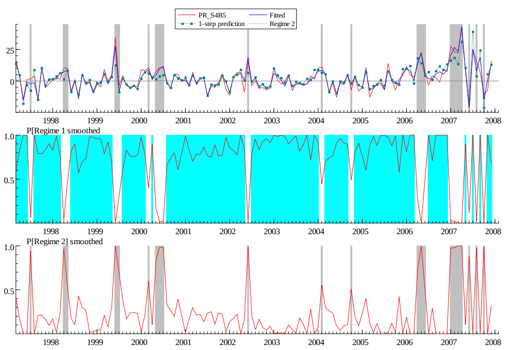
Panel 18: For S4B3



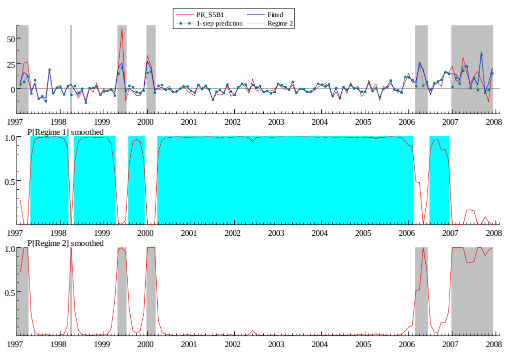
Panel 19: For S4B4



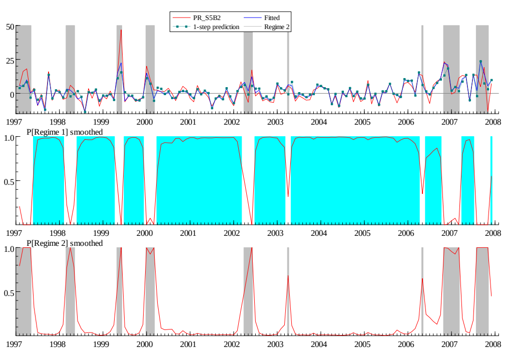
Panel 20: For S4B5



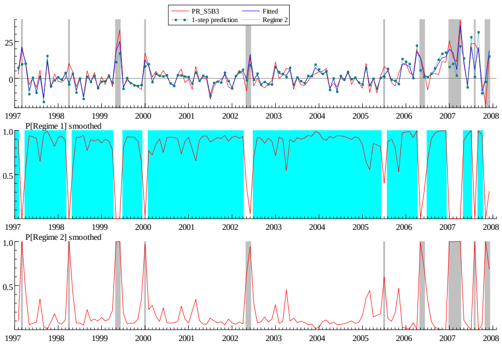
Panel 21: For S5B1



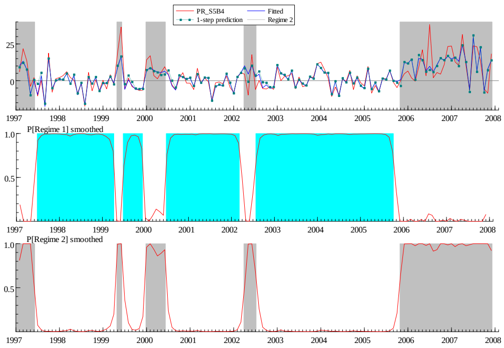
Panel 22: For S5B2



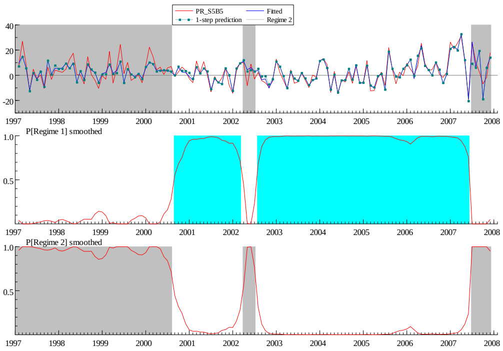
Panel 23: For S5B3



Panel 24: For S5B4



Panel 25: For S5B5



The parameter estimates of model (6.6) and the transition probabilities in Table 6.14 reveal regime 2 to be a highly volatile and relatively infrequent bull market state. The constant terms are highly positive and significant, which indicates that regime 2 corresponds to months with high positive returns for all portfolios. Again this lends further support to the stated view that the negative constants from the turnover and advances-declines ratio models in the infrequent bull state are caused by the large sentiment effects.

Market betas in regime 2 are similar to those in regime 1 for small size stock portfolios but are greater than those for middle to big size stocks. The same result has been found by Chen *et al*.(2009) in the threshold GARCH CAPM model, as market risks are greater in bull markets. However, size risks and distress risks are absent from regime 2. 14 out of the 25 portfolios have returns that are insignificantly correlated with SMB and 15 portfolios have returns uncorrelated to HML. These loadings on the fundamental risk factors show that in regime 2 all portfolio returns are sensitive to market returns no matter how good or bad the firm-level qualities.

In high contrast to the other sentiment proxies (turnover and advances-declines ratio) the impact on stock returns of dividend premium is insignificant in the bull market state of regime 2. This result is in line with the findings from the previous chapter that dividend premium is ignored when sentiment is positive, and it is not surprising since dividend premium is regarded as an indicator of the extent to which investors require instant payment. When investor sentiment is highly positive and stock markets achieve higher returns, investors do not care whether firms pay dividends or not, since all stocks provide good capital gains. Thus dividend premium only distinguishes strongly negative sentiment from the normal markets. The last column of Table 6.13 reports that volatilities in this regime are on average two times higher than those in regime 1.

6.5.3.3 Diagnostic Checking

The two-regime pricing model with dividend premium is not as well fitted to the data as the models with turnover and advances-declines ratio, especially for middle size stocks.

11 of the 25 portfolios show non-normally distributed residuals and residuals have significant ARCH (1-1) effects in 6 portfolios (revealing that the residuals are dependent on volatility). All portfolios with dependent and non-normally distributed residuals are of middle size stocks from S2 (the second smallest size group) to S4 (the second largest size group). Portmanteau tests show that there are 9 portfolios with serially correlated residuals. Again, except for one portfolio from the smallest size group (S1) and one portfolio from the biggest size group (S5), all the portfolios are for middle size stocks.

Considering that factor loadings on dividend premium are mainly insignificant, especially for regime 2, the residual results are consistently informative and revealing. They provide further evidence that dividend premium is not a good sentiment indicator, at least for regime shifts of middle size stock returns.

Table 6.15 Diagnostic Checking for the Markov-switching Pricing Model with Dividend Premium

This table reports descriptive statistics for the residuals from the two-regime MS model with dividend premium as the proxy of investor sentiment. The results columns show diagnostic results: Jarque-Bera normality test, ARCH (1-1) Engle test and Ljung-Box serial correlation test with 12 lags. Chi-squared statistics are reported with the corresponding probabilities in the square brackets.

	Nomality	ARCH(1-1)	Portmanteau
S1B1	4.042	0.120	32.506
	[0.133]	[0.730]	[0.636]
S1B2	3.782	2.569	39.398
	[0.151]	[0.112]	[0.320]
S1B3	1.237	0.038	26.232
	[0.539]	[0.842]	[0.880]
S1B4	2.307	2.221	26.561
	[0.316]	[0.139]	[0.874]
S1B5	0.753	0.257	49.826*
	[0.686]	[0.613]	[0.063]
S2B1	1.8674	0.061	31.635
	[0.393]	[0.805]	[0.676]
S2B2	1.464	0.763	31.382
	[0.481]	[0.384]	[0.688]
S2B3	19.364***	8.627***	50.109*
	[0.000]	[0.004]	[0.059]
S2B4	46.886***	6.154**	51.866**
	[0.000]	[0.015]	[0.042]
S2B5	2.185	1.905	31.922
	[0.336]	[0.170]	[0.663]
S3B1	6.798**	4.839**	44.848
	[0.033]	[0.030]	[0.148]
S3B2	10.091***	0.098	33.806
	[0.006]	[0.755]	[0.573]
S3B3	13.368***	2.052	37.975
	[0.001]	[0.155]	[0.379]
S3B4	33.716***	0.660	80.920***
	[0.000]	[0.418]	[0.000]
S3B5	47.743***	0.039	53.178**
	[0.000]	[0.843]	[0.032]
S4B1	3.749	0.488	69.358***
	[0.153]	[0.486]	[0.001]
S4B2	17.707***	6.575**	56.803**
	[0.000]	[0.012]	[0.015]
S4B3	10.390**	0.805	33.681
	[0.006]	[0.371]	[0.579]
S4B4	6.644**	5.087**	49.386*
	[0.036]	[0.026]	[0.068]
S4B5	13.511***	3.222*	40.957
	[0.001]	[0.075]	[0.262]
S5B1	0.842	0.398	46.625
	[0.656]	[0.529]	[0.111]
S5B2	0.691	0.084	37.497
	[0.708]	[0.772]	[0.400]
S5B3	0.720	0.163	50.185*
	[0.698]	[0.688]	[0.058]
S5B4	0.481	0.743	22.468
	[0.786]	[0.391]	[0.962]
S5B5	0.384	0.022	33.678
	[0.825]	[0.882]	[0.580]

Notes: (***), (**) and (*) denote significance at the 1%, 5% and 10% levels respectively. The *t*-statistics are in the square brackets.

6.6 Conclusion

This chapter studies regime-shifting asset pricing when investor sentiment is considered, with a nonlinear Markov-switching process applied to govern regime shifts. Three sentiment proxies, turnover, advances-declines ratio, and dividend premium, are specified separately into the model so as to make it possible both to investigate regime shifting behaviour and to interpret regime meanings. Diagnostics suggest that the MS asset pricing models provide a better fit to Chinese stock market data then the standard models since they effectively eliminate the apparent non-normality of the residuals that appears in both the Fama-French and the sentiment-based conditional asset pricing models.

The Markov-switching autoregressive models for the sentiment proxies show significant regime switching patterns for all the sentiment proxies and indicate that there are three regimes for turnover, two regimes for advances-declines ratio and two regimes for dividend premium. For turnover, the three regimes capture (1) a persistent, low volatility, and negative sentiment regime; (2) a transient, normal-market and low volatility regime; and (3) an infrequent, highly active, strongly optimistic sentiment-driven regime with long duration and high volatility. For the advances-declines ratio the revealed regimes are (1) a long-period, low volatility bear state, where buying commissions exceed selling commissions; and (2) a transient regime with strongly positive sentiment and relatively high volatility. For dividend premium, the two regimes are (1) a prolonged-period and highly volatile regime that consists of bull to normal market periods; and (2) a transient and low-volatility regime with strongly negative sentiment and a high premium for dividend-paying compared to non-dividend paying stocks. The three sentiment proxies appear to capture sentiment levels and transitions in different ways and it is appropriate to test their effects separately on stock returns.

The regime switching sentiment models provide evidences that Chinese stock returns are driven by fundamentals in some phases but by sentiment in other times. Applying the regime shifting asset pricing model with investor sentiment helps understand the formation of stock returns in Chinese stock markets.

The results of the MS asset pricing models suggest that in Chinese stock markets, market, size and distress risks are important determinants of stock returns in a low sentiment and bear market. This is robust shown by the regime 2 of the turnover model, regime 1 of the advances-declines ratio model, and regime 1 of the dividend premium model. Stock returns have low volatility in this bear state. Sentiment always positively influences stock returns even in this bear state. However, the bull market periods in the data are captured by the sentiment-driven regime, that is, regime 3 in the TURN model and regime 2 in the ADV/DEC model. The sentiment-driven state is infrequent and highly volatile. More importantly, fundamental risks become insignificant when sentiment effects are stronger.

Unlike the others, the effect of dividend premium becomes less significant in the infrequent bull market, which is in line with the regime performance of dividend premium: it distinguishes the extreme negative sentiment from the normal but becomes less important in a high sentiment market. Also, turnover as a sentiment indicator captures a transition state that links sentiment-driven state and fundamental-driven state. This state is not captured by advances-declines ratio and dividend premium. These robustly suggest that the three sentiment proxies capture investor sentiment in different ways, thus by separating the three sentiment proxies this work contribute the Baker and Wurgler (2006, 2007) literature.

Chapter 7 CONCLUDING REMARKS

7.1 Summary of this Thesis

Using monthly data for all Chinese A-share stocks, the composite Shanghai and Shenzhen stock index, macroeconomic and sentiment proxies, from January 1997 to December 2007, this thesis addresses the issue of asset pricing in Chinese stock markets incorporating investor sentiment. After reviewing the relevant literature and briefly introducing the Chinese economy and financial markets, the research starts by testing traditional asset pricing models. First, the three-factor Fama-French model is studied, using four samples that are differentiated according to sample selection and market capitalisation measures. Results from this model mainly shed light on its failure: although the model fits the data reasonably well, it performs poorly on the robustness diagnostics in terms of non-normally distributed and heteroskedastic residuals, omitted variables and structural breaks. Next I check whether these shortcomings can be eliminated by adding four more basic (macroeconomic) risk factors. However, the addition of industrial production growth, retail price inflation, the bond market return and changes in the RMB exchange rate provide little extra explanatory power to the Fama-French model.

Therefore I next consider the behavioural approach to asset pricing and incorporate investor sentiment to explain stock returns in China. Using the standard Fama-French model as the benchmark, I address how far sentiment can contribute to pricing theory. In particular, I find that sentiment effects help explain the Fama-French pricing errors directly, and also explain the Fama-French factors themselves. This suggests that the cognitive market, size and distress factors are themselves partly biased by the impact of investor sentiment; and that sentiment may enter into the model indirectly as a conditioning variable for these cognitive factors. I find an improvement in the asset pricing model when direct and indirect sentiment effects are taken into account, especially in the elimination of the key structural break. Nevertheless, the diagnostics still reveal some shortcomings in the sentiment-based conditional asset pricing model and call for further consideration.

Finally therefore, I adopt the Markov-switching framework to govern the non-linear relations between stock returns, risks, and investor sentiment. The relations among the three are indeed time-varying and regime-dependent. Using turnover, advances-declines ratio and dividend premium as the sentiment proxy respectively, I find stock returns are prone to be governed by fundamentals when the market is bearish and volatility is low, but more likely to be driven by investor sentiment in a bull market, usually accompanied by high volatility. The MS model successfully explains the time-variation of size-BE/ME sorted stock portfolio returns in China

Other key results include the following. First, the listed market value is the better measure for market capitalisation to weight asset returns, market index and book-to-market premium, but firm size is more appropriate to be represented by total market value. This finding helps to understand the free float issue in China where there is a large proportion of non-tradable shares. Second, the three sentiment proxies (turnover, advances-declines ratio and dividend premium) capture investor sentiment in different ways, and they therefore affect stock returns in different way. Thus my research benefits from accounting for these sentiment proxies separately rather than constructing a composite sentiment index.

7.2 Limitations and Directions for Future Research

Perhaps the main limitation of this thesis is the short 11 years data period. Research on mature markets usually uses a much longer span of data. However, it is difficult to extend the data further back in time as the number of shares would drop excessively. In addition, the +/-10% price limits were launched in December 1996, implying a structural change in price formation. The only way to deal with the short data problem is to extend the data forwards, which calls for further study.

Another problem that may evolve is the proxy for sentiment. We use three proxies for sentiment. However, there may be other proxies as well, such as the number of newly opened accounts (Li and Zhang, 2008). This proxy is not applied in this thesis because it is not suitable for monthly frequency data. Moreover, the Chinese market lacks direct survey data on investor sentiment. This would provide a straightforward overview of investors' confidence about market and help to check the validity of the indirect proxies.

One more behavioural variable with which to augment the Fama-French model is momentum. The momentum investment strategy stems from the commonly held view of short-term momentum and long-run reversal, and is in line with the prospective utility theory that past earnings/losses have effects on the current risk aversion level. Grundy and Martin (2001), George and Hwang (2004), Du (2007) take momentum into asset pricing consideration. Grundy and Martin describe the momentum variable by the return difference between the past 6-month winners and losers, while George and Hwang and Du use the past 52-week high price as the momentum factor to catch the reference point over a period. The Momentum factor is not employed in this thesis because it does not have a direct psychological foundation (such as turnover is based on social interaction, and dividend premium is according to time preference theory), but it is worth adding momentum factors into the augmented Fama-French model.

Besides applying other sentiment factors, there are two more key ideas for further research suggested by this thesis. One is to use higher frequency data. The work in this thesis was constrained in part by the use of macroeconomic data which is only available at monthly and lower frequencies. Since the macroeconomic risk factors turned out to be unimportant, it is natural to consider a study of daily data. Higher frequency data will enable the researcher to investigate more precisely how long sentiment effects last and when they are reversed. Higher frequency data will tell whether sentiment momentum is sustained over a few days or over weeks.

A second direction of research would address the arousal of investor sentiment. This thesis focuses on sentiment effects on asset pricing. The reverse relation is also interesting. We have pointed out briefly that sentiment may come from the anticipated outcomes and subjective evaluated probabilities, as well as the regularity that psychological theory suggested. We can investigate further the circumstance that sentiment arises from, for example, regulatory, legal and macroeconomic policy changes, or past market performance. These examples involves two aspects: the former calls for event studies to discover investor sentiment that is motivated by but rapidly overreacted good or bad information signals; the later uses perspective theory (Barberis, *et al*, 2001) and loss aversion (Grune and Semmler, 2008).

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