# Short-Selling Constraints and Assets Pricing

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# Abstract

Short-selling is a strategy in which an investor sells a security that he/she does not own in order to make profits from a falling price. To prevent abusive short-selling and price manipulation, stock exchange regulators sometimes impose restrictions on the short sales of stocks. Debate on whether short sales should be allowed, or restricted, has persisted for years among academics, practitioners and policy makers. In particular, financial economists have long been interested in studying the relation between short-sale constraints and market efficiency (such as stock price overvaluation, stock price discovery/adjustment, stock price volatility and stock liquidity). Despite the growing literature on short-sale constraints, however, some important questions still remain unanswered. These questions are the focus of this study.

This dissertation comprises three essays, and probes into three untouched questions related to short-sale constraints by employing the unique Hong Kong short-selling list. The first essay examines the different price effects on stock characteristics of two alternative short-sale regimes – one under which stocks are shortable and the other under which they are not. My empirical results in this essay show that under the no-short-selling regime, (a) stocks have higher risk-compensation-adjusted returns (i.e., abnormal returns); (b) stocks with a larger size perform slightly better in terms of their returns; (c) contemporaneous (lagged) illiquidity has a weaker negative (stronger positive) effect on returns; (d) the negative relation between dividend yields and future returns weakens; and (f) the presence of both short-sale constraints and opinion dispersion causes contemporaneous returns to rise and future returns to fall by more than the effect of the presence of the opinion dispersion alone.

The second essay investigates two questions: Do asset-pricing models perform differently across where short sales are constrained and where they are not? In which short-selling environment would the models possess more explanatory power? Applying both conventional model-performance analysis and Lewellen, Nagel and Shanken's (2010) new approach, I find that the CAPM and Fama-French three-factor models fare significantly better in capturing the time-series and cross-section of expected returns on stocks when their short-selling is allowed, than when it is not. The implications of the results are that it would produce biased estimates if applying the CAPM and its empirical models to non-shortable stocks/markets, and that a new asset-pricing model, which takes into account the short-selling status of stocks, is called for.

Following up that call, my third essay constructs what is termed as "a shortability factor" and adds it to the extant assets-pricing models. The empirical results show that not only does the shortability factor itself play a significant role in explaining both time-series and cross-sectional variations in expected portfolio returns, but the overall performances of the extant standard asset-pricing models are also enhanced to various degrees by including the new factor. This implies that the short-selling status of a stock cannot be ignored when estimating its cost of capital based on the asset-pricing models.

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## Chapter 1 Introduction

Short-selling is the practice by which investors borrow securities from the lender and immediately sell them to the market in a hope that the prices of the shorted securities will decline enabling the investors to profit by purchasing the securities from the market at lower prices to return them to the lender. The following flowchart shows the short-selling process.

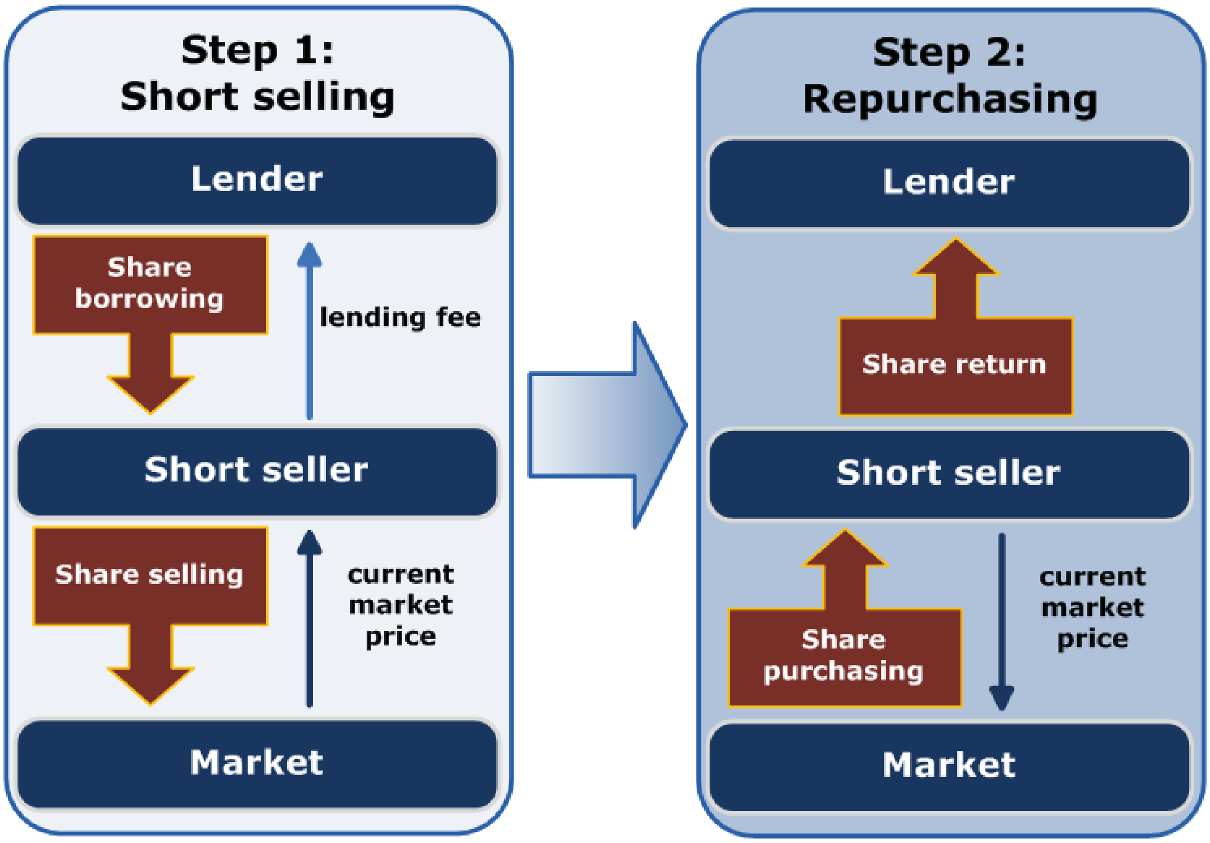


Figure1.1: The two step process of short-selling (source: Wikipedia, 2013)

Short selling has been viewed as a double-edged sword. On the one hand, short-selling activities may improve the efficiency of capital markets in allocating resources. Therefore, in early times, stock exchanges tended to encourage their members to borrow and lend securities for shorting purposes. As far as short sellers are concerned, they sometimes do make profits from shorting securities. On the other hand, however, short-selling activities are not without risk to short sellers, who may suffer huge losses if prices of shorted stocks increase. Furthermore, short-selling activities can speed up the decline of security prices during a financial crisis. Therefore, many market regulators tend to impose short-selling restrictions in order to prevent market crashes. As an example, short sales were recently banned during the 2007-2009 financial crises in many markets, because regulators feared that shorting activities could worsen the detrimental consequences of the crises. According to Bris, Goetzmann and Zhu (2007), among 46 developed and developing countries, 21 exercise restrictions on short-selling, or have a high cost of shorting.

The relation between short-sale regulations and market quality (including price discovery, return risk, market efficiency and so on) has attracted a great deal of attention from researchers. In fact, debate on shackling or unshackling short sellers among market regulators, practitioners and academia is continual. This dissertation embraces three projects all related to short-selling constraints, and explores three untouched issues. The first examines the role of stock characteristics (or, equivalently, firm characteristics) in linking short-selling constraints to stock returns. The second project investigates the relative performances of well-established asset pricing models across markets in which short-selling is, and is not, allowed. The third project augments the existing asset pricing models with a new factor mimicking the risk induced by short-sale constraints, and determines whether this can improve the performances of the augmented asset pricing models in the face of short-selling restrictions.

## 1.1 Short-Selling Restrictions and Research Questions

Short-selling activities are highly popular among market participants, including speculators. Using the short-selling strategy, a speculator sells a security that she does not own in order to profit from a falling market. The speculator will borrow the security from a third party and then immediately sell it on to the buyer. At a later date, the speculator must make good on the loan by buying back the security from the market to close the position. If the value of the security has fallen during this period, the speculator's profit will be the difference between the sale price and the repurchase price (minus interest charges and fees). If, however, the market moves against the speculator, she will incur limitless losses. Also, when a company's stock is sold short heavily by speculators, its share prices drop dramatically. Thus, short sellers are often blamed for causing a market crash. In order to protect investors from abusive short sales and price manipulation, many markets fully, or partially, prohibit short-selling.

Back to the early sixteenth century, a relatively large scale of short-selling activities took place through the Amsterdam Stock Exchange and investors made huge profits via short-selling activities, due to regulations on short sales being absent, or incomplete. Later, in 1609, the very first trade company, the Dutch East India Company, filed complaints against the Amsterdam Stock Exchange over large profits made by short-sellers, which led to the first regulation on short selling being enacted in 1610. Following this, regulations on short sales were integrated progressively in the US and then in other countries. Debate and complaints regarding short selling, however, continued. A fierce debate was triggered around the 1929 market crash. Among the many reasons for the crash, short sales took much of the blame because speculators were found to be using it to play the market opportunistically. In order to minimise the negative effect of short sales by speculators, the US market regulators were advised to impose various restrictions on short-selling in the 1930s. After these restrictions came into force shorting a share became more difficult and expensive, due to the gradual maturation of market regulations related to short selling.

Since the 1930s, research of short-selling constraints has been conducted both theoretically and empirically. Their effect on financial markets still remains controversial, despite the fact that short-selling constraints have been pervasive in major financial markets for many years. Among many unanswered questions, I consider the following three to be worth exploring: Are stock characteristics priced differently between the regime that bans short selling and the regime that allows short selling (Question 1)? Do short-selling restrictions make asset pricing models perform differently (Question 2)? Can short-selling restrictions be utilised to improve asset pricing models for more accurate practical uses (Question 3)? As will be seen in this thesis, my answers to these questions prove to be capable of filling the underlying voids in the existing literature, such that my findings should have important implications for market practitioners and market regulators.

## 1.2 Debate on Restricting Short-Sellers: The Motivation of the Research

Two conflicting theories about short-selling constraints were developed before and after 1980, and have been widely tested. They are overpricing theory (Miller, 1977) and non-overpricing theory (Diamond & Verrecchia, 1987; Bai, Chang & Wang, 2006). These two theories have motivated my three empirical studies in this dissertation. Therefore, I outline them in this subsection (Detailed reviews of relevant studies will appear in Chapters 3 through 5).

*Overpricing Theory*

Fama (1970) defines an efficient market as the market where security prices always fully reflect the available information. Seven years later, Miller (1977) predicts that prohibition on short-selling will reduce market efficiency. Under the assumption of heterogeneous expectations among investors, Miller suggests that short-selling constraints lead security prices to reflect more of the optimistic investors' opinions than the average potential investors' opinions, resulting in security prices being upward biased. This over pricing effect is because pessimistic investors cannot, due to their bearish beliefs, take short positions and so remain out of the market.

Empirical evidence supporting Miller's overpricing theory has been documented. The first empirical study in favour of Miller's intuition is Figlewski's (1981) single-period test. He shows that the absence of short sales of a stock will lead to some overvaluation of the stock if investors have bearish beliefs about the stock. Recently, Diether, Malloy and Scherbina (2002), Boehme, Danielsen and Sorescu (2006) and Chang, Cheng and Yu (2007) find strong evidence to support Miller's intuition in the US and other stock markets. It is worth mentioning that Chang et al. (2007) is the first study that employs direct short-sales constraints data in testing Miller's theory, which is free of measurement errors.

*No-overpricing Theory*

Against Miller's overpricing theory, Diamond and Verrecchia (1987) and Bai, Chang and Wang (2006) argue theoretically that the presence of short-selling constraints may lead to no change, or indefinite changes, in stock prices. The no-overpricing result of Diamond and Verrecchia (1987) hinges on the assumption that investors are both rational and risk-neutral. In adjusting their valuations, such investors, if less informed, will take into account the possibility that short-selling restrictions keep outside the market those investors more informed of negative news. As a result, stocks will not be systematically overpriced in equilibrium. The indefinite-pricing result of Bai, Chang and Wang (2006) is based on the assumption that rational investors are risk-averse. Short-sale constraints induce slower price discovery, which in turn increases risk. When rational and risk-averse investors are uninformed, they will perceive that the risk is increasing and, thus, require higher expected returns, causing current prices to fall. On the other hand, short-selling constraints prevent risk-averse investors from taking on negative positions to hedge other risks, thereby increasing their demand for the stocks and pushing up their prices.

Empirical evidence in support of the intuition of Diamond and Verrecchia (1987) has been more widely documented than that for Miller's (1977) intuition. Chen, Hong and Stein (2002) note that "the evidence for Miller's theory remains somewhat sparse, even after 25 years". They find no significant relation between short-selling constraints and stock returns. It should be emphasised that previous studies lead to either conflicting results as to whether Miller's overpricing exists, because they look at only one of the two conditions (short-sale constraints and divergent investor opinions) for overvaluation; or conclude that the Miller effect does exist, but only if the two conditions are taken into account simultaneously (Boehme et al., 2006).

Miller's overpricing theory is the foundation of my three short-selling related projects. In particular, the first project attempts to revisit the theory by taking different approaches than in previous studies and with an objective to add more evidence to the existing sparse evidence *for* the theory. The second and the third projects continue to build on Miller's (1977) overpricing theory, but also go way beyond this to investigate the classical asset pricing theories (such as CAPM), where short-sale constraints are present and have Miller's (1977) overpricing effect.

### 1.3 Objectives and Contributions of the Research

Miller's (1977) overvaluation theory and Diamond and Verrecchias' (1987) no-overvaluation theory have been widely examined in the US and international markets since the 1970s. Empirical studies have, however, shown mixed evidence regarding Miller's overpricing effect. Early studies include Figlewski (1981), Woolridge and Dickinson (1994), Asquith and

Meulbroek (1995) and Boehme, Danielsen and Sorescu (2006). More recent studies can be found in Chang et al. (2007), Boehmer, Jones and Zhang (2008), Diether, Lee and Werner (2009) and Beber and Pagano (2013). An immediate question arises here: Why is the evidence mixed even after 30 years? After reviewing the short-selling literature (the details of the literature review will be provided in Chapter 3), I find several reasons that could explain why the existing empirical results are conflicting. Among them, an important one is the availability of a direct measure of short-selling constraints. Lacking such a direct measure, most previous studies have used proxies to differentiate stocks according to their different degrees of shortability. For example, some studies use the level of institutional ownership of a stock as a proxy for its shortability. A problem with this practice is that a proxy may be contaminated with other effects. The institutional-ownership proxy may be correlated with some other stock characteristics, such as firm size, because institutional investors usually pick large stocks for ownership. In this case, it is hard to attribute detected overvaluation to short-sale constraints. Fortunately, short-selling regulations in the Hong Kong stock market make it possible to use a direct measure of short-selling constraints, and provide me with an ideal setting for carrying out empirical studies. With the direct measure available, I can examine the differences in pricing stock characteristics between stocks that are allowed to short and stocks that are not. I can also investigate the validity/performance of well-known asset-pricing models across these two groups of stocks, and construct a new factor related to short-selling restrictions to improve these models' practical values in the markets where shorting is banned.

Testing the overpricing theory, my first study takes a broader perspective. Previous studies usually treat stock characteristics[1] as control variables and so fail to look at how

[1] Firm characteristics controlled for in previous empirical studies include the firm size, the book to market ratio, the price to earnings ratio and the liquidity ratio.

differently stock characteristics are priced across different short-selling regimes. This omission is inappropriate, as abnormal returns are only part of stock returns. Short-sale restrictions affect stock returns not just directly by changing the abnormal-return component, but also indirectly via changing return responsiveness to stock characteristics. If the latter is true, then one will be able to use the information contained in stock characteristics (taken to be firm-specific risks) to improve stock return predictability under alternative short-selling regimes. That is, I believe that the broader perspective shall at least be more useful to market participants on a practical level. Out of these considerations, my first objective is to verify that stock characteristics are priced differently across the regime that allows shorting and the regime that does not. Using the uniqueness of Hong Kong regulations on short sales to distinguish between the two regimes and employing a panel regression model for those Hong Kong stocks that switch between the two regimes, I explore the interaction between the characteristics' variables and the distinct short-selling regimes. I find evidence of differences in some of their price effects. Under the no-short-selling regime: Stocks would have higher risk-compensation-adjusted returns; stocks of larger size may perform even better in terms of their returns; contemporaneous (lagged) illiquidity would have a weaker negative (stronger positive) effect on returns; the negative relations between dividend yields and future returns would weaken; and the presence of both short-selling constraints and opinion dispersion would cause contemporaneous returns to rise and future returns to fall by more than would the presence of opinion dispersion alone.

The second objective of this dissertation is to prove a common practice in empirical asset pricing testing to be a mistake that disregards the no-shorting-restriction assumption of asset pricing models. To this end, I investigate Question 2 posed above, which is a question not yet touched in the extant literature. The classical Capital Asset Pricing Model (CAPM) has a very important assumption – investors can take short positions on any risky assets in the market. Previous researchers have, however, never taken into account this assumption when applying the CAPM and its empirical extensions, such as the Fama-French three-factor model, to non-shortable markets, or assets. In the real world, many countries/markets make it difficult or even impossible for investors to short stocks by imposing various restrictions, or increasing costs, on short sales. Once again, an immediate question is; are estimates produced by the CAPM and its empirical models from non-shortable markets/assets accurate enough to be usable? Using both conventional asset-pricing test approaches and Lewellen, Nagel and Shanken's (2010) new approaches, I find that the CAPM and the Fama-French three-factor models fare significantly worse in capturing the expected returns on stocks that are not shortable, than for stocks that are shortable. These results imply that applying these widely-used asset-pricing models to the stocks/markets where short sales are restricted would likely generate biased estimates. Therefore, I find it necessary to remedy the mistake of ignoring the no-shorting-restriction assumption and applying the existing asset-pricing models indiscriminately to any markets, whether or not they are subject to short-sale constraints.

This resolution of mine then motivates Question 3, as posed above, which is, again, a question not yet attended to in the literature. One would naturally wonder how we can improve the CAPM and its empirical models to better fit the non-shortable assets/markets prevalent in the real world. My third research objective is to develop novel asset-pricing models by incorporating short-selling restrictions. To achieve this objective, I conceive a new factor mimicking the risk induced by short-selling restrictions. This is inspired by, for example, Carhart (1997) who incorporates the momentum factor into the Fama-French three-factor model. The unique Hong Kong short-selling regulations enable me to construct a shorting-restriction-related factor, along with the market factor, the size factor, the book-to-market factor and the momentum factor. Augmenting the extant asset pricing models with the shorting-restriction-related factor, I find that the new factor plays a significant role in explaining stock returns in both the time-series and the cross-sectional dimension. That is, my five-factor model has more explanatory power than the one-factor (CAPM), the Fama-French three-factor and the Carhart four-factor models, when applying it to the Hong Kong market where shortable and non-shortable stocks coexist.

## 1.4 Structure of the Dissertation

The main body of this dissertation embraces three essays, each related to one of the three research questions posed in Section 1.1. In order to organise the dissertation in a methodical manner, the three essays will appear as three independent chapters and in the sequence of asking the three questions. Specifically, the structure of this dissertation is as follows.

As all my three projects employ the short-selling data from the Hong Kong stock market, Chapter 2 introduces the Hong Kong Stock Exchange with the emphasis placed on its short-selling regulations. This is to assist the reader in understanding why the data is unique and how the regulations work. Chapter 3, as my first essay, focuses on Question 1. It is titled "The pricing of stock characteristics under opposite short-selling regimes." Chapter 4, as my second essay, deals with Question 2. It is titled "The validity of asset-pricing models where short-selling is restricted". Chapter 5 embraces my third essay and explores Question 3. It is titled "Short-selling constraints: Another risk factor for assets-pricing models". Finally, Chapter 6 summarises the key findings of the three essays, states their implications for market participants and regulators and indicates the limitations of present research, as well as possible directions for future research.

## Chapter 2 Hong Kong Short-selling Regulations

*The current short-selling system in Hong Kong is robust and has proven itself to work well over the last 10 years.*

- *Martin Wheatley*

*The CEO of the Securities and Futures Commission*

Hong Kong's regulations on short-selling[2] practices make its data unique and well-suited to serving my purposes of investigating accurately and directly the aforementioned three research questions. To show why this is so, I devote Chapter 2 to describing the regulations.

In line with reforming the system for borrowing and lending securities, the Hong Kong Stock Exchange (HKSE) introduced, in January 1994, a pilot scheme for regulated short selling. Only stocks that appear on the official list can be sold short. Under the pilot scheme, 17 securities could be sold short, provided that they were above the best current ask price (known as the "tick rule"). The scheme was revised in March 1996, with the number of designated securities for short selling increased and the tick rule abolished. In September 1998, due to the Asian financial crisis, regulators started to ban naked short selling, reinstate the uptick rule[3] and strictly enforce the T+2 settlement period. All short sales must be

[2] Short-selling regulations in the Hong Kong stock market differ from those of other countries in the following aspects. 1) A subset of stocks meeting certain criteria is always allowed to be sold short in the Hong Kong stock market. 2) All stocks in the U.S. and most European stock markets can be sold short, unless during certain periods such as a financial crisis when regulators impose bans temporarily on short-selling practice either for the whole stock market or for stocks from some particular sectors such as financial industry. 3) The "uptick rule", where short sales cannot take place at less than the best ask price, imposed by HKSE helps prevent short sales from having detrimental effects on market prices. But in the U.S, since February 24, 2010, the SEC has adopted a different uptick rule. The rule does not apply to all securities. It is trigged when a security's price decreases by 10% or more from the previous day's closing price and is effective until the close of the next day. 4) In the Hong Kong market, "naked" short selling is prohibited, that is, short sellers must arrange to borrow stocks before they execute short sales. In the US market, however, since the financial crisis in 2008, the SEC has banned "abusive naked short selling".

[3] The uptick rule states that any short sales transaction must be entered into at a price higher than the price of the previous trade. The purpose of the rule is to help alleviate downward pressure on security prices. Its impact

identified by brokers at the time of the order, and all members of the Exchange must maintain a ledger of daily short-sale transactions that is always available to the Exchange. The rules also require a full audit trail to be kept for covered short sales, meaning that, for instance, when clients place short selling orders, they must provide documentary confirmation to their brokers, or agents, that the sale is shorted and that it is covered.

The HKSE has revised the number of designated securities for short-selling on an irregular basis. As of December 31, 2009, which is the end of the sample period used in Essay 1 (or Chapter 3), out of 1,404 common stocks traded on the main board, 892 could be sold short. As of February 29, 2012, which is the end of the sample period used in Essay 2 (or Chapter 4) and Essay 3 (or Chapter 5), out of 1,498 common stocks traded on the Hong Kong Stock Exchange, 1,081 could be sold short.

The HKSE summarises four features of designated securities eligible for short selling, as follows:

*1. "Naked short selling is prohibited[4]", which means that short sellers need to arrange to borrow stocks before they execute short sales;*

*2. To make a short sale easily identifiable, exchange participants are required to put a market on each short-selling order when they submit it to the HKSE for execution;*

*3. Short-selling is only allowed for more liquid stocks determined by the HKSE; and*

varies as a function of the size of the investor. In particular, larger investors can work around the rule by placing a small buy order just prior to placing a heavier short for their real bets.

[4] Prohibiting naked short sales: Short-sellers must borrow, or arrange to borrow, the stock they want to sell before trading. They cannot locate a potential lender after concluding the transaction. Culp and Heaton (2008) argue that the prohibition leads to an increase of the fees charged by share lenders, because it increases the overall demand for borrowing shares.

*4. The "uptick rule", where short sales cannot take place at less than the best ask price, imposed by the HKSE, helps prevent short sales from having an abnormal effect on market prices.*

The HKSE also publicises eleven selection criteria for designated securities eligible for short-selling, as follows:

*1. All constituent stocks of indices, which are the underlying indices of equity index products traded on the Exchange;*

*2. All constituent stocks of indices, which are the underlying indices of equity index products traded on the Hong Kong Futures Exchange (HKFE);*

*3. All underlying stocks of stock options traded on the Exchange;*

*4. All underlying stocks of stock futures contracts (as defined in the rules, regulations and procedures of HKFE) traded on the HKFE;*

*5. Stocks eligible for structured product issuance pursuant to Rule 15A.35 of the Main Board Listing Rules, or underlying stocks of Structured Product traded on the Exchange;*

*6. Stocks with market capitalisation of not less than HK$3 billion and an aggregate turnover during the preceding 12 months to market capitalisation ratio of not less than 50%;*

*7. Exchange Traded Funds approved by the Board in consultation with the Commission;*

*8. All securities traded under the Pilot Program;*

*9. Stocks that have been listed on the Exchange for not more than 60 trading days, with a public float capitalisation of not less than HK$10 billion for a period of 20 consecutive trading days commencing from the date of their listing on the Exchange and an aggregate turnover of not less than HK$200 million during such period;*

*10. All underlying stocks of Structured Product, which is based on one single class of shares traded on the Exchange; and*

*11. Applicable Market Making Securities (other than the securities described in categories 7. and 8. above) approved by the Board in consultation with the Commission.* [5]

Table 2.1 contains the information on how individual stocks on the HKSE experience changes in the short-selling regulations. Columns 1 and 5 (labelled "change date") indicate the *effective* dates on which a revised list of designated securities had stocks added and/or removed for short-selling practice. Columns 2 and 6 (labelled "Addition") give the number of stocks that were added to the official list and, therefore, allowed to be sold short from the change date onwards. Columns 3 and 7 (labelled "Deletion") present the number of stocks that were deleted from the official list and, therefore, not allowed to be sold short from the change date onwards. Columns 4 and 8 (labelled "On-list stocks") give the total number of designated stocks that were, after addition and deletion, on the revised list for short-selling[6]. Note that Table 2.1 should not be used to calculate the total number of stocks that were allowed to be shorted over the sample period, nor the total number of stocks itself. To illustrate, consider an example where a stock is added to the list three times and deleted from the list twice, while another stock has two additions and one deletion. It would be wrong to

[5] On 10 May 2012, the HKSE announced that the eligibility criterion of the short-sales list related to the market capitalization and turnover velocity will be increased from $1 billion to $3 billion and from 40 per cent to 50 per cent respectively. The change reflects the fact that the average market capitalization of listed companies in Hong Kong has grown by around three times and the market turnover velocity has increased from around 40 per cent to over 50 per cent in the past decade. The new Regulation for short selling eligibility criteria has been approved by the Securities and Futures Commission and will take effect on 3 July 2012 (Tuesday). Investors and Exchange Participants may refer to Regulation 18 of the Eleventh Schedule of the Rules of the Exchange available on the HKEx website for the details. **http://www.hkex.com.hk/eng/newsconsul/hkexnews/2012/120510news.htm**

[6] For example, after the first addition, there were 17 stocks on the short-selling list effective from 3 January 1994. 96 stocks were added to the list and 0 stock was deleted from the list in the second revision effective from 25 March 1996. Therefore, the total number of stocks on the list was, 17+96-0=113 on that date.

infer that there are eight stocks by adding up five (additions) and three (deletions): The number of stocks is always two.

The list was established on January 3, 1994 and had been subsequently revised 80 times to December 31, 2009, which is the end of the sample period of Essay 1, and 108 times to February, 2012, which is the end of the sample period of Essay 2 and Essay 3. Each essay addresses different research questions: Essay 1 focuses on discovering the differences in the pricing of stock characteristics between different short-selling regimes; Essay 2 focuses on exploring the performance differences of asset-pricing models when applied to shortable assets and when applied to non-shortable assets; and Essay 3 focuses on constructing a new asset-pricing model by adding a short-selling related factor. Although all employ the Hong Kong designated short-selling list as the primary dataset, each essay will use different categories of all stocks traded on the HKSE, because they deal with different research questions. I will be detailing the differences of the data used in the three essays in, respectively, Chapters 3, 4 and 5.

**Table 2.1 Changes in the Official Short-Selling List**

**This table provides information on changes in the official short-selling list of the HKSE from January 1994 to February 2012, including the effective date on which a change took place ("Change date"), the number of stocks added to ("Addition") and deleted from ("Deletion" ) the list, and the total number of stocks appearing on the list ("No. of on-list stocks").**

| Change Date | Addition | Deletion | No. of on-list stocks | Change Date | Addition | Deletion | No. of on-list stocks | Change Date | Addition | Deletion | No. of on-list stocks |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 3/01/1994 | 17 | 0 | 17 | 8/07/2005 | 1 | 0 | 265 | 14/11/2008 | 6 | 144 | 366 |
| 25/03/1996 | 96 | 0 | 113 | 15/07/2005 | 1 | 0 | 266 | 12/02/2009 | 25 | 27 | 364 |
| 1/05/1997 | 129 | 1 | 241 | 15/08/2005 | 14 | 12 | 268 | 14/05/2009 | 13 | 22 | 355 |
| 12/01/1998 | 69 | 0 | 310 | 5/09/2005 | 1 | 0 | 269 | 10/07/2009 | 1 | 0 | 356 |
| 16/03/1998 | 15 | 0 | 325 | 28/10/2005 | 1 | 0 | 270 | 5/08/2009 | 49 | 16 | 389 |
| 9/11/1998 | 19 | 149 | 195 | 18/11/2005 | 11 | 7 | 274 | 5/11/2009 | 58 | 11 | 436 |
| 1/03/1999 | 7 | 7 | 195 | 20/02/2006 | 10 | 8 | 276 | 18/11/2009 | 1 | 0 | 437 |
| 20/09/1999 | 3 | 17 | 181 | 1/03/2006 | 2 | 0 | 278 | 3/12/2009 | 1 | 0 | 438 |
| 12/11/1999 | 1 | 0 | 182 | 29/05/2006 | 23 | 17 | 284 | 15/12/2009 | 1 | 0 | 439 |
| 28/02/2000 | 24 | 12 | 194 | 2/06/2006 | 1 | 0 | 285 | 24/12/2009 | 1 | 0 | 440 |
| 31/05/2000 | 7 | 0 | 201 | 2/06/2006 | 1 | 0 | 286 | 1/02/2010 | 65 | 8 | 497 |
| 28/08/2000 | 32 | 16 | 217 | 25/08/2006 | 38 | 10 | 314 | 1/03/2010 | 1 | 0 | 498 |
| 12/02/2001 | 15 | 11 | 221 | 1/09/2006 | 1 | 0 | 315 | 10/03/2010 | 1 | 0 | 499 |
| 14/05/2001 | 6 | 0 | 227 | 23/10/2006 | 1 | 0 | 316 | 25/03/2010 | 1 | 0 | 500 |
| 20/08/2001 | 9 | 11 | 225 | 27/10/2006 | 1 | 0 | 317 | 10/05/2010 | 59 | 12 | 547 |
| 3/12/2001 | 17 | 85 | 157 | 1/12/2006 | 55 | 9 | 363 | 16/07/2010 | 1 | 0 | 548 |
| 25/02/2002 | 7 | 14 | 150 | 5/03/2007 | 30 | 24 | 369 | 4/08/2010 | 40 | 19 | 569 |
| 21/05/2002 | 11 | 6 | 155 | 14/03/2007 | 1 | 0 | 370 | 30/08/2010 | 1 | 0 | 570 |
| 29/07/2002 | 24 | 5 | 174 | 19/04/2007 | 5 | 0 | 375 | 29/10/2010 | 47 | 18 | 599 |
| 29/11/2002 | 6 | 15 | 165 | 26/04/2007 | 4 | 0 | 379 | 15/11/2010 | 1 | 0 | 600 |
| 27/01/2003 | 5 | 7 | 163 | 21/05/2007 | 29 | 14 | 394 | 22/11/2010 | 2 | 0 | 602 |
| 19/05/2003 | 18 | 7 | 174 | 21/05/2007 | 1 | 0 | 395 | 20/12/2010 | 1 | 0 | 603 |
| 21/07/2003 | 1 | 16 | 159 | 29/05/2007 | 1 | 0 | 396 | 30/12/2010 | 1 | 0 | 604 |
| 4/08/2003 | 0 | 1 | 158 | 4/07/2007 | 1 | 0 | 397 | 28/01/2011 | 1 | 0 | 605 |
| 3/11/2003 | 36 | 5 | 189 | 17/07/2007 | 1 | 0 | 398 | 1/02/2011 | 1 | 0 | 606 |
| 6/01/2004 | 1 | 0 | 190 | 13/08/2007 | 137 | 9 | 526 | 25/02/2011 | 70 | 17 | 659 |
| 10/02/2004 | 29 | 3 | 216 | 27/08/2007 | 1 | 0 | 527 | 24/05/2011 | 65 | 18 | 706 |
| 7/04/2004 | 1 | 0 | 217 | 26/11/2007 | 64 | 23 | 568 | 9/06/2011 | 1 | 0 | 707 |
| 27/04/2004 | 26 | 4 | 239 | 14/12/2007 | 2 | 0 | 570 | 12/07/2011 | 2 | 0 | 709 |
| 1/07/2004 | 1 | 0 | 240 | 14/12/2007 | 1 | 0 | 571 | 12/08/2011 | 24 | 50 | 683 |
| 9/07/2004 | 1 | 0 | 241 | 18/02/2008 | 33 | 41 | 563 | 6/09/2011 | 1 | 0 | 684 |
| 2/08/2004 | 8 | 21 | 228 | 13/03/2008 | 1 | 0 | 564 | 3/11/2011 | 18 | 97 | 605 |
| 8/11/2004 | 9 | 11 | 226 | 13/05/2008 | 22 | 47 | 539 | 14/11/2011 | 1 | 0 | 606 |
| 7/02/2005 | 15 | 7 | 234 | 15/05/2008 | 1 | 0 | 540 | 2/02/2012 | 2 | 0 | 608 |
| 1/03/2005 | 2 | 0 | 236 | 3/06/2008 | 5 | 0 | 545 | 10/02/2012 | 12 | 39 | 581 |
| 17/05/2005 | 37 | 9 | 264 | 7/08/2008 | 10 | 51 | 504 | 29/02/2012 | 1 | 0 | 582 |

# Chapter 3 Moving between Opposite Short-selling Regimes: Are Stock Characteristics Priced Differently?

## 3.1 Introduction

In this chapter, I test Miller's (1997) overpricing intuition and investigate the possible pricing differences in the well-documented firm characteristics between two alternative short-selling regimes: One under which short selling is possible, and the other where it is not. The motivations of my two research objectives are stated below.

I am interested in testing Miller's (1977) overpricing prediction, due both to the importance of this prediction and the fact that some questions are left open by previous studies. Among the issues that have interested researchers is how short-sale constraints affect stock valuation. Miller (1977) predicts an overvaluation effect of short-sale constraints. Diamond and Verrecchia (1987) and Bai, Chang and Wang (2006), on the other hand, reach different conclusions to Miller (1977): The presence of short-selling constraints may lead to no change, or indefinite changes, in stock prices. The theoretical debate on the overvaluation effect of short-sale constraints also extends to empirical studies that examine the effect (Figlewski, 1981; Asquith & Meulbroek, 1995; Desai, Ramesh, Thiagarajan & Balachandran, 2002; Boehme, Danielsen & Sorescu, 2006; Chang et al., 2007; Charoenrook & Daouk, 2008). Such intensive interest by researchers in the price effect of short-sale constraints indicates that the issue is of significant importance. Have, however, previous studies fully researched the issue, so as to make a further inquiry redundant? My answer is no, based on the fact that none of them treats the short-selling ban as a regime and so their results are subject to subsequent queries of various kinds after being published. Additionally, the evidence given in the literature on this issue is still mixed.

In early empirical studies on short-selling restrictions, all of the authors use indirect measures to proxy for short-sale constraints.[7] Realising the drawbacks of the various indirect measures, a recent paper by Chang et al. (2007) opts for a direct measure of short-sale constraints, using an event-study methodology and providing evidence in support of Miller's theory. Contrary to these findings, however, Boehmer, Jones and Zhang (2008) and Diether, Lee and Werner (2009) report no significant price drops after the removal of the uptick rule (i.e., short-selling restrictions) in the US. In summary, empirical results reported so far are too inconclusive to help reach a verdict on conflicting theoretical predictions regarding overvaluation. This motivates me to continue to work on short-selling constraints.

I rely on data from the Hong Kong market for the following reasons. The first is that an ideal way to identify the "pure" overvaluation effect stemming only from a short-selling restriction is to compare the same stock across different short-selling regimes (e.g., the short-selling regime and the no-short-selling regime) in terms of their average prices (or returns). Comparing a stock that is restricted with another stock that is not restricted is likely to induce the problem that some confounding factors may well distort the results, leading to incorrect or imprecise conclusions, as it is impossible to control away all such factors as country characteristics and/or stock characteristics. That is, as far as testing overvaluation theories is concerned, the comparison of different stocks under different short-selling regimes is less accurately informative than comparison of results from the same stock undergoing different short-selling regimes. A short-selling restricted stock may exhibit returns higher than, lower than, or the same as, another, unrestricted stock, but it is hard to attribute the observation solely to the presence/absence of the short-selling restriction. These arguments apply to studies on stocks taken from the same country (exchange), and even more so to studies on

[7] Examples include short-selling feasibility indicator (Charoenrook & Daouk, 2008), short interest (Figlewski, 1981), option listings (Danielsen & Sorescu, 2001), breadth of ownership (Chen et al., 2002) and short-selling costs (Jones & Lamont, 2002).

stocks taken from different countries (exchanges). The Hong Kong data possess the advantage of enabling me to select stocks which alternate between opposite short-selling regimes more than once allowing for the carrying out of an empirical investigation in the ideal way mentioned above. Moreover, the Hong Kong data are not plagued with coincidence between short-selling bans and other public policy measures, such as TARP in the US.

Although employing data from the same market, this study differs from Chang et al. (2007). The authors treat the removal of short-selling constraints as an event, and detect significant price drops around the effective dates when stocks are added to the official short-selling list. An immediate question arises: Do such price drops also extend into the entire on-list period over which there are no short-sale constraints? This question is relevant: If the answer is no, it would imply that, for the remaining period of no short-sale constraints, overvaluation may come back, thereby violating Miller's theory. In addition, Chang et al. (2007) only consider the addition events and, hence, fail to address the following questions: What will happen when stocks are removed from the official list (i.e., when short-sale constraints are re-imposed on stocks)? Will there be significant price *hikes* around and after the effective *deletion* dates, as also predicted by the Miller theory? Therefore, it is necessary to complement Chang et al.'s (2007) addition-event evidence by exploring all these questions.[8] To this end, I adopt the same direct measure as in their study, but extend it to include the removal of individual stocks from the official list. It then follows naturally that, unlike Chang et al. (2007), I consider both the entire on-list period (referred to as the short-selling regime, or the SS regime for short) and the entire off-list period (referred to as the no-

[8] Chang et al. (2007) address the concern that price drops after addition events may be due to price pressure (not to the lifting of short-sale constraints) and, so, may be temporary. They argue that this concern is invalid, based on a window of 60 days, in which mean cumulative abnormal returns (CARs) remain negative throughout. Even if, however, the window is extended to, say, 120 days, it is still not long enough to cover the entire on-list period for many stocks that stay on the list for several years after their addition dates. On the other hand, if the window is extended to cover both the on-list and the subsequent off-list period, one would expect to see that CARs turn from negative to positive after deletion events. So, use of the observation that CARs remain negative throughout a window, however selected, can hardly be convincing in invalidating the concern.

short-selling regime, or the NSS regime for short) to determine any differences in stock price movements. If a lack of any one of the two conditions - short-sale constraints and opinion dispersion - means no overvaluation, then one would expect to see lower stock returns throughout the on-list period than throughout the off-list period, not only after the addition event dates in comparison to before these dates.

Furthermore, Chang et al. (2007) show that dispersion of opinions has a negative effect on cumulative abnormal returns (CARs) following the suspension of short-selling bans. They use this result to suggest that dispersion of opinions makes the overvaluation effect more dramatic. In fact, columns 1 to 3 and 7 to 8 of their Table V indicate that, when dispersion of opinions is zero (i.e., when investors' beliefs happen to be homogenous), CARs will become insignificantly different from zero. Only column 9 reports a significant negative estimate of the coefficient on intercept. These results provide strong evidence that short-selling bans and dispersion of opinions need to work together to induce overvaluation, which is consistent with Boehme, Danielsen and Sorescu's (2006) argument that both are required for the overvaluation effect to occur. As a step forward, I allow short-selling restrictions to impact the stock return directly, as well as indirectly via their interactions with dispersion of opinions. I do so to address a further question: When investors' beliefs happen to be homogenous, will short-selling bans still be able to induce overvaluation? Thus, by comparing two opposite short-sale regimes rather than focusing on addition event dates, one is able to find more convincing and complete overvaluation evidence if any exists.

In addition to testing the overvaluation effect, I also attempt to investigate whether and how stock characteristics are priced differently between the two distinct short-sale regimes. Traditional empirical asset pricing models, such as the multifactor model (Fama & French, 1992, 1993, 1996), do not take into account short-sale constraints pervasive in many security markets in the world. Faced with short-selling restrictions, investors' trading behaviour will be different than without such restrictions, which in turn may affect those anomalies well-documented in the asset pricing literature. The results on this issue should be of interest to practitioners who seek to minimise the trading costs of anomalies and so need to know the differences in the anomalies between shortable and non-shortable stocks.

Focusing on regime changes rather than addition/deletion events, I consider panel regression to be a more relevant method than an event study. There are two ways to estimate coefficients: The OLS; and the Fama-MacBeth (FM) procedure (Fama & MacBeth, 1973).[9] The FM procedure entails running *T* cross-sectional regressions and then computing the average of the *T* estimates for the coefficient in question. The FM procedure weights each period of data equally, however, even if there are a different number of observations per period; therefore, in an unbalanced panel data set, the coefficient estimates can differ (Cohen, Gompers & Vuolteenaho, 2002). Since my panel data are unbalanced, I opt for the OLS method for regression, but use the Panel Corrected Standard Errors (PCSE)[10]. Another advantage of OLS panel regression is that it alleviates the potential multicollinearity problem.

I examine individual stock returns rather than portfolio returns to eschew the data snooping problem. Lo and MacKinlay (1990) demonstrate that using portfolios formed on some characteristics suggested in previous studies to be related to average returns can distort inferences dramatically and lead to rejecting the null hypothesis too often. To prevent the aggravation of this problem caused by sorting to form portfolios, Brennan, Chordia and

[9] Either the OLS, or the FM estimate, of a coefficient is a constant for all cross-section units ($i = 1, 2, \ldots, N$) and all time points ($t = 1, 2, \ldots, T$). Petersen (2005) shows that the means and the standard errors of the OLS and FM estimates are almost identical and the correlation between the two estimates are never less than 0.999 in any of his simulations.

[10] Panel Corrected Standard Error (PCSE) computes standard error estimates for linear cross-sectional time-series models where the parameters are estimated by OLS, or Prais-Winsten, regression. When computing the standard errors and the variance-covariance estimates, PCSE assumes that the disturbances are heteroskedastic and contemporaneously correlated across panels.

Subrahmanyam (1998), Chui and Wei (1998) and Mobarek and Mollah (2005) all look at individual stock returns.

The remaining of this chapter is structured as follows. The next section conducts a literature review. Section 3.3 develops the testable hypotheses. Sections 3.4 and 3.5 describe the data and methodology used, respectively. Section 3.6 reports and discusses the results. Section 3.7 offers a summary and conclusions.

## 3.2 Literature Review

In this section, I review in more detail the previous studies that are related to my research in this chapter. As mentioned in the preceding section, Miller's (1977) overvaluation prediction is controversial, both theoretically and empirically. On the theoretical account, Miller (1977) theorises that constraining short sales will reduce market efficiency. Based on the assumption of heterogeneous expectations among investors, Miller argues that short-sale constraints lead securities to reflect more of the optimistic investors' opinions than of the average potential investors' opinions, resulting in upward biases of securities prices. That is, stock prices will be overvalued, as pessimistic investors cannot act on their bearish beliefs and remain out of the market.

Diamond and Verrecchia's (1987) study produces the no-overpricing result, which hinges, however, on the assumption that investors are both rational and risk-neutral. Specifically, in adjusting their valuations, investors, if less informed, will take into account the possibility that short-selling constraints keep outside the market those investors more informed about negative news. As a result, stocks will not be systematically over-priced in equilibrium. The indefinite-pricing result of Bai, Chang and Wang (2006) is based on the assumption that rational investors are risk-averse. Their reasoning is as follows. Short-selling constraints induce slower price discovery, which in turn increases risk. When rational and risk-averse investors are uninformed, they will perceive that the risk is increasing and, thus, require higher expected returns, causing prices to fall. On the other hand, a short-selling ban prevents risk-averse investors from taking on negative positions to hedge other risks, thereby increasing their demand for the stock and pushing up its price. The net effect of short-selling constraints on stock valuation is, therefore, ambiguous.

To empirically test Miller's overvaluation effect, Figlewski (1981), adopting the CAPM model, documents that homogenous investors can only push securities prices up, but heterogeneous investors may either increase, or decrease, stocks prices. Asquith and Meulbroek (1995) employ short interest to proxy for the level of shares that would be sold short if there were no short-sale constraints. They show that short interest has a statistically significant negative relation with subsequent abnormal returns. Desai et al. (2002), also using short interest data but taking a portfolio approach, suggest that heavily shorted stocks have significantly negative abnormal returns, implying that short-sale constraints lead to overpricing of stocks. Recent studies; such as Boehme, Danielsen and Sorescu (2006), Chang et al. (2007) and Charoenrook and Daouk (2008); have led to either conflicting results as to whether Miller's overpricing exists, or the result that the Miller effect does exist.

Unlike the above studies, which use indirect measures to proxy for short-sale constraints, Chang et al. (2007) employ a direct measure of short-sale constraints: The addition of individual stocks to the (Hong Kong) official list of designated securities that are allowed to be sold short. Based on the event study methodology, the authors detect significant price drops around the effective dates when stocks were added to the list (hence became shortable), and find that the role of differences of opinion is only to make the overvaluation effect more dramatic.

Studies of the US market, however, fail to find similar supportive evidence for the overvaluation theory. Apart from Boehmer, Jones and Zhang (2008) and Diether, Lee and Werner (2009), both mentioned in the preceding section, two more studies examine the stock price effect after the US re-imposed the short-selling ban in 2008. Boehmer and Wu (2013) document that the start of the short-selling bans are associated with a sharp increase in share prices for affected stocks, but the negative price effect from lifting the ban is only temporary. Since the former result could also be due to the concomitant announcements of bank bailout interventions, Harris, Namvar and Phillips (2009) control for that possibility and confirm that banned stocks experienced price inflation during the ban period, although the inflation of some banned stocks remained after the lifting of the ban.

Suspecting that the coincidence between the inception of short-selling bans and the implementation of the bank bailout programme (TARP) may make the price effects of the ban unidentifiable, Beber and Pagano (2013) turn to a study of 30 countries over the 2007-2009 crisis period for international evidence. They find that the over-pricing effects of short-selling bans apparently present in the US data are absent in the rest of the world.

From the above literature review, one can see that previous empirical studies fail to reach a consensus on the overvaluation theory. A closer look at these studies helps me to identify two gaps in the research, for which my study generates less disputable evidence. The two most important gaps include two failures: The failure to compare the different pricing behaviours of the *same* stock that undergoes different short-selling regimes; and the failure to perform regime analysis, rather than event analysis.

While the overvaluation theory has been extensively studied, the effects of short-selling restrictions on the pricing of stock characteristics have been largely ignored in the asset-pricing literature. One study that inspires my interest in investigating this issue is Bris et al. (2007). The authors consider 46 countries for testing the effects of short-sale constraints on market efficiency by comparing markets in which short sales are allowed, or practiced, with markets in which there are no short sales. The study documents that the markets with short-sale constraints have statistically significant less negative skewness in returns and more efficient price discovery, resulting in higher idiosyncratic risk and less price co-movements. This implies that the presence of short-selling restrictions will affect investor trading behaviours and, hence, the anomalies associated with firm characteristics. I regard firm characteristics as idiosyncratic risk factors. Therefore, it is very important, meaningful and interesting to look at the pricing differences of firm characteristics when stocks are moving between the shortable and non-shortable regimes.

It is worth mentioning that many existing studies on short-sale constraints, such as Berkman, Dimitrov, Jain, Koch and Tice (2009), also include some stock characteristics (e.g., size and book-to-market) in their empirical analyses. They take stock characteristics merely as control variables, however, while looking at other issues. Moreover, their indirect measures of short-sale constraints can, at best, proxy for different binding degrees of the constraints and cannot differentiate between two polar regimes. For example, a widely-used proxy for short-sale constraints is institutional ownership: It is assumed that the lower the level of institutional ownership, the higher the binding degree of short-sale constraints. If, however, stocks are on (off) the official list for short selling, they are anyway shortable (not shortable) no matter how high/low their institutional ownership is. Also, shortable stocks (on the list) could have lower institutional ownership than those which are not shortable (off the list) at all. In any event, institutional ownership is irrelevant to demarcating a certain stock concerning the presence and the nonexistence of short-sale constraints. While how the pricing of stock characteristics changes with changes in the binding degree of short-sale constraints is worth exploring, studying the yes-or-no short-sale cases should bring forth truly clear-cut differences in the pricing of stock characteristics between the two opposite regimes, if any such differences do exist.

To summarise, my work reported in this Chapter adds new contributions to the study of short-sale constraints by conducting regime analysis of Miller's overvaluation prediction, and of the pricing behaviours of stock characteristics through comparing the same stocks that traverse two opposite short-selling regimes.

## 3.3 Hypotheses

In this section, I develop seven hypotheses for testing; pertaining to the abnormal returns (alpha), firm size, book-to-market (B/M), illiquidity, earnings-to-price (E/P), dividend yields, and dispersion of opinion.

As reviewed above, Chang et al. (2007) argue that much of the negative cumulative abnormal returns can be attributed to the lifting of short-sale constraints, not to a downward price pressure around the addition-event date. To go beyond their unidirectional addition-event evidence and, more importantly, in accordance with Miller's (1977) overpricing theory, I conjecture that, on average, abnormal returns should increase significantly when stocks switch from the SS to the NSS regime, or decrease significantly when they switch from the NSS to the SS regime. Based on the regression model (3.1) specified later in this chapter, such bidirectional changes in average abnormal returns are embodied in Hypothesis 1, below.

*Hypothesis 1: The intercept, $\alpha$, from Equation (3.1) (interpreted as the mean abnormal return, or the mean risk-compensation-adjusted return) is higher when short-selling is not allowed than when it is allowed.*

The size effect in stock markets has been extensively studied. Banz (1981) documents that, in the US stock market, stocks with smaller market capitalisation are likely to have higher average returns than stocks with larger market capitalisations. Since Banz (1981), more empirical evidence has been generated in line with the size effect; i.e., the negative relation between firm size and stock returns has, however, had counterevidence, or no evidence, reported.[11] The size effect is interpreted as smaller firms paying a higher cost of capital, since they are often considered to be more financially distressed. Following this notion, if investors cannot short the stocks of smaller sized firms, the stocks will be more overpriced – i.e., the firms will pay an even higher cost of capital, other things being equal. Also, in Bai et al.'s (2006) theoretical model, it is predicted that the cost of capital is higher under short-sale constraints if there is a high degree of information asymmetry. Combining this theoretical prediction with my intuitive reasoning yields the second hypothesis, as stated below.

*Hypothesis 2: The effect of firm size on stock returns is more negative when short selling is not allowed than when it is allowed.*

My third focus is on detecting possible changes in the B/M effect across the SS and the NSS regime. There are two kinds of the B/M effect. One is known as the value effect (or premium), referring to a positive relation between stock returns and the B/M ratio. The other

[11] See, among others, Lamoureux and Sanger (1989), Jegadeesh (1992), Fama and French (1993, 1996), Daniel and Titman (1997), Chui and Wei (1998), Campbell (2000), Daniel, Titman and Wei (2001) and Sehgal and Tripathi (2005).

is called the growth effect, where the relation is negative. Most studies have found the value effect, while some have reported evidence for the growth effect.[12] The B/M ratio is also interpreted as a measure of risk (Fama & French, 1993, 1996). So, the higher the ratio, the higher the risk, and the higher should be the (value) premium as a compensation for this risk. Some investors, when perceiving such risk, may desire to take negative positions in the stocks, which would reduce the demand for, and hence the prices of, such stocks. Banning short sales, however, will prevent them from doing so, thereby shifting the overall demand for, and hence the prices of, the stocks upward. Accordingly, I hypothesise that:

*Hypothesis 3: The effect of B/M on stock returns is more positive when short selling is not allowed than when it is allowed.*

My fourth goal is to examine whether illiquidity is priced differently under the two opposite short-selling rules. Using the bid-ask spread as an illiquidity measure, Amihud and Mendelson (1986) show that illiquidity is priced. Chordia, Roll and Subrahmanyam (2001), Jones (2001), Amihud (2002) and Bekaert, Harvey and Lundblad (2007) find that illiquidity co-moves with returns and predicts future returns. Illiquidity is perceived by investors as a risk characteristic. A positive illiquidity shock (a rise in illiquidity) predicts high future illiquidity, which raises ex ante expected returns by lowering current prices/returns. Consistent with these rationales, many empirical studies (Amihud, 2002; Chordia et al., 2001; Acharya & Pedersen, 2005; Bekaert et al., 2007) suggest that illiquidity has a negative relation with contemporaneous stock returns, but a positive relation with future stock returns.

[12] The value effect has been documented in Stattman (1980), Rosenberg, Reid and Lanstein (1985) and Chan, Hamao and Lakoniskok (1991). The growth effect has been documented in Harris and Marston (1994) and Cooper, Gulen and Schill (2008).

Diamond and Verrecchia (1987) predict an increase in the bid-ask spread and, hence, in illiquidity when short-selling is prohibited. The rise in illiquidity reflects the lower supply of stocks for sales, because some investors, who want to sell stocks but do not own them, cannot participate in the market. Charoenrook and Daouk (2008) confirm that illiquidity is higher in markets where short-selling is not possible. I go further to ask whether the change in illiquidity due to changes of the short-sale regime will change the illiquidity effect on stock returns. The decreased supply of stocks due to short-sale constraints should lead to excess demand for them, including those with increased illiquidity. This in turn should, *ceteris paribus*, raise their prices/returns. Based on the above reasoning, I formulate a hypothesis as follows:

*Hypothesis 4: The effects of lagged and contemporaneous illiquidity on stock returns are less negative (more positive) when short selling is not allowed than when it is allowed.*

Fama and French (1992) show that average returns increase with the E/P ratio when it is positive. This is because, if current earnings are positive, they proxy for expected future earnings; also, high-risk stocks with high expected returns will have low prices relative to their earnings. The authors also find that the positive relation between average returns and positive E/P is due to the positive correlation between E/P and B/M. This suggests that the positive slope on E/P is likely to capture part of the value premium. To the extent that this is true, I expect to see that the changing pattern of E/P is similar to that of B/M across the NSS and the SS regime. That is:

*Hypothesis 5: The effect of E/P on stock returns is more positive when short selling is not allowed than when it is allowed, if E/P captures part of the B/M effect.*

According to La Porta, Lopez-de-Silanes, Shleifer and Vishny (2000) and Faccio, Lang and Young (2001), dividends play a significant role in limiting insider expropriation. Thus, if investors prefer the stocks that return cash flows to outside shareholders to those that do not, they will be willing to pay a premium for the former. In this case, a rise in dividend yields would imply a fall in future returns. If stocks are overpriced, however, the premium that investors have to pay will be smaller, suggesting that a given rise in dividend yields would reduce future returns by a smaller amount. Equivalently, I hypothesise that:

*Hypothesis 6: The effect of dividend yields on future stock returns is less negative when short selling is not allowed than when it is allowed.*

In Miller's overpricing theory, an important factor is dispersion of investor opinion: In the presence of short-sale constraints, differences of opinion lead to stock price overvaluation. Consistent with the Miller hypothesis, Diether et al. (2002) find that stocks with higher dispersion of opinion forecast lower future returns. More recently, Berkman et al. (2009) use various measures of differences of opinion in quarters *prior to* the earnings-announcement quarter and find that greater differences of opinion *forecast* lower earnings-announcement-period returns. They attribute this negative relation to the conjecture that, upon the release of new information via earnings announcements, differences of opinion among investors are reduced, leading to lower average returns around the announcement events. This conjecture in effect means that a negative inter-temporal relation between differences of opinion and returns implies a positive contemporaneous relation between them, and vice versa. Accordingly, in my panel regression analysis, it would be one-sided to focus on either a contemporaneous, or an inter-temporal, relation. In addition, Boehme et al. (2006) explore the valuation effects of the interaction between differences of opinion and short-sale constraints. They provide robust evidence of significant overvaluation for stocks that are subject to both of these conditions simultaneously. Motivated by the above-cited works, I conjecture that:

*Hypothesis 7: The effect of dispersion of opinion on current stock returns is more positive, but the effect of dispersion of opinion on future stock returns is more negative, when short selling is not allowed than when it is allowed.*

## 3.4 Data

As described in Chapter 2, since 1994, two opposite short-sale regimes have coexisted in the Hong Kong stock market. If a stock is added to the list, I state that it switches from the NSS regime to, and thereafter stays under, the SS regime, where its short selling is permitted. If a stock is deleted from the list, I state that it switches from the SS regime to, and thereafter stays under, the NSS regime, where its short selling is forbidden. My definitions of the SS and NSS regimes are based on the effective dates, rather than the announcement dates, of changing the short-selling status of a stock. This is because only from the effective dates onwards can the added stock be sold short, or the deleted stock cannot be sold short. Among the stocks on the Hong Kong stock exchange, some have never been added to the list, while others have never been removed from the list since their first addition. There are eleven criteria for stocks to qualify for short-selling, which are downloadable from the website of the Hong Kong Stock Exchange.

The uniqueness of Hong Kong's regulations on short sales presents me with an ideal laboratory for exploring the differences in pricing behaviour due to a stock changing from one regime to the other. Specifically, based on the designated short-selling list (See Table 2.1 in Chapter 2), I divide all stocks traded on the Hong Kong Stock Exchange into three categories. Category 1 contains stocks that have never been added to the list, meaning that they stay under the NSS regime throughout my sample period. There are 514 stocks in this category, most of which are small-cap stocks. Category 2 comprises stocks that have never been removed from the list since their first addition to the list. That is, they experienced either no, or just one, change in the short-selling regime throughout my sample period from January 1, 1994 to December 31, 2009. There are 376 stocks in this category, the majority of which are large-cap stocks. Category 3 embraces stocks that are added to and deleted from the list at least once; namely, they alternate between the SS and the NSS regime more than once over my sample period. There are 514 stocks in this category.

Comparing different stocks (from either a single market, or multiple markets) under different short-selling regimes makes it harder to identify the pure pricing effect than it is to compare the same stocks that experience different regimes. This may be the reason why previous studies on short-sale constraints have yielded conflicting and unconvincing evidence. Thus, if I was to examine Category 1 and Category 2, I would likely go astray in a similar way: It would again be difficult to disentangle the detected those due to regime changes, from differences due to other concurrent factors. On the other hand, if no changes in the pricing behaviour are detected, it is also difficult to conclude that regime changes do not have price effects, since other concurrent factors could nullify regime changes. Such factors arise from the fact that stocks in Category 1 are not the same stocks as those in Category 2, even if these different stocks satisfy the eleven criteria for being qualified for short-selling. In view of all these considerations and minimising the possible endogeneity problem, I opt for Category 3 for the empirical investigation, as stocks in this category have gone through more than one change in the short-selling regime, and changes in their other characteristics (e.g., size) are not as drastic as the differences between Category 1 (Small Caps) and Category 2 (Large Caps). Hong Kong's unique short-sale regulations make my choice of Category 3 possible, which differentiates my study from the recent ones of short-sale bans in other markets, such as the US.

Despite the fact that this paper reports the results for Category 3's stocks only, I collect the required data for all 1,404 stocks. The data includes closing prices, market values, B/M ratios, trading volumes (turnovers), shares outstanding, E/P ratios and dividend yields. These data were sourced from DataStream. I also downloaded the bid and ask data on individual stocks from SIRCA. To be included in my analysis, I require that stocks must have at least 18 months' data on the variables used. Applying these screening criteria, I deleted 52 stocks from Category 3, which leaves me with 462 stocks for analysis. Although the required data are all readily reported at daily frequency in the data sources noted above, I obtained monthly data by applying certain methods of frequency conversion. So, my sample period spans the period from January 1994 through to December 2009 inclusive. In addition, the monthly number of stocks ranges from 206 (January 1994) to 461 (July, 2008 through December, 2009), and the numbers of months for which a stock has data available ranges from 18 (1 stock) to 102 (205 stocks), resulting in an unbalanced panel.

### 3.5 Methodology

My panel data (after screening) are unbalanced: The number of stocks varies across different months, with the minimum and maximum number of companies being, respectively, 208 (January 1994) and 464 (December 2009). Such unbalanced panel data limits the usefulness of the Fama-MacBeth procedure (Fama & Macbeth, 1973) in estimating coefficients, as different periods' estimates correspond to different sets of cross-sections. It is also inappropriate to use those panel data regressions that estimate the intercepts separately for each company, as the minimum (effective) number of time-series observations in my sample is 18, thereby causing the problem of small-sample bias for the estimated slope coefficients. Moreover, my research questions are concerned with differences in the intercepts between the stocks under the SS regime and the stocks under the NSS regime, not between individual stocks. In view of these considerations, I adopt the OLS panel regression model (fixed-effect), as follows.

To test the seven hypotheses developed in Section 3.3, I specify the following empirical baseline panel regression model:

$$R_{i,t} \text{ (or } r_{i,t}) = \alpha + \beta_i R_{mt} + \boldsymbol{\gamma Z} + \boldsymbol{\theta C} + \mu_i + e_{i,t} \tag{3.1}$$

where $\gamma = [\gamma 1\ \ \gamma 2\ \ \ldots\ \gamma 8]$, Z = [$SZ_{i,t-1}$ $BM_{i,t-1}$ $ILQ_{i,t}$ $ILQ_{i,t-1}$ $EP_{i,t-1}$ $YLD_{i,t-1}$ $DO_{i,t}$ $DO_{i,t-1}$], $\theta = [\theta_1\ \ \theta_2\ \ \theta_3]$ and C = [$RET_{1\text{-}3}$ $RET_{4\text{-}6}$ $RET_{7\text{-}12}$]'. The definitions of the variables in Equation (3.1) are given in Table 3.1. All the variables included in my analysis are common in the empirical asset-pricing literature. As the variables display considerable skewness (not reported), all of them except the dividend yield ($YLD_{i,t}$) take the logarithmic form to mitigate the skewness problem. The dividend yield contains some observations of zero, while other variables do not. See Brennan et al. (1998) for similar functional-form treatments of $YLD_{i,t}$ and other variables.

Equation (3.1) indicates that I classify regressors into three groups: The market risk factor (i.e., the beta associated with $R_{mt}$ or $r_{mt}$); the vector of stock characteristics (***Z***); and the vector of control variables (***C***). Equation (1) also demonstrates that I examine a cross-sectional relation between current returns and lagged characteristics variables (except for $ILQ_{i,t}$ and $DO_{i,t}$). That is, I am mainly interested in the forecasting power of stock characteristics for returns.[13]

[13] In the empirical asset-pricing literature, most studies (e.g., Fama & French, 1992; Brennan et al., 1998, 2001; Korajczyk & Sadka, 2008) look at the cross-sectional relation between current returns and *lagged* stock/portfolio characteristics. Others (e.g., Chui & Wei, 1998; Liu, 2006) focus on the contemporaneous, cross-sectional relation between returns and stock/portfolio characteristics. My study falls into the former strand of the literature. In particular, I follow Korajczyk and Sadka (2008) (who cross-sectionally regress monthly returns on asset *i* for month *t* against a vector of characteristics for asset *i* observed at month *t*-1), but with slight modification.

**Table 3.1 Description of variables**

| Variables | Description |
|---|---|
| $r_{i,t}$ | Raw returns on stock *i* in month *t*. Monthly returns are calculated as the sum of daily returns in month *t*, while daily returns are calculated as the difference between the natural logarithm of the daily closing stock price of the current (business) day and that of the previous (business) day. |
| $R_{i,t}$ | Excess returns on stock *i* in month *t* (i.e., $r_{i,t}$ less the risk-free rate). The risk-free rate is proxied by the HK one-month inter-bank offer rate.[14] |
| $r_{mt}$ | Raw returns on the market portfolio, using the Hang Seng Index returns and my self-constructed value-weighted average returns of all shares traded on the HKSE. The method of calculation is the same as for $r_{i,t}$. |
| $R_{mt}$ | Excess returns on the market portfolio in month *t* (i.e., $r_{mt}$ less the risk-free rate). |
| $SZ_{i,t}$ | Size, calculated as the natural logarithm of the average market value of stock *i* in month *t*. |
| $BM_{i,t}$ | Book-to-market ratio, calculated as the natural logarithm of the average book-to-market ratio of stock *i* in month *t*. |
| $ILQ_{i,t}$ | Illiquidity, measured by the natural logarithm of the average bid-ask spread divided by its mid-point, of stock *i* in month *t*. |
| $ILQ_{i,t-1}$ | $ILQ_{it}$ lagged 1 month. |
| $EP_{i,t}$ | Earnings-to-price ratio, calculated as the natural logarithm of the average earnings-to-price ratio of stock *i* in month *t*. |
| $YLD_{i,t}$ | Dividend yield, measured by the average of the dividend per share as a percentage of the share price for stock *i* in month *t*. |
| $DO_{i,t}$ | Differences in opinion, proxied by stock *i*'s turnover (measured by volume) divided by its number of shares outstanding in month *t*. |
| $DO_{i,t-1}$ | $DO_{i,t}$ lagged 1 month. |
| $SDM_{i,t-1}$ | A proxy for dispersion of opinions, calculated as the standard deviation of the errors from regressing stock *i's* daily raw returns against the daily ASI returns over one or two months prior to the first day of the current month *t*, in natural logarithm. |
| *RET1-3* | Cumulative returns over the three months ending at the beginning of the current month (i.e., from month *t*-3 to month *t*-1). *RET1-3_SS* represents *RET1-3* under the SS regime. *RET1-3_NSS* represents *RET1-3* under the NSS regime. |
| *RET4-6* | Cumulative returns over the three months ending three months previously (i.e., from month *t*-6 to month *t*-4). *RET4-6_SS* represents *RET4-6* under the SS regime. *RET4-6_NSS* represents *RET4-6* under the NSS regime. |
| *RET7-12* | Cumulative returns over the three months ending six months previously (i.e., from month *t*-12 to month *t*-7). *RET7-12_SS* represents *RET1-12* under the SS regime. *RET7-12_NSS* represents *RET7-12* under the NSS regime. |
| $u_i$ | The time-invariant individual specific effect not included in the regression. |
| $\xi_{it}$ | The remainder disturbances, which vary with firms and time. |

*Note:* "Average" means taking the sum of daily observations within a given month and then dividing the sum by the number of trading days in that month. This gives me the average monthly observations of a variable.

[14] Many studies on the Hong Kong stock market have used the HK one-month inter-bank rate to proxy for the risk-free rate, such as Chang *et al*. (2007) and Lam and Tam (2011), to name just a few. My study reported in this chapter follow these studies, especially Chang et al (2007). The purpose of doing so is to make my results comparable with theirs.

Some remarks may be in order. First, when computing market portfolio returns ($R_{m,t}$ or $r_{mt}$), I construct the value-weighted average returns of all shares traded on the HKSE in month $t$ (to be referred to as all-share index returns, or ASI returns) alongside the use of the Hang Seng Index (HSI) returns. The HSI has only 43 constituent companies, although it covers approximately 65% of the total market capitalisation in Hong Kong, while my sample contains more than 10 times the number of companies in the HSI. In addition, there is debate in the literature about the sensitivity of results to the use of different index returns as a proxy for market portfolio returns (Bruner et al., 2008). Due to this debate, I will report my results based on the two proxies for the HK market.

Second, I include both current and lagged measures of illiquidity ($ILQ_{i,t}$ and $ILQ_{i,t-1}$) in Equation (3.1), because Amihud (2002) and Bekaert et al. (2007) show that illiquidity predicts future returns with a positive sign, but is contemporaneously negatively correlated with returns. While focusing on structural change due to regime switching, I attempt to determine whether evidence from the Hong Kong data is consistent with these previous results. In addition, Amihud (2002) notes that the bid-ask spread is a finer and better measure of illiquidity than other measures, provided that the required microstructure data are available. Since such data are available, I adopt this measure of illiquidity, but use the ratio of the bid-ask spread to its mid-point.

Third, the E/P ratio ($EP_{i,t}$) does not have negative observations, so I do not have to separate $EP_{i,t}$ into positive $EP_{it}$ and a dummy for negative $EP_{it}$, as in, for example, Fama and French (1992) and Eun and Huang (2007).

Fourth, I proxy dispersion of opinion ($DO_{i,t}$) by a stock’s turnover (that is, the number of its shares traded) divided by the number of its shares outstanding. Berkman et al. (2009)

argue that this is one of the best short-term measures of $DO_{i,t}$, as it can be computed using recent data. The higher the $DO_{i,t}$, the more divergent opinions will be about a certain stock *i*.

Fifth, Jegadeesh (1990) shows that thin trading will cause risk-adjusted returns to exhibit negative first-order serial correlation. In order to control for the biases, or spurious relations, due to possible thin trading, I include three lagged return variables ($RET_{1-3}$ $RET_{4-6}$ $RET_{7-12}$). This also allows me to determine whether momentum effects exist.

Finally, I use a fixed-effect panel model, because Hausman's (1978) test (not reported) decisively rejects the random-effect in favour of the fixed-effect model. $\mu_i$ denotes the *unobservable* individual stock's specific effect, or the *unexplained* cross-sectional variation.

Examining the incremental explanatory power of stock characteristics (and control variables) beyond the CAPM benchmark, I move the market risk factor to the left-hand side of Equation (3.1). Then, I add a regime indicator variable $SS_{i,t}$ to Equation (3.1) to interact with all the regressors. $SS_{i,t}$ equals 1 if stock *i* is on the official list (i.e., in the SS regime) in month *t*, 0 if it is off the list (i.e., in the NSS regime) in month *t*, and a pro rata value if it on the list for part of month *t*. The modifications lead to:

$$R^*_{i,t} \text{ (or } r^*_{i,t}) = \alpha + \alpha_1\left(1 - SS_{i,t}\right) + \boldsymbol{\gamma Z} + \boldsymbol{\gamma}_1\left[\left(\mathbf{1} - \boldsymbol{SS}\right)\boldsymbol{Z}\right] + \boldsymbol{\theta C} + \boldsymbol{\theta}_1\left[\left(\mathbf{1} - \boldsymbol{SS}\right)\boldsymbol{C}\right] + \mu_i + e_{i,t} \qquad (3.2)$$

where $R^*_{i,t} \equiv R_{i,t} - SS_{i,t}\beta_{iSS}R_{mt} - (1-SS_{i,t})\beta_{iNSS}R_{mt}$ (or $r^*_{i,t} \equiv r_{i,t} - SS_{i,t}\beta_{iSS}r_{mt} - (1-SS_{i,t})\beta_{iNSS}r_{mt}$), $\boldsymbol{\gamma_1} = [\gamma'_1 \;\; \gamma'_2 \;\; \ldots \;\; \gamma'_8]$, $\mathbf{1} - \boldsymbol{SS} = \text{diag}[1-SS_{i,t-1} \;\; 1-SS_{i,t-1} \;\; 1-SS_{i,t} \;\; 1-SS_{i,t-1} \;\; 1-SS_{i,t-1} \;\; 1-SS_{i,t-1} \;\; 1-SS_{i,t} \;\; 1-SS_{i,t-1}]$ and $\boldsymbol{\theta_1} = [\theta'_1 \;\; \theta'_2 \;\; \theta'_3]$. Other variables and parameters are defined as for Equation (3.1). Every regressor in Equation (3.2) has an additional interaction term associated with the NSS regime (symbolised by $1-SS_{i,t}$). This enables me to test differences arising from regime changes. For example, $\gamma'_1$ measures the effect of firm size when the stock is under the NSS regime (i.e., when $SS_{i,t}$ = 0). If $\gamma_1^{'}$ is negative and statistically significant, I will be able to accept *Hypothesis 2* that the effect of firm size on stock returns is more strongly negative when the stock does not qualify for short sales than when it does qualify. In addition, to obtain observations on the beta-adjusted excess (or raw) returns $R_{i,t}^{*}$ (or $r_{i,t}^{*}$) or, equivalently, to estimate $\beta_{iSS}$ and $\beta_{i\mathrm{NSS}}$ (the betas associated with, respectively, the SS and the NSS regime), I simply run a regression of the excess (raw) stock returns $R_{i,t}$ (or $r_{i,t}$) against $SS_{i,t}R_{mt}$ and $(1-SS_{i,t})R_{mt}$ (or against $SS_{i,t}r_{mt}$ and $(1-SS_{i,t})r_{mt}$) for each individual stock *i*.

### 3.6 Empirical results

Table 3.2 sets out some descriptive statistics for the variables used in my empirical work. As can be seen from the table, the variables should all be free of outliers, as they fall within reasonable ranges. I test the equality of means between the raw stock returns under the SS and NSS regimes (i.e., between -0.0014 and 0.0001) with the t-statistic (-15.84) and the Satterthwaite-Welch-test statistic (-16.17). Both of them decisively reject the equality hypothesis, indicating that the former mean is smaller than the latter at a higher than 1% level. This may be viewed as preliminary evidence that a stock is overvalued under the ban regime, as compared to the no-ban regime. To ensure no spurious regression, I perform two panel unit-root tests (IPS and ADF-Fisher), which indicate that my panels are indeed stationary. Although not shown in the table for the sake of brevity, the variables are, as usual, non-normal. This may cause the regression errors to be non-normal and heteroscedastic. This does not, however, concern me very much. Orme and Yamagata (2006) show that, under non-normality, the commonly used *F* test statistic (for fixed effects) still provides asymptotically valid inferences. As for the panel heteroscedasticity problem, I resort to the PCSEs as a solution.

**Table 3.2 Selected summary statistics**

| Variables | Pooled median | Pooled mean | Pooled max | Pooled min | Pooled std dev | Pooled unit root |
|---|---|---|---|---|---|---|
| $r_{i,t}$ | 0.000 | -0.006 | 3.393 | -3.399 | 0.213 | No |
| $R_{i,t}$ | -0.042 | -0.042 | 3.335 | -3.460 | 0.217 | No |
| $r_{i,t\_SS}$ | -0.001 | -0.001 | 0.058 | -0.130 | 0.010 | No |
| $r_{i,t\_NSS}$ | 0.000 | 0.000 | 0.162 | -0.486 | 0.010 | No |
| $r_{mt\_HSI}$ | 0.013 | 0.006 | 0.255 | -0.347 | 0.078 | No |
| $R_{mt\_HSI}$ | -0.021 | -0.029 | 0.193 | -0.447 | 0.084 | No |
| $r_{mt\_ASI}$ | 0.012 | 0.007 | 0.271 | -0.348 | 0.078 | No |
| $R_{mt\_ASI}$ | -0.024 | -0.033 | 0.211 | -0.468 | 0.086 | No |
| $SZ_{i,t}$ | 6.382 | 6.403 | 13.120 | 1.910 | 1.305 | No |
| $BM_{i,t}$ | 0.165 | 0.105 | 3.971 | -8.608 | 1.001 | No |
| $ILQ_{i,t}$ | -3.837 | -3.720 | 0.693 | -9.011 | 0.878 | No |
| $EP_{i,t}$ | -2.238 | -2.315 | 5.438 | -9.777 | 1.096 | No |
| $YLD_{i,t}$ | 0.008 | 0.026 | 1.097 | 0.000 | 0.044 | No |
| $DO_{i,t}$ | -6.998 | -7.140 | 1.046 | -21.378 | 2.042 | No |

*Notes*. *(a)*,This table presents selected descriptive statistics for each variable (pooled together) involved in the panel data regressions. Two panel unit-root tests (IPS and ADF-Fisher) are used in judging whether a panel unit root is present. *(b)*, Market value is downloaded from Datastream with the unit in thousand. *(c)*, I am not using P/E ratio, as the value of earning per share may be Zero.

Another concern pertains to the fact that, when residuals are correlated across firms, or across time, the OLS (and the FM) standard errors can be biased (Petersen, 2005). Thus, I test for autocorrelation of order 1 in the residuals, with the Durbin-Watson statistics in Tables 3.3 and 3.4 indicating no evidence of autocorrelation. Having ascertained the non-existence of autocorrelation, I then calculate the Beck and Katz (1995) PCSEs. The PCSE is especially relevant to my study: It is precisely aimed at adjusting for both panel heteroscedasticity and contemporaneous correlation of the residuals across firms (Beck & Katz, 1995).

Several messages emerge from Tables 3.3 and 3.4. Let me begin by considering alpha – the risk-compensation-adjusted return. The two tables indicate that both *Intercept* and the (1-$SS_{i,t}$) coefficient are positive and highly significant, in all of the eight models. This suggests that the risk-compensation-adjusted return is significantly higher under the NSS regime, where short sales are forbidden, than under the SS regime, where short sales are permitted. The SS regime makes alpha drop by a range between 0.1388 and 0.1695, depending on which model specification is used. I take these observations as strong evidence in support of *Hypothesis 1*. My regime-change evidence complements Chang et al.'s (2007) addition-event evidence: Significant price drops are not just a temporary phenomenon following the dates of removing short-sale constraints; rather, they prevail permanently throughout the entire period when there are no short-sale constraints. I view this finding as more complete and convincing support for Miller's (1977) overvaluation theory.

Turning to the effect of firm size, I observe no qualitative differences between the two tables. The estimated coefficient of $SZ_{i,t-1}$ is negative and highly significant throughout. There is, therefore, very strong evidence of the well-known size effect for the HK stock market. As far as the estimated (1-$SS_{i,t-1}$)*$SZ_{i,t-1}$ coefficient is concerned, it is again negative throughout. It is, however, insignificantly different from zero in six of the eight models, and is significant at the 10% level in the remaining two models (columns 4 and 5 of Table 3.4). These observations serve my purpose to test *Hypothesis 2*: I find moderate evidence that short-selling restrictions would reinforce the size effect.

Next, I consider the B/M effect. As can be seen from the two tables, the estimated $BM_{i,t\text{-}1}$ coefficient is positive and significant at the 1% level across the eight model specifications. This indicates that the well-known value effect is present in the HK stock market. Regarding the estimated $(1\text{-}SS_{i,t\text{-}1})*BM_{i,t\text{-}1}$ coefficient, however, both Table 3.3 and Table 3.4 show that it is insignificant, albeit positive as expected. Based on these observations, I cannot claim any evidence in favour of *Hypothesis 3*. Some researchers (e.g., Nagel, 2005; Phalippou, 2007) attribute the value effect to tight short-sale constraints. If this is true I expect to see that, moving from the SS to the NSS regime, stocks would significantly raise their value effects on returns. My findings reported here do not, however, lend strong support to the expectations.

**Table 3.3 Panel regressions with beta-adjusted excess returns as the dependent variable**

| Regressor | All-Share Index Returns | | Hang Seng Index Returns | |
|---|---|---|---|---|
| *Intercept* | 0.155*** (8.616) | 0.158*** (8.521) | 0.159*** (8.663) | 0.159*** (8.430) |
| $(1\text{-}SS_{i,t})$ | 0.141*** (7.249) | 0.139*** (6.962) | 0.156*** (7.861) | 0.151*** (7.445) |
| $SZ_{i,t\text{-}1}$ | -0.016*** (-6.475) | -0.017*** (-6.715) | -0.016*** (-6.201) | -0.016*** (-6.249) |
| $(1\text{-}SS_{i,\,t\text{-}1})*SZ_{i\ t\text{-}1}$ | -0.003 (-1.320) | -0.003 (-1.126) | -0.003 (-1.233) | -0.003 (-1.053) |
| $BM_{i,\,t\text{-}1}$ | 0.030*** (10.12) | 0.031*** (10.10) | 0.033*** (11.04) | 0.034*** (10.87) |
| $(1\text{-}SS_{i,\,t\text{-}1})*BM_{i,\,t\text{-}1}$ | 0.000 (0.082) | 0.000 (0.151) | 0.000 (0.047) | 0.000 (0.031) |
| $ILQ_{i,t}$ | -0.056*** (-16.53) | -0.056*** (-15.99) | -0.061*** (-17.60) | -0.060*** (-16.88) |
| $(1\text{-}SS_{i,t})*ILQ_{i,t}$ | 0.001 (0.385) | 0.001 (0.293) | 0.006 (1.627) | 0.006 (1.493) |
| $ILQ_{i,t\text{-}1}$ | 0.020*** (5.740) | 0.019*** (5.466) | 0.021*** (5.938) | 0.021*** (5.753) |
| $(1\text{-}SS_{i,t\text{-}1})*ILQ_{i,t\text{-}1}$ | 0.013*** (3.506) | 0.013*** (3.460) | 0.012*** (3.216) | 0.012*** (3.069) |
| $EP_{i,\,t\text{-}1}$ | 0.000 (0.042) | 0.000 (0.169) | 0.001 (0.322) | 0.001 (0.396) |
| $(1\text{-}SS_{i,\,t\text{-}1})*EP_{i,\,t\text{-}1}$ | 0.002 (0.789) | 0.002 (0.913) | 0.001 (0.641) | 0.002 (0.812) |
| $YLD_{i,\,t\text{-}1}$ | -0.124** (-2.365) | -0.109** (-2.017) | -0.118** (-2.213) | -0.107* (-1.947) |
| $(1\text{-}SS_{i,\,t\text{-}1})*YLD_{i,\,t\text{-}1}$ | 0.068 (1.218) | 0.047 (0.824) | 0.068 (1.217) | 0.051 (0.885) |
| $DO_{i,t}$ | 0.032*** (18.78) | 0.032*** (18.68) | 0.035*** (20.22) | 0.035*** (20.24) |
| $(1\text{-}SS_{i,t})*DO_{i,t}$ | 0.014*** (7.891) | 0.014*** (7.677) | 0.013*** (7.032) | 0.013*** (6.723) |
| $DO_{i,t\text{-}1}$ | -0.022*** (-13.39) | -0.023*** (-13.45) | -0.024*** (-14.21) | -0.025*** (-14.43) |
| $(1\text{-}SS_{i,t\text{-}1})*DO_{i,\,t\text{-}1}$ | -0.007*** (-4.042) | -0.007*** (-3.772) | -0.006*** (-3.411) | -0.006*** (-3.108) |
| *RET*1-3_SS | - | 0.004 (0.737) | - | 0.011** (2.276) |
| *RET*1-3_NSS | - | 0.004 (0.797) | - | 0.009* (1.755) |
| *RET*4-6_SS | - | -0.010 (-2.123) | - | -0.021*** (-4.444) |
| *RET*4-6_NSS | - | -0.004 (-0.905) | - | -0.008* (-1.770) |
| *RET*7-12_SS | - | 0.015*** (4.322) | - | 0.016*** (4.373) |
| *RET*7-12_NSS | - | 0.008*** (2.735) | - | 0.007** (2.267) |
| *Adjusted-*$R^2$ | 11.17% | 11.39% | 11.78% | 12.06% |
| *Durbin-Watson stat* | 2.024 | 2.032 | 2.021 | 2.041 |

*Notes*. This table reports the panel regression results of the models with and without past returns as control variables for the All-share index returns (in columns 2 and 3) and for the Hang Seng Index returns (in columns 4 and 5). The dependent variable is $R^*_{i,t} \equiv R_{i,t} - SS_{i,t}\beta_{iSS}R_{mt} - (1\text{-}SS_{it})\beta_{iNSS}R_{mt}$ (or $r^*_{i,t} \equiv r_{i,t} - SS_{i,t}\beta_{iSS}r_{mt} - (1\text{-}SS_{it})\beta_{iNSS}r_{mt}$). The constructed All-Share Index and the Hang Seng Index are used respectively to calculate $R_{mt}$ (or $r_{mt}$). In parentheses are *t*-statistics, obtained by using the robust PCSEs. *DW* is the Durbin-Watson statistic. $^{*}$, $^{**}$ and $^{***}$ indicate statistical significance at the 10%, 5% and 1% levels, respectively.

**Table 3.4 Panel regressions with beta-adjusted raw returns as the dependent variable**

| Regressor | All-Share Index Returns | | Hang Seng Index Returns | |
|---|---|---|---|---|
| *Intercept* | 0.159*** (8.824) | 0.163*** (8.773) | 0.158*** (8.607) | 0.158*** (8.413) |
| $(1-SS_{i,t})$ | 0.161*** (8.262) | 0.160*** (8.037) | 0.170*** (8.584) | 0.165*** (8.185) |
| $SZ_{i,t-1}$ | -0.016*** (-6.455) | -0.017*** (-6.637) | -0.014*** (-5.698) | -0.015*** (-5.711) |
| $(1-SS_{i,\,t-1})*SZ_{i\ t-1}$ | -0.004 (-1.550) | -0.003 (-1.446) | -0.005* (-1.880) | -0.004* (-1.775) |
| $BM_{i,\,t-1}$ | 0.030*** (10.04) | 0.032*** (10.20) | 0.034*** (11.27) | 0.035*** (11.20) |
| $(1-SS_{i,\,t-1})*BM_{i,\,t-1}$ | 0.002 (0.575) | 0.002 (0.573) | 0.000 (0.096) | 0.000 (0.086) |
| $ILQ_{i,t}$ | -0.062*** (-18.06) | -0.061*** (-17.51) | -0.067*** (-19.15) | -0.065*** (-18.41) |
| $(1-SS_{i,t})*ILQ_{i,t}$ | 0.005 (1.415) | 0.005 (1.358) | 0.010*** (2.609) | 0.009** (2.479) |
| $ILQ_{i,t-1}$ | 0.023*** (6.517) | 0.022*** (6.322) | 0.024*** (6.830) | 0.024*** (6.717) |
| $(1-SS_{i,t-1})*ILQ_{i,t-1}$ | 0.011*** (2.947) | 0.011*** (2.826) | 0.009** (2.441) | 0.009** (2.241) |
| $EP_{i,\,t-1}$ | 0.001 (0.557) | 0.001 (0.711) | 0.002 (0.811) | 0.002 (0.950) |
| $(1-SS_{i,\,t-1})*EP_{i,\,t-1}$ | 0.001 (0.516) | 0.002 (0.712) | 0.001 (0.311) | 0.001 (0.506) |
| $YLD_{i,\,t-1}$ | -0.155*** (-2.965) | -0.138** (-2.544) | -0.149*** (-2.806) | -0.134** (-2.437) |
| $(1-SS_{i,\,t-1})*YLD_{i,\,t-1}$ | 0.095* (1.722) | 0.074 (1.305) | 0.010* (1.774) | 0.080 (1.394) |
| $DO_{i,t}$ | 0.032*** (19.12) | 0.032*** (19.00) | 0.035*** (20.76) | 0.036*** (20.77) |
| $(1-SS_{i,t})*DO_{i,t}$ | 0.014*** (7.587) | 0.014*** (7.400) | 0.012*** (6.537) | 0.012*** (6.234) |
| $DO_{i,t-1}$ | -0.023*** (-13.63) | -0.024*** (-13.74) | -0.024*** (-14.31) | -0.025*** (-14.56) |
| $(1-SS_{i,t-1})*DO_{i,\,t-1}$ | -0.006*** (-3.605) | -0.006*** (-3.353) | -0.006*** (-3.254) | -0.006*** (-2.967) |
| *RET*1-3_SS | - | 0.006 (1.254) | - | 0.012** (2.507) |
| *RET*1-3_NSS | - | 0.005 (0.966) | - | 0.009* (1.840) |
| *RET*4-6_SS | - | -0.012** (-2.501) | - | -0.021*** (-4.326) |
| *RET*4-6_NSS | - | -0.003 (-0.589) | - | -0.006 (-1.349) |
| *RET*7-12_SS | - | 0.0160*** (4.551) | - | 0.0160*** (4.482) |
| *RET*7-12_NSS | - | 0.010*** (3.390) | - | 0.010*** (2.877) |
| *Adjusted-*$R^2$ | 11.89% | 12.17% | 12.41% | 12.72% |
| *Durbin-Watson stat* | 2.027 | 2.038 | 2.026 | 2.047 |

*Notes*. This table reports the panel regression results of the models with and without past returns as control variables for the All-share index returns (in columns 2 and 3) and for the Hang Seng Index returns (in columns 4 and 5). The dependent variable is $R^*_{i,t} \equiv R_{i,t} - SS_{i,t}\beta_{iSS}R_{mt} - (1\text{-}SS_{it})\beta_{iNSS}R_{mt}$ (or $r^*_{i,t} \equiv r_{i,t} - SS_{i,t}\beta_{iSS}r_{mt} - (1\text{-}SS_{it})\beta_{iNSS}r_{mt}$). The constructed All-Share Index and the Hang Seng Index are used respectively to calculate $R_{mt}$ (or $r_{mt}$). In parentheses are *t*-statistics, obtained by using the robust PCSEs. *DW* is the Durbin-Watson statistic. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

The fourth message pertains to the effect of illiquidity. Both contemporaneous and lagged illiquidity are worth noting. Regarding $ILQ_{i,t}$ (contemporaneous illiquidity), Tables 3.3 and 3.4 show that its coefficient is negative and has the highest level of statistical significance of all the estimated coefficients reported; meanwhile the $(1\text{-}SS_{i,t})*ILQ_{i,t}$ coefficient is positive and insignificant in six models, but significant at a higher than 5% level in the remaining two models (columns 4 and 5 of Table 3.4). The former result indicates that there is a strong negative relation between returns and contemporaneous illiquidity, which is consistent with the conjecture of Amihud (2002) and Bekaert et al. (2007). My interest is, however, not in confirming this result. Rather, I am concerned with *structural change* in the effect due to the short-sale regime's change. In this regard, the latter result provides some weak evidence which allows me to accept part of *Hypothesis 4* concerning contemporaneous illiquidity: Stocks subject to short-sale constraints have a fall-down (in absolute terms) in their illiquidity effects (negative) on their contemporaneous returns.

As for structural change in the effect of lagged illiquidity, even stronger evidence can be discerned from the two tables. The estimation results for the $(1\text{-}SS_{i,t\text{-}1})*ILQ_{i,t\text{-}1}$ coefficient are consistent in terms of their positive sign and high statistical significance across Tables 3.3 and 3.4. In other words, I obtain very strong evidence in favour of part of *Hypothesis 4* in relation to lagged illiquidity: Stocks subject to binding short-sales constraints have a significant run-up in their illiquidity effects (positive) on their *future* returns. Note, I also detect a positive sign of the $ILQ_{i,t\text{-}1}$ coefficient with a higher than 1% level of statistical significance, as demonstrated in both Tables 3.3 and 3.4. This result is consistent with another conjecture maintained by Amihud (2002) and Bekaert et al. (2007): Excess returns reflect compensation for expected market illiquidity, so an increase in current illiquidity raises expected market illiquidity, thereby requiring higher future excess returns.

The fifth result concerns the effect of the E/P ratio. One can see from the two tables that the ratio's coefficient ($EP_{i,t\text{-}1}$) remains positive throughout the eight models with different dependent variables and with, or without, past returns as control variables. Although this positive sign is consistent with previous findings (e.g., Fama & French, 1992; Eun & Huang, 2007), the $EP_{i,t\text{-}1}$ coefficient is statistically insignificant at all. In addition, the estimated (1-$SS_{i,t\text{-}1}$)*$EP_{i,t\text{-}1}$ coefficient is also positive, but insignificantly different from zero. These results imply that stocks eligible for short-selling are indifferent from those that are ineligible in terms of *no* E/P effect on returns (including beta-adjusted excess and beta-adjusted raw returns). That is, I fail to find evidence in support of *Hypothesis 5.*

Pertaining to the effect of dividend yields, the estimated coefficient on $YLD_{i,t\text{-}1}$ is consistently negative in the two tables, and is significant at a higher than 5% level in all but one case (column 5 of Table 3.3), where the 10% level is reported. My detected negative relation between stock returns and lagged dividends is not new (see, for example, La Porta et al., 2000; Faccio et al., 2001). What is new is that the coefficient on (1-$SS_{i,t\text{-}1}$)*$YLD_{i,t\text{-}1}$ is positive across the eight models. As far as statistical significance is concerned, however, only two models (columns 2 and 4 of Table 3.4) indicate a 10% level. Despite statistical insignificance, the (1-$SS_{i,t\text{-}1}$)*$YLD_{i,t\text{-}1}$ coefficient is economically significant, in the sense that its absolute value is greater than half of that of the $YLD_{i,t\text{-}1}$ coefficient in most cases. So, there is still some evidence in support of *Hypothesis 6* that stocks subject to short-sale constraints would have a less negative relation between their dividends and future returns than those that can be shorted.

Finally, let me inspect the results related to dispersion of opinion. I consider both cotemporaneous and un-cotemporaneous cross-sectional relations between stock returns and differences of opinion. Tables 3.3 and 3.4 reveal that the estimates of the $DO_{i,t}$ coefficient are positive and significant at a higher than 1% level, implying that high *DO* stocks tend to have more undervalued prices than do low *DO* stocks, even if both stocks can be sold short. This may be because, even though the stocks are allowed to be shorted, actual shorting of them may not be active enough to eliminate the overvaluation. Moreover, such overvaluation becomes even more significant under the regime where stocks cannot be shorted. This is evidenced by the $(1\text{-}SS_{i,t})*DO_{i,t}$ coefficient also being positive and significant at a higher than 1% level. My conjecture stated in *Hypothesis 7* is, therefore, supported. By incorporating the interaction between dispersion of opinion and short-sale constraints, I am able to confirm Boehme et al.'s (2006) result, but in a comparative way: Stocks subject to both dispersion of opinion and short-selling restrictions demonstrate more significant overvaluation than stocks subject to the former condition only. This is in line with part of *Hypothesis 7*.

Furthermore, the inter-temporal cross-sectional relations between stock returns and differences of opinion can be described by the $DO_{i,t\text{-}1}$ and $(1\text{-}SS_{i,t\text{-}1})*DO_{i,t\text{-}1}$ coefficients. In contrast to the aforementioned contemporaneous case, they are now both negative, but also significant at a higher than 1% level. That is, high *DO* stocks tend to more often predict lower future returns than do low *DO* stocks, even if both stocks can be shorted. These findings conform to the findings of Diether et al. (2002), although the authors use dispersion of analysts' earnings forecasts in their analysis. They find that stocks with higher dispersion in analysts' earnings forecasts earn lower *future* returns than otherwise similar stocks. In this paper, I provide further, strong evidence that stocks with high *DO* would predict *even lower* future returns when they are not eligible for shorting than when they are. This conforms to the other part of *Hypothesis 7*.

The above results remain largely unchanged whether, or not, past returns are used as control variables. Indeed, the only qualitative difference appears with regard to the statistical significance of the $(1-SS_{i,t-1})*YLD_{i,t-1}$ coefficient in Table 3.4. There, it is shown that dropping the control variables would turn the coefficient estimate from being insignificant to being significant at the 10% level (columns 2 and 4 of Table 3.4). Such a difference, however, is too trivial to alter my conclusions.

Some additional remarks are in order regarding options. Banned stocks with option products may still find some “bypasses” around the no-short-selling regime through which they can short. In other words, options should work to blur the demarcation between the short-selling and no-short-selling regimes, and so neutralise the significance of the difference in the price/return behaviour between the two regimes. My sample is, however, largely free of this “option problem”. After screening my sampled stocks, I find, out of 462 stocks, only two stocks (China CITIC Bank Corporation and China Railway Construction Corp.) have had option products; starting from November 13, 2007 and June 24, 2008, respectively. I then delete these stocks and re-run the panel regressions, but the results remain qualitatively unchanged.

## 3.7 Summary and conclusions

Issues related to short-sale constraints challenge academics, policymakers and participators alike. In particular, how short-sale constraints may affect asset pricing and behavioural finance is a focus of many academic studies. Using the unique short-sale regulations in the Hong Kong stock market, I join these research endeavours by developing and testing seven hypotheses in the area of asset pricing. Recent studies add to the evidence against Miller's (1977) overpricing theory, further dwarfing the already sparse evidence for the theory. To generate more convincing evidence either for, or against, the overvaluation effect, I conceive a novel and pertinent empirical identification strategy: Examining the differences between the ban (NSS) and the no-ban (SS) regime in terms of the same stock's return behaviour. This strategy makes it inevitable for me to look at individual stock returns, rather than portfolio returns, and to employ a panel data regression, rather than an event study. In addition, investigating the alternation of a stock between opposite short-selling regimes induces the need to probe how the market anticipates the changes in the short-selling regime over time. My contributions to the literature are embodied in the conclusions, as summarised below.

First, I show that stocks earn significantly higher abnormal returns in the ban regime (i.e., throughout the entire off-list period over which short sales are prohibited) than in the no-ban regime (i.e., throughout the entire on-list period over which short sales are allowed). I also show that the ban regime and greater differences of opinion among investors reinforce each other in further increasing current, while further decreasing future, returns on individual stocks. By demonstrating that the ban regime impacts positively on returns both directly and via divergent opinions "adding fuel to the fire", I am able to claim that the ban regime alone can induce overvaluation and divergent opinions only make overvaluation more dramatic.

Second, I show that stocks with larger sizes may perform even better in terms of their returns if they are not allowed to be sold short, than if they are. Third, it is uncertain whether the value effect in the Hong Kong stock market will increase when stocks move into the NSS regime. The fourth discovery is that contemporaneous illiquidity has a weaker negative effect, while lagged illiquidity has a stronger positive effect on stock returns after stocks enter the regime where short-selling is restricted. The fifth finding is that there is no difference between the two opposite regimes in terms of the E/P effect, which is indistinguishable from zero. My sixth result is the moderate evidence that, when stocks are constrained for short sales, the negative relation between their dividend yields and future returns weakens. The seventh and final observation pertains to the detected structural break in the effect of dispersion of opinion on stock returns: The presence of both short-sale constraints and opinion dispersion causes contemporaneous returns to rise and future returns to fall by more than the presence of opinion dispersion alone.

The above results are robust to the use of two indices as a proxy for the market portfolio, to the use of excess and raw returns and, more importantly, to the inclusion of past returns in regressions. Among the results, the three most unambiguous and interesting ones stand out; those related to the risk-compensation-adjusted return, illiquidity, and dispersion of opinion. These results are in line with Miller's (1977) overvaluation theory and are consistent with, or further strengthen, some previous empirical studies that test the theory. What distinguishes my study from prior ones, however, is that I employ a direct measure of short-sale constraints, take stocks being shortable and non-shortable as being under two distinct regimes rather than as affected by different events, compare the same stocks that experience opposite short-selling regimes, and apply panel data regression of empirical asset pricing models to individual stocks.

# Chapter 4 The Validity of the CAPM and the Fama-French Three-factor Model Where Short Sales Are Restricted

## 4.1 Introduction

Do asset-pricing models, such as the theoretical CAPM and the empirical Fama-French three-factor model (Fama & French, 1993) perform differently when short sales are constrained and when they are not? If yes, how much difference would there be and in which short-selling status would the models possess more explanatory power? These untouched questions concern whether one needs to modify the extant asset-pricing models by allowing for short-sale constraints to improve their applicability/testability in practice. As the first attempt to answer these questions in the literature, I investigate them in this chapter.

As a milestone in asset-pricing finance, the mean-variance CAPM developed by Sharpe (1964) and Linter (1965) has been most widely used by practitioners and academic researchers[15]. The underlying assumptions about perfection in competitive markets simplify the building of the model and permit one to consider only the mean and variance of the returns. The assumptions are, however, so strong as to have aroused a stream of research in regards to relaxing which of them would lead to failure of the theory. Several results have been reported, as follows. Among the CAPM assumptions,[16] the absence of short-sale constraints is the most restrictive one (Black, 1972). The homogeneous-expectations

[15] Welch (2008) finds that about 75% of finance professors recommend using CAPM. Graham and Harvey (2001) survey 392 CFOs within US firms and find that CAPM is by far the most popular method in estimating the cost of equity capital with 73.5% of the surveyed firms always, or almost always, relying on CAPM.

[16] Fama summarizes, (1) All investors focus on a single holding period, and they seek to maximize the expected utility of their terminal wealth by choosing among alternative portfolios on the basis of each portfolio's expected return and standard deviation. (2) All investors can borrow or lend an unlimited amount at a given risk-free rate of interest and there are no restrictions on short sales of any assets. (3) All investors have identical estimated of the expected returns, variances, and covariance among all assets (that is, investors have homogeneous expectations). (4) All assets are perfectly divisible and perfectly liquid (that is, marketable at the going price). (5) There are no transaction costs. (6) There are no taxes. (7) All investors are price takers (that is, all investors assume that their own buying and selling activity will not affect stock prices).

assumption does not significantly affect the validity of the CAPM (Lintner, 1969). The normality and risk-averse-investor assumptions are generally regarded as an acceptable approximation to reality (Black, 1972). The absence of transaction cost and tax is widely claimed to be only a minor idealization which hardly hardly affects the substantive implications of the CAPM (Brennan, 1975 and Goldsmith 1976). Nevertheless, the assumption of no short-sale restrictions with full use of proceeds clearly diverges from reality, according to the following observations.

In many markets, short sales are not allowed. Sharpe (1991) reports that many institutional investors are prohibited from taking short positions, either by explicit rules, or by the implicit threat of lawsuit for violating fiduciary standards. Even if short sales are allowed, there exist various constraints that prevent investors/arbitrageurs from freely shorting their assets. Jones (2002) documents that some restrictions adopted in the US in the 1930s made short sales difficult. These restrictions included the requirement to secure written authorisation before lending a customer’s shares, and the prohibition of short sales on downticks. The latter restriction was strengthened a few years later to require that all short-selling be executed on a strict uptick. In September 2000, the end of France’s monthly settlement system led to a restriction list of stocks that investors could buy, or sell, short. In September 2008, due to the financial crisis, regulatory authorities, including the SEC (The US Securities and Exchange Commission), the FSA (The UK Financial Services Authority) and the AMF (the French financial regulator), decided to ban short selling for a limited period. The length of this ban was not the same in all countries. It was overturned in October 2008 in the United States, but is still in effect in other countries. Apart from regulatory restrictions, costs and risks also greatly reduce short-selling activities.

Short-selling restrictions are part of the investment environment faced by a vast majority of portfolio managers and investors whose decisions rely on asset-pricing models. Therefore, it is of interest to investigate the performance of these models in two alternative short-selling statuses and determine whether the models would capture more, or less, of the time variation in, and the cross-section of, stock returns when short-selling is banned than when it is not. The investigation is particularly warranted with respect to the CAPM: The CAPM is a cornerstone of modern portfolio theory, while the three-factor model (or the four-factor model) is an empirical asset-pricing model without specifying the underlying economic model that governs asset pricing (Fama & French, 2011). Moreover, CAPM's underlying assumptions also extend to the empirical three-factor model and other models. Thus, I regard testing CAPM across two opposite short-selling statuses as testing theory; namely, the possible changes in the validity of the CAPM theory when applied in circumstances where its fourth assumption is relaxed. I also, however, perform the test using the three-factor model.

To be fair, researchers have studied the importance of short-sale constraints for asset-pricing theory. Ross (1977) finds that, when negative positions are excluded, the CAPM no longer holds. He also shows, however, that with risk-free assets that can be borrowed/lent freely, the market portfolio should be efficient, even if risky assets are not allowed to be sold short. Sharpe (1991) argues that, when short sales are not allowed, the market portfolio will not be mean-variance efficient. In recent years, some empirical tests of asset-pricing models have explicitly taken into consideration short-sale constraints. Hansen, Heaton and Luttmer (1995) use short-sale constraints to model transaction costs. Jagannathan and Wang (1992, 1993) demonstrate that, when portfolio weights are constrained to be non-negative, the NYSE-AMEX market portfolio is mean-variance inefficient. Similar evidence is provided in

Wang (1998). Nevertheless, these studies are concerned with the relation between short-sale constraints and portfolio efficiency. A question that remains unanswered is how short-sale constraints/bans affect the performance of asset-pricing models in explaining asset returns. Using unique short-selling rules from the Hong Kong stock market, my study attempts to probe this question.

I do so by comparing the abilities of the CAPM and the three-factor model in explaining the expected returns on stocks that can be sold short and the expected returns on stocks that cannot. It is well-known that the CAPM is unable to explain some well-documented anomalies. Many studies have indicated that firm characteristics also contribute to the cross-sectional variations in expected stock returns, such as firm size (Banz, 1981), earnings to price ratio (Basu, 1985), book-to-market ratio (Rosenberg, Reid & Lanstein, 1985) and past returns (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993). Moving beyond the theoretical CAPM model in empirical tests, Fama and French (1992, 1996, 1997, 1998, 2004, 2006) propose and employ the three-factor model that allows for some of these anomalies, such as the size and value effects. The three-factor model has now become a standard empirical asset-pricing model. Furthermore, Carhart (1997) proposes a four-factor model that adds the momentum effect to the three-factor model. After that, more multi-factor models are proposed, albeit they are quite controversial, such as Pastor and Stambaugh's (2003) liquidity factor model and Ho and Hung's (2012) sentiment factor model. As noted above, both the CAPM and empirical asset pricing models all assume that short sales are permitted and, therefore, are supposed to be applicable only in markets without short-sale constraints. Thus, it remains to be uncovered whether they fare better, worse, or equally well in the markets subject to short-sale restrictions. The focus of my testing will be on the CAPM and the Fama-

French three-factor model, because they are far more widely used than other proposed empirical asset-pricing models.

I implement both the conventional tests and the new tests proposed by Lewellen, Nagel and Shanken (2010) in answering my research question. To test model performance/validity, the conventional approach mainly relies on the significance levels of intercepts, factor loadings and $R^2$ in the time-series regression, which have been widely used by researchers.[17] In general, insignificant intercepts (alphas), either averaged across 25 Fama and French (Fama & French, 1993) size-B/M portfolios, or jointly insignificant based on the GRS (Gibbons, Ross & Shanken, 1989) test statistic, together with significant factor loadings and high $R^2$, are indicators of a model's "goodness of fit". Following the convention, I use the GRS F-statistic, the average absolute alpha, the Sharpe ratio and $R^2$ (including its adjusted value) to gage and compare model performances, after running time-series regressions.

In fact, the time-series regression is only the first pass in the Fama-MacBeth two-pass method (Fama & MacBeth, 1973). Although important studies such as Fama and French (2012) only consider time-series asset pricing tests, I go further to conduct cross-sectional regression analysis as well, which is the second pass in the Fama-MacBeth method. This is done to ensure that the test results are more convincing. Recently, Lewellen, Nagel and Shanken (2010) review and critique the standard practice in the cross-sectional asset pricing literature: Researchers evaluate models based on high cross-sectional $R^2$ and small pricing errors in the cross-sectional regression for 25 size-B/M portfolios. The authors show that such

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[17] See Fama and French (1992, 1993, 1996, 2011), Ho and Hung (2009), Karolyi and Wu (2012). Fama and French (1993) state that "…the slopes and $R^2$ values show whether mimicking portfolios for risk factors …capture shared variation in stock and bond returns…"

asset pricing tests are often highly misleading. To mitigate the problems, they offer several suggestions.

The first is to enrich the dimensionality of the cross-section beyond the 25 size-B/M portfolios. The 25 portfolios are sorted by size and the B/M ratio. This sorting procedure results in a set of portfolios that exhibit a strong relation between loadings on the size and B/M factors, and expected returns. Hence, Lewellen et al. (2010) suggest adding portfolios formed on other characteristics. Following their suggestion, I add to the left-hand side (LHS) of the time-series regression model more test assets/portfolios that are not systematically related to the size and B/M characteristics, or to the 25 size-B/M portfolios. Specifically, I use Hong Kong industry portfolios (indices) to span part of the cross-sectional space.

The second suggestion is to use the generalised least squares (GLS) cross-sectional $R^2$ instead of the ordinary least squares (OLS) $R^2$. As the GLS $R^2$ is determined by the proximity of the mimicking portfolios to the minimum-variance boundary, it is superior to the OLS $R^2$ in that "it has a useful economic interpretation in terms of the relative mean-variance efficiency of a model's factor-mimicking portfolios" (Lewellen et al., 2010). Therefore, I mainly rely on the GLS $R^2$, while also reporting the OLS $R^2$.

The third suggestion is to report confidence intervals for test statistics such as the cross-sectional GLS $R^2$, Shanken's (1985) cross-sectional $T^2$, and so on. When there are high sampling errors in the test statistics, it is insufficient to rely only on the point estimates and the *p*-values. A confidence interval shows the range of true parameters that are consistent with the data. That is, it not only reveals the high sampling errors by showing a wide range of parameters, but also avoids taking any stand on the right null hypothesis (Lewellen et al., 2010). Therefore, I will report the confidence intervals for both the OLS and the GLS cross-sectional $R^2$, as well as for Shanken's (1985) $T^2$.

When evaluating model performances across shortable versus non-shortable portfolios, I use different test assets as the LHS variables. Hence, I cannot directly compare the GLS $R^2$s, or $T^2$s, related to non-shortable portfolios with those related to shortable portfolios. Instead, I compute the main component of the GLS $R^2$, or the $T^2$ statistic, referred to this as the $T^2$-related unexplained squared Sharpe ratio *q*, for comparison purposes. This ratio is the distance that a model's mimicking portfolios are from the minimum variance boundary, measured as the difference between the maximum generalised squared Sharpe ratio and that attainable from the mimicking portfolios[18]. In general, the smaller the unexplained squared Sharpe ratio (GLS-related, or $T^2$-related), the better the model will be in explaining the cross section of expected returns.

The remaining of this chapter proceeds as follows. In Section 4.2, I conduct a review of the relevant literature. Section 4.3 describes the data used and the preparatory work for the empirical tests. Section 4.4 reports and discusses the results produced from the conventional approach (time-series regression analysis). Section 4.5 reports and discusses the results produced from the Lewellen, Nagel and Shanken (2010) improved approach (cross-sectional regression analysis). Section 4.6 concludes.

[18] Lewellen, Nagel and Shanken (2010) define GLS $R^2=1-q/Q$, where Q depends on the LHS variables only, and $T^2 = \frac{q*T}{(1+\gamma' \Sigma_F^{-1} \gamma)}$, where γ depends on the LHS variables (Shanken, 1985).

## 4.2 Literature review

In the literature, there are some theoretical discussions on the impact of short-sale constraints on the validity of asset-pricing models. These discussions mainly pertain to the mean-variance CAPM, which is a theoretically generated asset-pricing model. The CAPM is based on several strict assumptions about perfection in competitive markets, among which the absence of short-sale constraints is the most stringent one (Black, 1972). Since the early 1970s, researchers have started thinking about the applicability of the CAPM when some of the underlying assumptions are relaxed. Lintner (1969) shows that the violation of the homogeneous-expectation assumption does not significantly affect the validity of the CAPM. Black (1972) argues that the assumptions of the normal distribution of asset returns and of investors' mean-variance preferences in portfolio selection are an acceptable approximation to reality. He also examines the nature of capital market equilibrium when riskless assets are absent and when short-selling of riskless assets is not allowed, and finds that in both cases the CAPM still holds. He fails, however, to consider short-selling constraints on risky assets in both of these cases. Ross (1977) then looks at the validity of the CAPM when short-selling of risky assets is not allowed, or when short-selling is allowed, but penalised, which is more realistic. He shows that the presence of short-sale restrictions does not change the mean-variance efficiency of a market portfolio, and so, does not invalidate the CAPM.

The above-cited studies are theoretical in nature. To the best of my knowledge, there has been no empirical research that tests the performance of asset-pricing models in the environment of restricting short-sales. One possible reason for this could be a lack of the required data: One would need data on such individual stocks that can be classified as either shortable, or non-shortable, or that can be stratified according to the degree of shortability.

Since January 1994, the Hong Kong stock market has had some stocks allowed to be sold short and others banned from short-selling. This particular feature of the Hong Kong market makes the required data available, which then enables me to empirically explore the *relative* performance of asset-pricing models in explaining returns on shortable versus non-shortable stocks.

My study is related to several strands of the literature. The first strand concerns the impact of short-selling restrictions on the distribution of asset returns, such as mean (first-order moment), volatility (second-order moment) and skewness (third-order moment). There are both theoretical and empirical studies related to the first-order moment. Some theoretical studies argue that short-sale constraints can cause stock prices to be upward biased, because only optimistic investors' opinions will be incorporated into the prices. These arguments can be found in Jarrow (1980), who models Miller's idea in the CAPM framework, and in Figlewski (1981), who adopts a standard one-period model and reaches a similar conclusion. Harrison and Kreps (1978) and Morris (1996) conclude that, when short-selling is prohibited, stock prices can be higher than otherwise, because of the opportunity to speculate. Duffie, Garleanu and Pedersen (2002) employ a dynamic model to show that, even when short-selling is allowed, the prospect of lending fees could push stock prices even above the valuation from the most optimistic investors. Contrary to the above arguments, Diamond and Verrecchia (1987) argue that, in their rational expectations framework, traders will take into consideration the existence of short-selling restriction when they form expectations. Thus, stocks will not be overpriced on average.

Empirical work related to the first-order moment is also abundant. Chang et al. (2007), relying on the special setting of the Hong Kong stock market, find evidence of overvaluation of stocks that are banned from short-selling. Such overvaluation is stronger for stocks with greater dispersion of investor opinion, a conclusion that is highly supportive of Miller (1977). Similar evidence can be found in Danielsen and Sorescu (2001) and Ofek and Richardson (2003), who document a negative relation between stock prices and option trading, which can be seen as a way to alleviate short-selling constraints; and in Boulton and Braga-Alves (2010), who look at the 2008 naked short-sale restrictions on 19 financial firms in the US and document a positive (negative) market reaction to the announcement (expiration) of the short-sale restrictions. Li and Bai (2012) demonstrate that a short-selling ban will increase the expected returns of the affected stocks, and this effect can be permanent under the ban regime. All these studies indicate that short-selling restrictions can affect the mean of stock returns.

Short-selling restrictions can also affect the distribution of stock returns in terms of volatility and skewness. Hong and Stein (2003) predict that short-sale constraints cause the returns to be more negatively (or less positively) skewed. This is the case because, in their heterogeneous agent model, short-sale constraints increase the frequency of extreme negative stock returns. Contrary to their prediction, however, Chang et al. (2007) find that individual stock returns show more positive skewness when short sales are prohibited. They also find that stocks are more volatile when they are allowed to be sold short, suggesting that short-selling activities may destabilise the market. Bris, Goetzmann and Zhu (2007), examining the impact of short-sale constraints on market efficiency in 46 equity markets around the world, also find strong evidence that, in markets without short-selling, either because it is prohibited, or because it is not practiced, aggregate market returns tend to be less negatively skewed. This finding is also contrary to Hong and Stein’s (2003) prediction.

The empirical observation that short-sale constraints affect the distribution of stock returns implies that the distribution of shortable stock returns must be different from that of non-shortable stock returns. Less controversial is the observation that the latter has a greater mean than the former. So, it is natural to expect that asset-pricing models perform differently in terms of, for example, risk-adjusted returns (alphas) with shortable versus non-shortable stocks. To determine whether this is the case, I examine the theoretically generated asset-pricing model, the CAPM, and the empirically relevant asset-pricing model, the Fama-French three-factor model, as they are commonly used in application (Carhart, 1997; Kosowski et al., 2006; Fama & French, 2010, 2011). Applying the models separately to shortable and non-shortable stocks can help me to quantify the differences in the size and value patterns, and in the size and value premiums, across the two types of stocks. Therefore, here comes the null hypothesis of this study, the CAPM and the three-factor model perform better when the short selling is allowed than when it is not. In this sense, my study is also related to another strand of research - researches that test asset-pricing models in different settings, which are be reviewed below.

The most recent papers in this strand include Fama and French (2011) and Korolyi and Wu (2012). Fama and French (2011) explore whether empirical asset-pricing models capture the value and momentum patterns in international average returns across four regions (North America, Europe, Japan and Asia Pacific). Korolyi and Wu (2012) extend Fama and French (2011) by dividing risk factors into “global” and “local” factors. The tests in both papers are akin to the mean-variance spanning tests of Huberman and Kandel (1987). That is, for a given set of test asset portfolios, the authors evaluate each model based on its explanatory power, the magnitude of the model's pricing errors (the absolute magnitude of the intercepts) and the GRS F-test statistic (Gibbons et al., 1989).

My study is similar to the above-cited studies in that I also evaluate the performance of asset-pricing models, however, I differ from them in the following ways. First, they compare the performance of different models in explaining the same cross-sectional returns. That is, they apply different models, namely the CAPM, the three-factor and the four-factor model, or models with global and/or local factors, to the same set of LHS asset portfolio returns. Then, they evaluate the explanatory power of each model in capturing the cross-section of the same expected returns. In my study, however, I evaluate the performance of each asset-pricing model for different LHS portfolios returns. Specifically, I use the same right-hand-side factors to explain returns on shortable portfolios and then returns on non-shortable portfolios. In this way, I compare the relative performance of an asset-pricing model across different groups of stocks with different short-selling statuses.

Second, in addition to all the conventional tests adopted in their studies, I also employ the cross-sectional tests suggested by Lewellen et al. (2010) to strengthen my empirical results. For example, I not only look at the point estimates and p-values of the test statistics, but also rely on the confidence intervals of the test statistics for statistical inferences and economic judgements. These exercises yield richer information about the explanatory power of an asset-pricing model.

My study is the first empirical work in the literature that examines and compares the ability of asset-pricing models in capturing the cross-sectional return of stocks that are shortable versus stocks that are not shortable. It should shed light on the issues concerning the applicability of asset-pricing models in those markets subject to short-sale constraints.

## 4.3 Data and portfolio construction

According to the information provided in Chapter 2, this study again employs the Hong Kong short-selling list. As of February 29, 2012, which is the end of my sample period, the list had been subsequently revised 102 times and, out of 1,498 common stocks traded on the Hong Kong Stock Exchange (HKSE), 1,081 could be sold short. See Table 2.1 in Chapter 2 for a presentation of the changes in the list.

The uniqueness of Hong Kong's regulations on short-sales also offers me an ideal laboratory for exploring the differences in model performance that are due to the differences between stocks being shortable and stocks being non-shortable. Based on the designated short-selling list, I divide all stocks traded on the HKSE into two sub-groups. Briefly, at a time point, an individual stock stays either in the short-selling constrained/banned status, or in the no-constraint/ban status. Hereafter, I refer to stocks on the list as shortable stocks (SS); and refer to stocks off the list as non-shortable stocks (NSS).

To construct the risk factors and form portfolios, I collect the following data for all individual stocks traded on the HKSE; closing prices, market value (ME), book value (BE), the number of shares outstanding, and the Hong Kong 3-month Treasury-bill rate (T-bill)[19]. All data are obtained from the Datastream database.

Following Fama and French (1992, 1993) in constructing risk factors, I sort, at July of year *t*, all Hong Kong listing firms into two groups based on size (ME), and into three groups

[19] In Chapter 3, I used the Hong Kong one-month inter-bank rate as a proxy for the risk-free rate. Here, however, I employ the Hong Kong 3-month Treasury-bill rate instead, for the following reasons. First, studies on multi-factor asset-pricing models have typically employed the 3-month Treasury-bill rate, following Fama and French (1992, 1993). My study reported here falls into this strand of the asset pricing literature, so using T-rate as a proxy makes my study consistent with others in the literature. Second, either the inter-bank rate or the T-bill rate cannot fully represent the risk-free rate, because they all involve certain degree of credit risk (e.g., the downgrading from AAA to AA* of the US treasury bonds is a good example).

based on book-to-market ratios (BE/ME). Stocks whose market values (ME) are above (below) the cross-sectional median are classified as big (small) stocks, denoted by B (S). The top (bottom) one-third of stocks with the highest (lowest) book-to-market ratios are classified as high (low) BM stocks, denoted by H (L), and the remaining one-third are classified as median BM stocks, denoted as M. These independent 2×3 sorts allow me to construct six size and book-to-market portfolios (S/L, S/M, S/H, B/L, B/M and B/H) from the intersections of the two size and the three book-to-market groups. For example, the S/L portfolio contains stocks in the small-size group that are also in the low book-to-market group, and the B/H portfolio contains the big-size stocks that also have high book-to-market ratios. Monthly value-weighted returns on the six portfolios are calculated from July of year $t$ to June of year $t+1$, with the portfolios rebalanced in June of year $t+1$. I calculate returns beginning in July of year $t$ by using the available accounting data on book equity from July of year $t-1$ through June of year $t$. To be included in the tests, a firm must have closing prices for December of year $t-1$ and June of year $t$, and book equity for year $t-1$. In addition, to make an asset-pricing model comparable across shortable and non-shortable stocks in terms of its performance, I require that data for both types of stocks be available in identical sample periods. This is achieved, however, at the cost of a short sample period (98 time-series observations). Below are the details of each risk factor to be used in the regressions.

The size factor is represented by the portfolio returns denoted as SMB (small minus big), meant to mimic the risk factor related to size. The SMB returns are calculated as the difference, each month, between the simple average of the returns on the three small-stock portfolios (S/L, S/M and S/H) and the simple average of the returns on the three big-stock portfolios (B/L, B/M and B/H):

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

This difference is largely free of the influence of BE/ME, focusing on the different return behaviours of small and big stocks.

The BE/ME factor is represented by the portfolio returns denoted as HML (high minus low), meant to mimic the risk factor related to book-to-market equity. The HML returns are calculated as the difference, each month, between the simple average of the returns on the two high-BE/ME portfolios (S/H and B/H) and the simple average of the returns on the two low-BE/ME portfolios (S/L and B/L).

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

HML is largely free of the size factor in returns, focusing on the different return behaviours of high-BE/ME and low-BE/ME stocks.

## Table 4.1 Summary statistics for risk factors

I construct the Market risk factor by using all Hong Kong shares. The all-share index is value weighted.

I break all Hong Kong stocks into two size groups based on the breakpoints for the bottom 50% (Small) and top 50% (Big) of the ranked values of ME. I also break all Hong Kong stocks into three book-to-market equity groups based on the breakpoints for the bottom 33% (Low), middle 43% (Medium) and top 33% (High) of the ranked values of BE/ME. Then I construct six portfolios (S/L, S/M, S/H, B/L, B/M and B/H) from the intersections of the two ME and three BE/ME groups. For example, the S/L portfolio contains the stocks in the small-ME group that are also in the low-BE/ME group, the B/H portfolio contains the big-ME stocks that are also in the low-BE/ME group and the B/H portfolio contains the big-ME stocks that also have high BE/MEs. Monthly value-weighted returns on the six portfolios are calculated from July of year t to June of t+1, with the portfolios reformed in June of t+1. I calculate returns beginning in July of year t to be sure that book equities for year t-1 are known. Size risk factor (SMB) is the average of the returns on the small-stock portfolios minus the returns on the big-stock portfolios:

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

Likewise, the B/M risk factor (HML) is the average of the returns on the high-B/M portfolios minus the returns on the low-B/M portfolios:

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

The market factor is proxied by excess market returns denoted as RM-RF. RM is the returns on the value-weighted portfolio of all of the shares in the Hong Kong market and RF is the Hong Kong monthly 3-month Treasury bill rate (T-bill).

To make an asset-pricing model comparable across banned and non-banned stocks in terms of its performance, I require that data for both types of stocks be available in identical sample periods. This is achieved, however, at the cost of a rather short sample period (only 90 time-series observations are employed).

| | RM-RF | SMB | HML |
|---|---|---|---|
| Mean | -0.006[20] | 0.023 | 0.004 |
| t-Mean | -0.970 | 3.310 | 0.940 |
| Median | -0.004 | 0.013 | 0.004 |
| Minimum | -0.177 | -0.167 | -0.115 |
| Maximum | 0.152 | 0.252 | 0.132 |
| Std Dev | 0.054 | 0.065 | 0.041 |

20 According to Fama & French (1992), if the market risk premium is not different from zero, this implies that the systematic risk of the CAPM is not rewarded. Many empirical studies including Boudoukh and Richardson and Smith (1993) present evidence that the expected market risk premium is, at times, significantly less than zero. Such results imply that the market portfolio is on the negatively sloped portion of the mean-variance frontier – a violation of one of the CAPM's restrictions and also an indication that the CAPM is flawed. That empirical evidence often rejects the CAPM has prompted researchers to consider additional risk factors for improving the explanatory power of asset-pricing models beyond that of the CAPM.

True mimicking portfolios for the common risk factors in returns should minimise the variance of firm-specific factors. The six size-BE/ME portfolios in SMB and HML are value weighted, which is in the spirit of minimising variance. More importantly, the use of value-weighted components results in mimicking portfolios that capture the different return behaviours of small and big stocks, or of high-BE/ME and low-BE/ME stocks, in a way that corresponds to realistic investment opportunities.

The market factor is proxied by excess market returns, denoted as RM-RF. RM is the monthly returns on the value-weighted portfolio of all shares traded in the Hong Kong market and RF is the monthly Hong Kong 3-month Treasury bill rate (T-bill).

The summary statistics of risk factors are presented in Table 4.1. During my sample period, the market underperformed risk free assets, resulting in a negative market risk premium, which is, however, statistically insignificant. The book-to-market factor HML is statistically insignificant, but the size factor SMB provides a significant risk premium of 2.3%.

## 4.4 Conventional Time-series Tests

Table 4.2 reports the means and standard deviations of 25 shortable and 25 non-shortable size-B/M portfolio returns, and there are some interesting observations. Among the shortable stocks, there seems to be a book-to-market effect; that is, value stocks generally outperform growth stocks, but there is no size effect, meaning that small stocks do not outperform large stocks within each BE/ME quintile. When looking at stocks that are banned from short-selling, there is a significant size effect: All small stocks outperform large stocks within each BE/ME quintile. There is also a book-to-market effect within each size quintile, but it is weaker than the size effect. Comparing the mean returns of the two sets of 25 portfolios, one can see that stocks that are banned from short-selling significantly outperform stocks not subject to the ban. Regarding return volatility, I can see that all the standard deviations of non-shortable portfolio returns are greater than, or equal to, those of shortable portfolio returns.

**Table 4.2 Summary statistics of monthly excess returns for 25 shortable and 25 non-shortable portfolios formed on size and B/M**

At the end of June of each year, I construct 25 shortable size-B/M portfolios. The size breakpoints are the 20th, 40th, 60th and 80th percentiles of market capitalisation. The B/M quintile breakpoints are 20th, 40th, 60th and 80th percentiles of book-to-market ratio. The intersections of the 5x5 independent size and B/M sorts for those stocks produce 25 value-weighted size-B/M portfolios. In the same way, I also construct 25 non-shortable size-B/M portfolios. The risk free rate is monthly Hong Kong 3-month Treasury bill rate.

| Book-to-Market Equity (BE/ME) Quintiles | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
| Panel A: Summary statistics on shortable portfolios | | | | | | | | | | | |
| | Means | | | | | | Standard Deviations | | | | |
| Small | -0.010 | -0.023 | -0.011 | -0.004 | 0.002 | Small | 0.171 | 0.110 | 0.107 | 0.093 | 0.109 |
| 2 | -0.011 | -0.004 | -0.005 | 0.005 | -0.005 | 2 | 0.101 | 0.106 | 0.099 | 0.104 | 0.096 |
| 3 | 0.001 | 0.001 | -0.001 | -0.003 | 0.011 | 3 | 0.081 | 0.081 | 0.092 | 0.095 | 0.106 |
| 4 | -0.004 | -0.006 | 0.000 | -0.003 | -0.001 | 4 | 0.081 | 0.086 | 0.086 | 0.100 | 0.089 |
| Big | -0.002 | -0.005 | -0.007 | -0.001 | 0.001 | Big | 0.067 | 0.077 | 0.062 | 0.073 | 0.090 |
| Panel B: Summary statistics on non-shortable portfolios | | | | | | | | | | | |
| | Means | | | | | | Standard Deviations | | | | |
| Small | 0.081 | 0.054 | 0.039 | 0.054 | 0.071 | Small | 0.188 | 0.165 | 0.156 | 0.166 | 0.195 |
| 2 | 0.016 | 0.038 | 0.040 | 0.029 | 0.032 | 2 | 0.133 | 0.128 | 0.134 | 0.111 | 0.108 |
| 3 | 0.031 | 0.013 | 0.006 | 0.025 | 0.009 | 3 | 0.135 | 0.116 | 0.101 | 0.124 | 0.104 |
| 4 | -0.001 | 0.003 | 0.009 | 0.010 | 0.007 | 4 | 0.119 | 0.087 | 0.093 | 0.101 | 0.106 |
| Big | -0.013 | -0.005 | 0.003 | 0.010 | 0.015 | Big | 0.088 | 0.096 | 0.082 | 0.085 | 0.100 |

Panel C: Difference between shortable portfolios and non-shortable portfolios

| | Shortable portfolios | Non-shortable portfolios |
|---|---|---|
| Mean | -0.003 | 0.023 |
| Differences | -0.027 | |
| t - differences | -5.062 | |

Table 4.3 presents the regression results for the CAPM model. Panel A is concerned with the shortable size-B/M portfolios. Most of the alphas are insignificantly different from zero and all of the betas are statistically significant. The 25 adjusted $R^2$s fall between 37.6% and 82.9%. Overall, the CAPM explains the returns of large stocks better than the returns of small stocks. Panel B indicates that, for non-shortable size-B/M portfolios, most alphas are significantly different from zero, with some exceptions in the portfolios consisting of very large stocks with low book-to-market ratios. The adjusted $R^2$s, ranging from 8.1% to 71.4%, are lower than those from the regressions for shortable stocks. Overall, judged by the $R^2$ alone, the CAPM appears to be a proper model in capturing the returns of stocks in the Hong Kong stock market. The model is, however, more applicable to shortable stocks than to non-shortable stocks.

**Table 4.3 Summary statistics for CAPM regressions to explain monthly excess returns on shortable and non-shortable portfolios formed on size and B/M**

The regressions use the CAPM model with market factor to explain the excess returns of shortable portfolios.

Panel A: Shortable portfolios

| Summary statistics for regressions: $R_{i\ s}-R_f=a_i+b_i(R_m-R_f)+e_i$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Book-to-Market Equity (BE/ME) Quintiles | | | | | | | | | | | |
| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
| | | | a | | | | | | t(a) | | |
| Small | -0.001 | 0.015 | -0.002 | 0.003 | 0.011 | Small | -0.085 | 1.884 | -0.303 | 0.397 | 1.642 |
| 2 | -0.005 | 0.006 | 0.003 | 0.014 | 0.004 | 2 | -0.568 | 1.002 | 0.516 | 2.536 | 0.588 |
| 3 | 0.008 | 0.008 | 0.007 | 0.005 | 0.020 | 3 | 1.531 | 1.762 | 1.401 | 0.879 | 3.436 |
| 4 | 0.003 | 0.002 | 0.008 | 0.006 | 0.007 | 4 | 0.756 | 0.412 | 1.853 | 1.181 | 1.480 |
| Big | 0.004 | 0.002 | -0.002 | 0.005 | 0.009 | Big | 1.268 | 0.513 | -0.585 | 1.221 | 1.625 |
| | | | b | | | | | | t(b) | | |
| Small | 1.961 | 1.534 | 1.520 | 1.284 | 1.632 | Small | 7.392 | 10.707 | 11.084 | 10.525 | 12.788 |
| 2 | 1.192 | 1.700 | 1.521 | 1.665 | 1.463 | 2 | 7.701 | 16.333 | 13.854 | 16.123 | 13.294 |
| 3 | 1.210 | 1.277 | 1.456 | 1.460 | 1.682 | 3 | 12.890 | 15.314 | 15.107 | 13.905 | 15.350 |
| 4 | 1.316 | 1.395 | 1.416 | 1.653 | 1.453 | 4 | 17.282 | 16.478 | 18.394 | 18.680 | 16.901 |
| Big | 1.133 | 1.296 | 1.002 | 1.150 | 1.395 | Big | 19.925 | 20.772 | 16.199 | 14.986 | 14.405 |
| | | | $R^2$ | | | | | | Adj $R^2$ | | |
| Small | 0.383 | 0.566 | 0.583 | 0.557 | 0.650 | Small | 0.376 | 0.561 | 0.578 | 0.552 | 0.646 |
| 2 | 0.403 | 0.752 | 0.686 | 0.747 | 0.668 | 2 | 0.396 | 0.749 | 0.682 | 0.744 | 0.664 |
| 3 | 0.654 | 0.727 | 0.722 | 0.687 | 0.728 | 3 | 0.650 | 0.724 | 0.719 | 0.684 | 0.725 |
| 4 | 0.772 | 0.755 | 0.794 | 0.799 | 0.765 | 4 | 0.770 | 0.752 | 0.791 | 0.796 | 0.762 |
| Big | 0.819 | 0.831 | 0.749 | 0.719 | 0.702 | Big | 0.817 | 0.829 | 0.746 | 0.715 | 0.699 |

**Table 4.3 Summary statistics for CAPM regressions to explain monthly excess returns on shortable and non-shortable portfolios formed on size and B/M (continued)**

The regressions use the CAPM model with market factor to explain the excess returns of non-shortable portfolios.

Panel B: Non-shortable portfolios

| Summary statistics for regressions: $R_{i\_ns}-R_f=a_i+b_i(R_m-R_f)+e_i$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Book-to-Market Equity (BE/ME) Quintiles | | | | | | | | | | | |
| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
| | | a | | | | | | t(a) | | | |
| Small | 0.087 | 0.061 | 0.048 | 0.061 | 0.080 | Small | 4.557 | 3.789 | 3.539 | 3.766 | 4.353 |
| 2 | 0.024 | 0.044 | 0.048 | 0.037 | 0.038 | 2 | 2.074 | 3.676 | 3.928 | 4.089 | 4.094 |
| 3 | 0.037 | 0.021 | 0.013 | 0.030 | 0.016 | 3 | 2.887 | 2.141 | 1.610 | 2.562 | 1.989 |
| 4 | 0.006 | 0.009 | 0.016 | 0.017 | 0.015 | 4 | 0.554 | 1.320 | 2.290 | 2.230 | 1.739 |
| Big | -0.007 | 0.002 | 0.010 | 0.017 | 0.021 | Big | -0.935 | 0.242 | 2.094 | 2.851 | 2.409 |
| | | b | | | | | | t(b) | | | |
| Small | 1.051 | 1.215 | 1.648 | 1.259 | 1.693 | Small | 2.965 | 4.052 | 6.493 | 4.186 | 4.959 |
| 2 | 1.453 | 1.119 | 1.312 | 1.335 | 1.189 | 2 | 6.859 | 4.999 | 5.826 | 8.013 | 6.855 |
| 3 | 1.087 | 1.340 | 1.259 | 1.019 | 1.297 | 3 | 4.514 | 7.492 | 8.443 | 4.643 | 8.470 |
| 4 | 1.187 | 1.090 | 1.259 | 1.339 | 1.335 | 4 | 5.958 | 8.562 | 9.970 | 9.516 | 8.606 |
| Big | 1.037 | 1.255 | 1.296 | 1.199 | 1.084 | Big | 7.680 | 9.345 | 14.947 | 10.975 | 6.741 |
| | | $R^2$ | | | | | | Adj $R^2$ | | | |
| Small | 0.091 | 0.157 | 0.324 | 0.166 | 0.218 | Small | 0.081 | 0.148 | 0.316 | 0.157 | 0.210 |
| 2 | 0.348 | 0.221 | 0.278 | 0.422 | 0.348 | 2 | 0.341 | 0.212 | 0.270 | 0.415 | 0.341 |
| 3 | 0.188 | 0.389 | 0.448 | 0.197 | 0.449 | 3 | 0.179 | 0.383 | 0.441 | 0.188 | 0.443 |
| 4 | 0.287 | 0.454 | 0.530 | 0.507 | 0.457 | 4 | 0.279 | 0.448 | 0.525 | 0.502 | 0.451 |
| Big | 0.401 | 0.498 | 0.717 | 0.578 | 0.341 | Big | 0.395 | 0.492 | 0.714 | 0.573 | 0.333 |

Table 4.4 reports the results of testing the Fama-French three-factor model. Panel A concerns shortable size-B/M portfolios. Of the 25 alphas, 4 are statistically significant, as compared with 2 out of 25 for the CAPM regression (See Panel A of Table 4.3). The $R^2$s (ranging from 50.2% to 84.8%) and the adjusted $R^2$s (ranging from 48.5% to 84.3%) all improve for each of the 25 portfolios, when compared with their CAPM counterparts. Most of the small- and medium-sized portfolios have significant coefficients on the SMB risk factor and most high-BM stocks have significant loadings on the HML risk factor. Comparing Panel B with Panel A, one can see that, for non-shortable size-B/M portfolios, 8 out of 25 alphas are significantly different from zero at the 95% level or higher, while only 4 are significant for the shortable portfolios. The $R^2$s (ranging from 41.4% to 83.2%) and the adjusted $R^2$s (ranging from 39.3% to 82.6%) associated with the non-shortable portfolios are almost all lower than those for the corresponding shortable portfolios. The overall results in Table 4.4 again suggests that the three-factor model works better in explaining returns on shortable stocks than on non-shortable stocks.

In order to see the differences in the intercepts and the slope coefficient estimates in an asset-pricing model between the two short-selling statuses, I employ a dummy variable SS in the time-series regression for each of the three asset-pricing models. The results are set out in Tables 4.5 and 4.6.

**Table 4.4 Summary statistics for Fama-French three-factor regressions to explain monthly excess returns on shortable and non-shortable portfolios formed on size and B/M**

Panel A: Shortable portfolios

| Summary statistics on regressions: $R_{i\_s}-R_f=a_i+b_i(R_m-R_f)+s_iSMB+h_iHML+e_i$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Book-to-Market Equity (BE/ME) Quintiles | | | | | | | | | | | |
| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
| | | a | | | | | | t(a) | | | |
| Small | -0.020 | -0.026 | -0.011 | -0.012 | -0.004 | Small | -1.427 | -3.424 | -1.413 | -2.341 | -0.785 |
| 2 | -0.018 | -0.003 | -0.004 | 0.007 | -0.005 | 2 | -2.353 | -0.507 | -0.679 | 1.223 | -0.951 |
| 3 | 0.003 | 0.006 | 0.001 | -0.006 | 0.014 | 3 | 0.607 | 1.261 | 0.256 | -1.134 | 2.383 |
| 4 | -0.001 | 0.000 | 0.006 | 0.002 | 0.002 | 4 | -0.119 | 0.054 | 1.405 | 0.482 | 0.479 |
| Big | 0.006 | 0.004 | 0.000 | 0.006 | 0.006 | Big | 2.003 | 1.278 | -0.009 | 1.437 | 1.287 |
| | | b | | | | | | t(b) | | | |
| Small | 1.954 | 1.504 | 1.481 | 1.245 | 1.538 | Small | 7.839 | 11.095 | 10.961 | 13.145 | 15.908 |
| 2 | 1.133 | 1.645 | 1.523 | 1.632 | 1.377 | 2 | 8.019 | 17.005 | 14.228 | 16.456 | 13.776 |
| 3 | 1.223 | 1.259 | 1.425 | 1.366 | 1.613 | 3 | 13.010 | 14.571 | 15.055 | 15.639 | 15.143 |
| 4 | 1.313 | 1.391 | 1.397 | 1.612 | 1.380 | 4 | 16.770 | 15.854 | 17.493 | 17.985 | 16.869 |
| Big | 1.183 | 1.337 | 0.991 | 1.060 | 1.246 | Big | 21.503 | 21.643 | 15.624 | 15.135 | 15.637 |
| | | s | | | | | | t(s) | | | |
| Small | 0.894 | 0.446 | 0.313 | 0.596 | 0.560 | Small | 4.448 | 4.076 | 2.875 | 7.810 | 7.183 |
| 2 | 0.521 | 0.295 | 0.308 | 0.280 | 0.279 | 2 | 4.570 | 3.784 | 3.567 | 3.506 | 3.456 |
| 3 | 0.213 | 0.061 | 0.221 | 0.343 | 0.189 | 3 | 2.808 | 0.874 | 2.888 | 4.865 | 2.205 |
| 4 | 0.108 | 0.088 | 0.041 | 0.092 | 0.118 | 4 | 1.706 | 1.240 | 0.643 | 1.279 | 1.789 |
| Big | -0.038 | -0.067 | -0.096 | -0.127 | -0.051 | Big | -0.858 | -1.339 | -1.877 | -2.243 | -0.787 |
| | | h | | | | | | t(h) | | | |
| Small | 0.141 | 0.213 | 0.245 | 0.278 | 0.557 | Small | 0.427 | 1.186 | 1.371 | 2.214 | 4.355 |
| 2 | 0.373 | 0.327 | 0.025 | 0.209 | 0.481 | 2 | 1.993 | 2.552 | 0.173 | 1.593 | 3.633 |
| 3 | -0.043 | 0.100 | 0.188 | 0.531 | 0.384 | 3 | -0.347 | 0.877 | 1.496 | 4.594 | 2.722 |
| 4 | 0.030 | 0.032 | 0.106 | 0.225 | 0.394 | 4 | 0.288 | 0.272 | 1.003 | 1.896 | 3.633 |
| Big | -0.264 | -0.222 | 0.048 | 0.456 | 0.768 | Big | -3.622 | -2.719 | 0.568 | 4.916 | 7.282 |
| | | $R^2$ | | | | | | Adj $R^2$ | | | |
| Small | 0.502 | 0.645 | 0.630 | 0.757 | 0.817 | Small | 0.485 | 0.633 | 0.618 | 0.748 | 0.810 |
| 2 | 0.546 | 0.805 | 0.727 | 0.787 | 0.750 | 2 | 0.530 | 0.798 | 0.718 | 0.780 | 0.741 |
| 3 | 0.683 | 0.733 | 0.755 | 0.802 | 0.766 | 3 | 0.672 | 0.723 | 0.746 | 0.795 | 0.757 |
| 4 | 0.780 | 0.760 | 0.797 | 0.811 | 0.805 | 4 | 0.773 | 0.752 | 0.790 | 0.805 | 0.798 |
| Big | 0.845 | 0.848 | 0.759 | 0.786 | 0.816 | Big | 0.840 | 0.843 | 0.751 | 0.779 | 0.809 |

**Table 4.4 Summary statistics for Fama-French three-factor regressions to explain monthly excess returns on shortable and non-shortable portfolios formed on size and B/M (continued)**

Panel B: Non-shortable portfolios

| Summary statistics on regressions: $R_{i\_ns}-R_f=a_i+b_i(R_m-R_f)+s_iSMB+h_iHML+e_i$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Book-to-Market Equity (BE/ME) Quintiles | | | | | | | | | | |
| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
| | | | a | | | | | | t(a) | | |
| Small | 0.050 | 0.032 | 0.022 | 0.025 | 0.042 | Small | 3.413 | 2.204 | 1.862 | 1.900 | 2.688 |
| 2 | 0.001 | 0.018 | 0.018 | 0.012 | 0.011 | 2 | 0.056 | 1.869 | 2.013 | 2.238 | 2.184 |
| 3 | -0.009 | 0.001 | -0.009 | 0.000 | -0.006 | 3 | -0.905 | 0.189 | -1.865 | -0.009 | -1.264 |
| 4 | -0.020 | -0.008 | 0.003 | -0.002 | -0.006 | 4 | -2.460 | -1.623 | 0.525 | -0.323 | -1.081 |
| Big | -0.019 | -0.007 | 0.001 | 0.005 | 0.002 | Big | -2.752 | -1.012 | 0.333 | 0.979 | 0.359 |
| | | | b | | | | | | t(b) | | |
| Small | 1.303 | 1.231 | 1.684 | 1.195 | 1.599 | Small | 4.968 | 4.701 | 7.908 | 5.086 | 5.676 |
| 2 | 1.557 | 1.159 | 1.230 | 1.206 | 1.099 | 2 | 9.576 | 6.792 | 7.494 | 12.043 | 11.925 |
| 3 | 1.197 | 1.376 | 1.206 | 0.837 | 1.173 | 3 | 6.937 | 10.428 | 13.459 | 5.887 | 13.187 |
| 4 | 1.138 | 1.033 | 1.188 | 1.258 | 1.155 | 4 | 7.799 | 11.535 | 10.798 | 12.637 | 11.794 |
| Big | 0.992 | 1.231 | 1.246 | 1.112 | 0.912 | Big | 8.052 | 9.432 | 16.421 | 12.669 | 7.673 |
| | | | s | | | | | | t(s) | | |
| Small | 1.909 | 1.282 | 1.183 | 1.493 | 1.537 | Small | 9.027 | 6.071 | 6.889 | 7.882 | 6.764 |
| 2 | 1.119 | 1.197 | 1.173 | 0.900 | 1.066 | 2 | 8.538 | 8.699 | 8.860 | 11.141 | 14.344 |
| 3 | 1.370 | 0.991 | 0.896 | 1.100 | 0.833 | 3 | 9.849 | 9.313 | 12.401 | 9.591 | 11.611 |
| 4 | 1.058 | 0.672 | 0.452 | 0.713 | 0.672 | 4 | 8.988 | 9.309 | 5.095 | 8.876 | 8.509 |
| Big | 0.464 | 0.363 | 0.304 | 0.418 | 0.600 | Big | 4.674 | 3.451 | 4.969 | 5.910 | 6.262 |
| | | | h | | | | | | t(h) | | |
| Small | -1.081 | 0.074 | -0.045 | 0.517 | 0.673 | Small | -3.114 | 0.212 | -0.159 | 1.663 | 1.804 |
| 2 | -0.407 | -0.063 | 0.572 | 0.778 | 0.598 | 2 | -1.889 | -0.278 | 2.632 | 5.867 | 4.899 |
| 3 | -0.406 | -0.067 | 0.382 | 1.080 | 0.750 | 3 | -1.778 | -0.382 | 3.221 | 5.736 | 6.370 |
| 4 | 0.381 | 0.376 | 0.427 | 0.510 | 1.021 | 4 | 1.973 | 3.171 | 2.935 | 3.874 | 7.875 |
| Big | 0.290 | 0.169 | 0.297 | 0.504 | 0.970 | Big | 1.777 | 0.978 | 2.955 | 4.340 | 6.165 |
| | | | $R^2$ | | | | | | Adj $R^2$ | | |
| Small | 0.546 | 0.414 | 0.565 | 0.536 | 0.514 | Small | 0.530 | 0.393 | 0.550 | 0.520 | 0.497 |
| 2 | 0.650 | 0.587 | 0.650 | 0.809 | 0.832 | 2 | 0.637 | 0.572 | 0.638 | 0.802 | 0.826 |
| 3 | 0.620 | 0.697 | 0.818 | 0.692 | 0.830 | 3 | 0.606 | 0.686 | 0.811 | 0.681 | 0.825 |
| 4 | 0.651 | 0.753 | 0.675 | 0.775 | 0.803 | 4 | 0.639 | 0.745 | 0.664 | 0.767 | 0.796 |
| Big | 0.545 | 0.567 | 0.802 | 0.751 | 0.671 | Big | 0.529 | 0.552 | 0.796 | 0.743 | 0.660 |

Table 4.5 reports the coefficient estimates on the dummy variables and the interaction terms to show the difference in the CAPM regression loadings between shortable and non-shortable portfolios, as well as the $R^2$s and the adjusted $R^2$s. The dummy variables have significantly negative coefficients for micro and small stocks, while most of the coefficient estimates on the interaction terms are insignificant. This indicates that, ceteris paribus, the small shortable stocks tend to underperform the small non-shortable stocks, however, this is rarely the case for the medium, or large stocks. The shortable and non-shortable stocks, in general, do not differ in their sensitivity to the market risk.

Table 4.6 gives the difference results pertaining to the three-factor model. With regard to the size effect, shortable and non-shortable stocks show a significant difference in the sensitivity to the SMB risk factor. The significant negative coefficients on the interaction term between the dummy variable SS and the SMB risk factor suggest that, ceteris paribus, shortable stocks are significantly more sensitive to the SMB risk factor than non-shortable stocks, however, these two types of stocks do not have systematic difference in the sensitivity to the HML risk factor.

I then use the GRS F-statistic to compare the performances of the two asset-pricing models in explaining shortable/non-shortable stock returns. Table 4.7 reports the GRS F-statistics for each of the one-factor and three-factor models for, respectively, shortable and non-shortable portfolios. Consider the one-factor CAPM model first. Shortable portfolios have a GRS statistic of 1.233, whereas non-shortable portfolios have a GRS statistic of 2.473. The higher GRS F-statistic with non-shortable portfolios rejects the null hypothesis that the 25 alphas are jointly equal to zero more strongly than that with shortable portfolios. This suggests that the CAPM works better in the shorting-permitted environment than in the shorting-banned environment, even though both of them fail to pass the GRS F test.

**Table 4.5 Difference in CAPM regressions between shortable and non-shortable portfolios**

This table only reports the differences in the estimated time-series coefficients between the model with 25 shortable size-B/M portfolios and the model with 25 non-shortable portfolios. ss=1 indicates that portfolio *i* is formed using shortable stocks, while ss=0 indicates that portfolio *i* is formed using non-shortable stocks. ss measures the difference in the abnormal return. b' measures the difference in the beta of the market factor. The sample period used for the regressions is from January 2004 to February 2012, with 98 monthly observations.

| Regressions: $R_{i\_all}-R_f=a_i+ss_i+b_i(R_m-R_f)+b'_i ss(R_m-R_f)+e_i$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Book-to-Market Equity (BE/ME) Quintiles | | | | | | | | | | | |
| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
| | | | ss | | | | | | t(ss) | | |
| Small | -0.086 | -0.076 | -0.051 | -0.058 | -0.069 | Small | -3.598 | -4.231 | -3.258 | -3.340 | -3.502 |
| 2 | -0.028 | -0.039 | -0.045 | -0.023 | -0.035 | 2 | -2.010 | -2.910 | -3.305 | -2.139 | -3.142 |
| 3 | -0.030 | -0.013 | -0.006 | -0.025 | 0.004 | 3 | -2.134 | -1.196 | -0.591 | -1.931 | 0.382 |
| 4 | -0.003 | -0.007 | -0.008 | -0.011 | -0.008 | 4 | -0.248 | -0.871 | -0.991 | -1.260 | -0.804 |
| Big | 0.011 | 0.000 | -0.012 | -0.012 | -0.012 | Big | 1.354 | -0.003 | -2.044 | -1.630 | -1.225 |
| | | | b' | | | | | | t(b') | | |
| Small | 0.910 | 0.319 | -0.128 | 0.025 | -0.061 | Small | 2.054 | 0.961 | -0.443 | 0.077 | -0.166 |
| 2 | -0.261 | 0.581 | 0.209 | 0.331 | 0.274 | 2 | -0.994 | 2.354 | 0.833 | 1.687 | 1.335 |
| 3 | 0.123 | -0.063 | 0.197 | 0.442 | 0.385 | 3 | 0.476 | -0.319 | 1.110 | 1.816 | 2.044 |
| 4 | 0.129 | 0.305 | 0.157 | 0.314 | 0.118 | 4 | 0.605 | 1.998 | 1.063 | 1.886 | 0.665 |
| Big | 0.096 | 0.041 | -0.294 | -0.049 | 0.311 | Big | 0.658 | 0.278 | -2.760 | -0.363 | 1.659 |
| | | | $R^2$ | | | | | | Adj $R^2$ | | |
| Small | 0.270 | 0.334 | 0.427 | 0.292 | 0.352 | Small | 0.258 | 0.323 | 0.417 | 0.280 | 0.341 |
| 2 | 0.377 | 0.453 | 0.443 | 0.580 | 0.505 | 2 | 0.366 | 0.444 | 0.434 | 0.572 | 0.496 |
| 3 | 0.323 | 0.502 | 0.572 | 0.388 | 0.591 | 3 | 0.312 | 0.493 | 0.565 | 0.378 | 0.584 |
| 4 | 0.440 | 0.605 | 0.652 | 0.652 | 0.585 | 4 | 0.430 | 0.598 | 0.646 | 0.646 | 0.578 |
| Big | 0.557 | 0.628 | 0.730 | 0.640 | 0.505 | Big | 0.550 | 0.621 | 0.726 | 0.633 | 0.496 |

*Note, this table reports the differences only.*

### Table 4.6 Difference in Fama-French three-factor regressions between shortable and non-shortable portfolios

This table only reports the differences in the estimated time-series coefficients between the model with 25 shortable size-B/M portfolios and the model with 25 non-shortable portfolios. ss=1 indicates that portfolio *i* is formed using shortable stocks, while ss=0 indicates that portfolio *i* is formed using non-shortable stocks. ss measures the difference in the abnormal return. b' measures the difference in the beta of the market factor. s' measures the difference in the coefficient of the size factor. h' measures the difference in the coefficient of the value factor. The sample period used for regressions is from January 2004 to February 2012, with 98 monthly observations.

Regressions: $R_{i\_all}$-$R_f$=$a_i$+$ss_i$+$b_i(R_m-R_f)$+$b'_i ss(R_m-R_f)$+$s_i SMB$+$s'_i ssSMB$+$h_i HML$+$h'_i ssHML$+$e_i$

| Book-to-Market Equity (BE/ME) Quintiles | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
| | | | ss | | | | | | t(ss) | | |
| Small | -0.069 | -0.058 | -0.033 | -0.037 | -0.046 | Small | -3.456 | -3.532 | -2.329 | -2.637 | -2.797 |
| 2 | -0.019 | -0.020 | -0.022 | -0.006 | -0.016 | 2 | -1.586 | -1.876 | -2.057 | -0.730 | -2.180 |
| 3 | -0.006 | 0.007 | 0.011 | -0.005 | 0.020 | 3 | -0.504 | 0.849 | 1.468 | -0.586 | 2.639 |
| 4 | 0.020 | 0.008 | 0.003 | 0.004 | 0.008 | 4 | 2.224 | 1.122 | 0.400 | 0.563 | 1.137 |
| Big | 0.025 | 0.012 | -0.001 | 0.001 | 0.003 | Big | 3.329 | 1.461 | -0.261 | 0.131 | 0.419 |
| | | | b' | | | | | | t(b') | | |
| Small | 0.652 | 0.273 | -0.204 | 0.050 | -0.061 | Small | 1.801 | 0.927 | -0.808 | 0.197 | -0.205 |
| 2 | -0.424 | 0.485 | 0.293 | 0.425 | 0.278 | 2 | -1.969 | 2.475 | 1.497 | 3.017 | 2.046 |
| 3 | 0.026 | -0.117 | 0.219 | 0.529 | 0.440 | 3 | 0.134 | -0.740 | 1.677 | 3.171 | 3.171 |
| 4 | 0.174 | 0.358 | 0.209 | 0.354 | 0.225 | 4 | 1.052 | 2.854 | 1.540 | 2.642 | 1.765 |
| Big | 0.191 | 0.106 | -0.256 | -0.052 | 0.335 | Big | 1.415 | 0.735 | -2.584 | -0.462 | 2.340 |
| | | | s' | | | | | | t(s') | | |
| Small | -1.015 | -0.836 | -0.870 | -0.897 | -0.977 | Small | -3.477 | -3.517 | -4.277 | -4.391 | -4.067 |
| 2 | -0.599 | -0.902 | -0.865 | -0.620 | -0.788 | 2 | -3.448 | -5.703 | -5.472 | -5.451 | -7.182 |
| 3 | -1.157 | -0.930 | -0.676 | -0.757 | -0.643 | 3 | -7.304 | -7.312 | -6.430 | -5.625 | -5.749 |
| 4 | -0.950 | -0.585 | -0.411 | -0.620 | -0.554 | 4 | -7.114 | -5.782 | -3.745 | -5.741 | -5.382 |
| Big | -0.502 | -0.430 | -0.400 | -0.545 | -0.651 | Big | -4.617 | -3.692 | -5.016 | -6.019 | -5.638 |
| | | | h' | | | | | | t(h') | | |
| Small | 1.222 | 0.139 | 0.290 | -0.240 | -0.116 | Small | 2.551 | 0.357 | 0.869 | -0.714 | -0.293 |
| 2 | 0.779 | 0.389 | -0.547 | -0.569 | -0.117 | 2 | 2.733 | 1.500 | -2.110 | -3.049 | -0.650 |
| 3 | 0.363 | 0.167 | -0.195 | -0.548 | -0.366 | 3 | 1.395 | 0.800 | -1.128 | -2.482 | -1.993 |
| 4 | -0.351 | -0.344 | -0.321 | -0.286 | -0.627 | 4 | -1.603 | -2.075 | -1.786 | -1.611 | -3.714 |
| Big | -0.553 | -0.391 | -0.249 | -0.048 | -0.201 | Big | -3.099 | -2.047 | -1.904 | -0.326 | -1.063 |
| | | | $R^2$ | | | | | | Adj $R^2$ | | |
| Small | 0.555 | 0.522 | 0.600 | 0.607 | 0.605 | Small | 0.537 | 0.502 | 0.584 | 0.591 | 0.588 |
| 2 | 0.616 | 0.685 | 0.689 | 0.801 | 0.802 | 2 | 0.601 | 0.672 | 0.677 | 0.793 | 0.794 |
| 3 | 0.643 | 0.710 | 0.790 | 0.737 | 0.797 | 3 | 0.628 | 0.698 | 0.781 | 0.726 | 0.789 |
| 4 | 0.692 | 0.757 | 0.732 | 0.794 | 0.804 | 4 | 0.679 | 0.747 | 0.721 | 0.785 | 0.796 |
| Big | 0.657 | 0.677 | 0.788 | 0.767 | 0.737 | Big | 0.643 | 0.664 | 0.779 | 0.758 | 0.726 |

Note, this table reports the differences only.

**Table 4.7 Summary statistics and intercepts for the CAPM, the Fama-French three-factor model regressions to explain monthly excess returns on shortable portfolios and non-shortable portfolios.**

The GRS F-statistic tests whether all the 25 intercepts in each of the four time-series regressions are zero. lal is the average absolute intercept. $R^2$ is the average $R^2$, while Adj $R^2$ is the average adjusted $R^2$. I save 25 R-squares of shortable portfolios and 25 R-squares of non-shortable portfolios, and then use paired difference testing to examine the differences. I save 25 adjusted R-squares of shortable portfolios and 25 adjusted R-squares of non-shortable portfolios, and then use paired difference testing to examine the differences. The unexplained Sharpe ratio, SR*(a)*, is the core component of the GRS F-statistic (the squared root of the unexplained squared Sharpe ratio, $\theta_z^2$). The sample distribution of the GRS F-statistic in each of the four cases is obtained by simulations with 40,000 replications. The sample period used for regressions is from January 2004 to February 2012, with 98 monthly observations.

| | shortable portfolios | | | | | | non-shortable portfolios | | | | | | difference in $R^2$ and Adj $R^2$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GRS | p value | lal | SR*(a)* | $R^2$ | Adj $R^2$ | GRS | p value | lal | SR*(a)* | $R^2$ | Adj $R^2$ | $R^2$ | t | Adj $R^2$ | t |
| CAPM | 1.233 | 0.000 | 0.006 | 0.649 | 0.689 | 0.685 | 2.473 | 0.000 | 0.031 | 0.919 | 0.361 | 0.353 | 0.328 | 13.314 | 0.332 | 13.313 |
| FF Three-Factor | 1.731 | 0.000 | 0.007 | 0.814 | 0.749 | 0.740 | 2.316 | 0.000 | 0.013 | 0.941 | 0.670 | 0.659 | 0.079 | 3.159 | 0.081 | 3.159 |

**Critical values of the GRS statistics**

| | 2.5% | 5.0% | 50% | 90% | 95% | 97.5% | 99% |
|---|---|---|---|---|---|---|---|
| CAPM_shortable | 0.000 | 0.000 | 0.029 | 0.162 | 0.227 | 0.290 | 0.378 |
| CAPM_non-shortable | 0.000 | 0.000 | 0.025 | 0.138 | 0.193 | 0.247 | 0.319 |
| FF Three-Factor_shortable | 0.076 | 0.107 | 0.350 | 0.669 | 0.785 | 0.902 | 1.035 |
| FF Three-Factor_non-shortable | 0.091 | 0.125 | 0.399 | 0.764 | 0.896 | 1.021 | 1.193 |

Turning to the three-factor model, the GRS F-statistics are all higher than the critical value at the 1% level. Shortable portfolios have a GRS statistic of 1.732, whereas non-shortable portfolios have a GRS statistic of 2.316. Similar to the CAPM, the higher GRS value with non-shortable portfolios rejects the null hypothesis more strongly than does that with shortable portfolios. This suggests that the three-factor model also works better in the shorting-permitted environment than in the shorting-banned environment, even though both of them fail to pass the GRS F test. An interesting observation is that, for non-shortable stocks, the GRS statistics generally decrease when I add more risk factors to the asset-pricing model, indicating the incremental explanatory power of the size and book-to-market factors. For shortable portfolios, however, the GRS statistics increase with the size and book-to-market factors added.

Comparing the absolute values of the alphas is also informative. Table 4.7 demonstrates that, for each of the two asset-pricing models, the absolute values of the alphas are lower for the shortable portfolios than for the non-shortable portfolios. This provides additional evidence that the two models work better in capturing returns on shortable stocks than on non-shortable stocks.

Comparing the unexplained Sharpe ratio, SR*(a)*[21], in the CAPM, I can see that the unexplained Sharpe ratio of shortable portfolios is 0.65, which is smaller than that of the non-shortable portfolios, at 0.814. This implies that the single factor model explains more return variations for shortable stocks than for non-shortable stocks. Similarly, the three-factor model

[21] SR(a) is the core component of the GRS test. The value of SR*(a)* is the square root of $\theta_z^2$, the unexplained squared Sharpe ratio. Lewellen, Nagel and Shanken (2010) define $\theta_z^2 = \alpha'\sum^{-1}\alpha$. In this study, $\theta_z^2$ is the squared Sharpe ratio of the tangency portfolio minus the value-weighted all-share Hong Kong index. Whereas, q, the core component of $T^2$, is defined as, $q = \alpha'\sum^{-1}y^*\alpha$, the distance that a model's mimicking portfolios are from the minimum-variance frontier. Regarding these definitions, it can be seen that the difference between $\theta_z^2$ and $q$ is $q$ has y*, which is a factor loading (see Shanken, 1985; Lewellen et al., 2010).

indicates that the unexplained Sharpe ratio of shortable portfolios (0.92) is smaller than that of non-shortable portfolios (0.941). Accordingly, the three-factor model explains more return variations for shortable than for non-shortable portfolios.

When comparing the average $R^2$ and the average adjusted $R^2$ across the two opposite short-selling statuses, it is revealed that all the two asset-pricing models have much greater explanatory powers for shortable portfolio returns than for non-shortable portfolio returns. Taking the CAPM as an example, the average $R^2$ increases from 36.1% in the non-shortable case, to 68.9% in the shortable case. Such an increase is significant not only statistically (paired-wise t-statistic of 13.14), but also economically (an overall increase of 91%). The average adjusted $R^2$ increases even more, from 35.3% to 68.5%. Put differently, the explanatory power of the CAPM model increases by 94% when it is applied to shortable stocks. Pertaining to the three-factor models, the result is similar, though not as strong as the CAPM. Specifically, the average $R^2$ increases by 12% and the average adjusted $R^2$ increases by 11%. This increase is also highly significant statistically.

Based on the conventional time-series analysis, I conclude that the CAPM and the three-factor model fare significantly better in capturing the time-series stock returns when their shorting is allowed than when it is not.

### 4.5 Enhanced Cross-Sectional Tests

When carrying out cross-sectional tests, I also consider the regressions where 33 Hong Kong tradable industrial portfolios are added to the LHS 25 size-B/M portfolios as the dependent variables, following the suggestion made by Lewellen, Nagel and Shankens (2010). In addition, I report the p-values as well as confidence intervals of the statistics, also as suggested by Lewellen, Nagel and Shankens (2010).

The test assets are Fama and French's 25 size-B/M portfolios, either used alone, or used along with 33 industry portfolios (total of 58 portfolios), as the dependent variables. Note that I now have different test asset portfolios, shortable versus non-shortable, that appear on the LHS of the same model (the CAPM, *or* the three-factor model). In this case, the GLS $R^2$ becomes uninformative regarding whether a model performs better, or worse, under one short-selling regime than under the other.[22] Therefore, I mainly use the $q$ and $T^2$ statistics and their confidence intervals, to evaluate and compare the performance of each asset-pricing model. $q$, the distance that a model's mimicking portfolios are from the minimum variance boundary, measures the difference between the maximum generalised squared Sharpe ratio and that attainable from a model's mimicking portfolios. Hence, the smaller the value of $q$, the more cross-sectional variations in expected returns the tested model can explain.

Table 4.8 presents the results from the cross-sectional regressions of average excess returns on the estimated factor loadings for both the CAPM and the Fama-French three-factor model. From the table, one can see that for all the eight cases considered, regressions of shortable portfolios consistently generate a smaller $q$ than those of non-shortable portfolios. For example, the CAPM with 25 *shortable* size-B/M portfolios as the regressants yields a $q$ of 0.361, which is less than half the $q$ (= 0.794) from the CAPM with 25 *non-shortable* size-B/M portfolios as the regressants. The 95% confidence interval of $q$ from the shortable

[22] The definition GLS $R^2 \equiv 1 - q/Q$ (see Appendix A in Lewellen, Nagel & Shankens, 2010) indicates that the GLS $R^2$ depends on both $q$ and $Q$. While $q$ has an economic interpretation for judging a model's performance, $Q$ does not. $Q$ changes only if the LHS variables change, thereby impairing the important information conveyed by changes in $q$. Thus, the CAPM and the three-factor model will have the same $Q$ under the same short-selling regime, but different $Q$ under different regimes. The latter fact makes the GRS $R^2$ incomparable between a model for shortable stocks and the same model for non-shortable stocks, however, the GRS $R^2$ is comparable between the CAPM and the Fama-French three-factor model when they have the same LHS variables.

portfolios' regressions in the CAPM is [0.172, 0.368], which is also much narrower and lower than that from the non-shortable portfolios' regressions, which is [0.000, 0.729]. Both the sample value and the confidence interval of $q$ indicate that the CAPM possesses more explanatory power for shortable than for non-shortable portfolios. This result does not change even after I add 33 industry portfolios to the LHS of the CAPM regression model.

Table 4.8 also shows that the three-factor regression with 25 shortable size-B/M portfolios as the regressants yields a q of 0.360, which is less than half of the q (0.641) from the three-factor regression with 25 non-shortable size-B/M portfolios as the regressants. The 95% confidence interval of q from the shortable-portfolio regressions in the three-factor model is [0.083, 0.338], which is also much narrower than that from the non-shortable-portfolio regressions, which is [0.000, 0.414]. Both the sample value and the confidence interval of q indicate that the three-factor model possesses more explanatory power for shortable than for non-shortable portfolios. Again, this result holds even after I add 33 industry portfolios to the LHS of the three-factor regression model.

**Table 4.8 Additional empirical tests (Lewellen, Nagel and Shankens' (2010) approach)**

The table reports the cross-sectional regression results with Fama and French's 25 size-B/M portfolios used alone, or together with 33 industry portfolios, as the test assets. The OLS $R^2$ is an adjusted $R^2$. The cross-sectional $T^2$ statistic tests whether pricing errors in a cross-sectional regression are all zero, with the simulated *p*-value in brackets; *q* is the distance that a model's mimicking portfolios are from the minimum-variance frontier, measured as the difference between the maximum generalised squared Sharpe ratio and that attainable from the mimicking portfolios. The sample estimate of *q* is reported in the thirteenth column. Ninety-five percent confidence intervals (simulations) for the true OLS $R^2$s, GLS $R^2$s and *q* are reported in brackets next to the sample values. Each confidence interval is obtained by simulations with 40,000 replications. Coefficient estimates and their t-values are computed according to Shanken and Zhou (2007). The GRS F-statistic tests whether all intercepts in a set of four regressions are all zero, with this reported in the last column. The sample period used for regressions is from January 2004 to February 2012, with 98 monthly observations.

| | | | | | | | | | **40,000 replications** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CAPM (25 size-B/M) | Const | t | β | t | | | | | OLS $R^2$ | GLS $R^2$ | $T^2$ | q | GRS |
| Shortable | -1.062 | -1.970 | 0.566 | 0.789 | | | | | -0.007[-0.043, 0.270] | 0.017[0.000, 0.135] | 34.995[p=0.000] | 0.361[0.172, 0.368] | 1.233 [p=0.000] |
| Non-shortable | 2.174 | 1.580 | -1.734 | -1.434 | | | | | -0.023[-0.043, 0.233] | 0.026[0.000, 0.168] | 66.896[p=0.050] | 0.794[0.000, 0.729] | 2.473 [p=0.000] |
| CAPM (25 + 33 ind.) | Const | t | β | t | | | | | OLS $R^2$ | GLS $R^2$ | $T^2$ | q | GRS |
| Shortable | -0.501 | -2.242 | 0.124 | 0.207 | | | | | -0.017[-0.018, 0.074] | 0[0.000, 0.021] | 138.229[p=0.000] | 1.411[1.021, 1.439] | 1.032 [p=0.000] |
| Non-shortable | 0.940 | 4.271 | -0.688 | -1.123 | | | | | -0.015[-0.018, 0.084] | 0.006[0.000, 0.031] | 225.889[p=0.000] | 2.316[0.641, 2.367] | 1.812 [p=0.000] |
| FF (25 size-B/M) | Const | t | β | t | s | t | h | t | OLS $R^2$ | GLS $R^2$ | $T^2$ | q | GRS |
| Shortable | -1.073 | -1.926 | 0.571 | 0.789 | 0.006 | 0.007 | -0.001 | -0.002 | 0.029[-0.102, 0.468] | 0.019[0.007, 0.301] | 32.988[p=0.000] | 0.360[0.083, 0.338] | 1.731[p=0.000] |
| Non-shortable | 1.278 | 0.912 | -1.346 | -1.109 | 2.864 | 3.99 | 0.091 | -0.173 | 0.783[0.678, 0.905] | 0.214[0.157, 0.627] | 39.173[p=0.463] | 0.641[0.000, 0.414] | 2.316[p=0.000] |
| FF (25 + 33 ind.) | Const | t | β | t | s | t | h | t | OLS $R^2$ | GLS $R^2$ | $T^2$ | q | GRS |
| Shortable | -0.487 | -2.151 | 0.092 | 0.152 | 0.208 | 0.282 | -0.694 | -1.470 | 0.152[0.024, 0.390] | 0.018[0.005, 0.121] | 117.093[p=0.000] | 1.385[0.664, 1.215] | 1.845 [p=0.000] |
| Non-shortable | 0.925 | 4.199 | -0.696 | -1.136 | 2.674 | 3.990 | -0.361 | -0.826 | 0.669[0.562, 0.789] | 0.077[0.023, 0.136] | 419.912[p=0.460] | 2.151[0.000, 1.501] | 1.918 [p=0.000] |

The cross-sectional $T^2$ statistic tests whether pricing errors in the cross-sectional regressions are all zero. I generate the finite-sample distribution of the statistic by simulations with 40,000 replications, with which to compute the p-value. According to Table 4.8, all the $T^2$ statistics from shortable portfolios' and non-shortable portfolios' regressions are statistically significant, with all the *p*-values being 0.000. Lewellen et al. (2010) argue that it is insufficient to look at the point estimates of some statistics, as confidence intervals are more informative. Hence, I use confidence intervals for testing the CAPM (Figure 4.1) and the three-factor model (Figure 4.2).

Although not drawn from cross-sectional tests, I include the GRS F statistics in the last column of Table 4.8, as they covey some new messages not reported in Section 4.4. I can see that after expanding the cross-sectional dimension by adding 33 industry portfolios to the 25 size-B/M portfolios, regressions using shortable portfolios generate the GRS statistics of 1.032 and 1.845 for, respectively, the CAPM and the Fama-French three-factor model. The two figures are both smaller than their counterparts produced by regressions using non-shortable portfolios for the CAPM (1.182) and the three-factor model (1.918). Hence, the GRS tests on both the CAPM and the Fama-French three-factor model indicate that, either before or after expanding the cross-sectional dimension, the two asset-pricing models perform better in explaining the time-series variation in shortable portfolio returns than in non-shortable portfolio returns.

Figure 4.1 and Figure 4.2 depict the sample distribution of the $T^2$ statistic as a function of the unexplained squared Sharpe ratio $q$. Given the sample $T^2$ from each test, I find the confidence interval for $q$ by slicing along the y-axis (fixing $T^2$ then scanning across). In Figure 4.1, the confidence intervals for $q$ under the sample $T^2$ are all much wider and higher for non-shortable portfolios than for shortable portfolios. For example, the top left graph shows the results from testing the CAPM with 25 shortable size-B/M portfolios only. Given the sample $T^2$ of 34.99, the 95% confidence interval of the unexplained squared Sharpe ratio $q$ is [0.172, 0.368]. In the top right panel, the CAPM with 25 non-shortable size-B/M portfolios only, yields the confidence interval of $q$ equal to [0.890, 1.548] for the sample $T^2$ of 66.90.

**Figure.4.1. Sample distribution of the $T^2$ statistic and confidence interval for q.**

The figures below provide a test of CAPM using monthly returns on Fama and French's 25 size-B/M portfolios (shortable or non-shortable) and 25 size-B/M + 33ind. The sample distribution of the $T^2$ statistic, for a given value of the ture unexplained squared Sharpe ratio($T^2$-related), q , is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q , given the sample F statistic, is found by slicing along the y-axis (fixing F then scanning across).

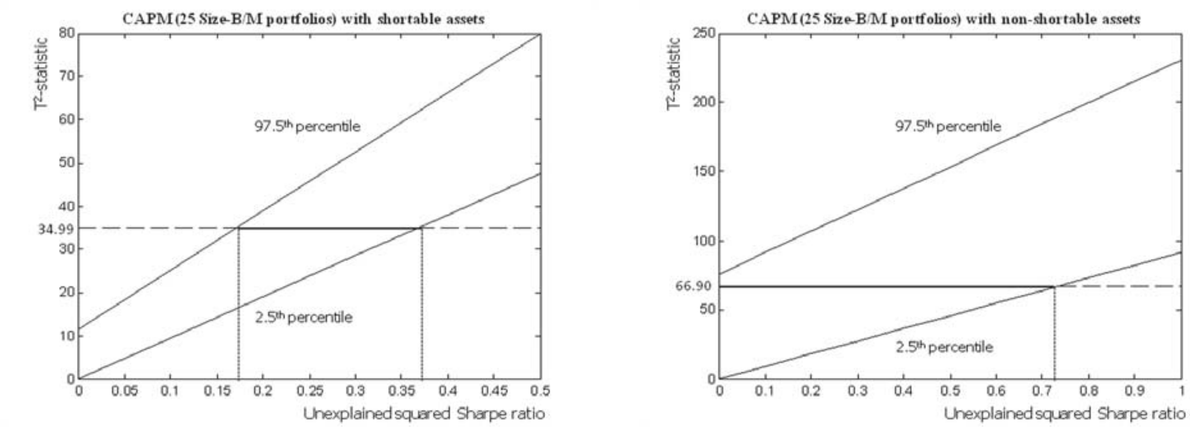
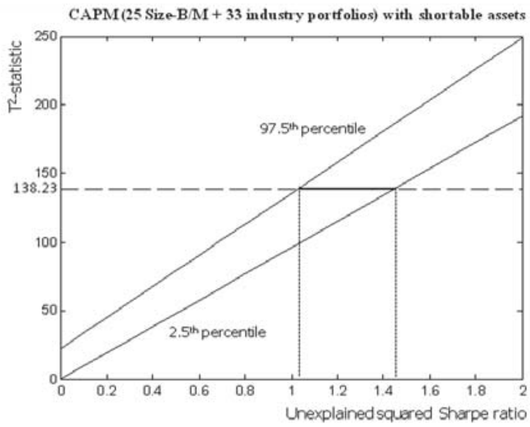


**Figure.4.1(continued). Sample distribution of the $T^2$ statistic and confidence interval for q.**

The figures below provide a test of CAPM using monthly returns on Fama and French's 25 size-B/M portfolios (shortable or non-shortable) and 25 size-B/M + 33ind. The sample distribution of the $T^2$ statistic, for a given value of the ture unexplained squared Sharpe ratio($T^2$-related), q , is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the smaple distribution). A confidence interval for q , given the sample F statistic, is found by slicing along the y-axis (fixing F then scanning across).



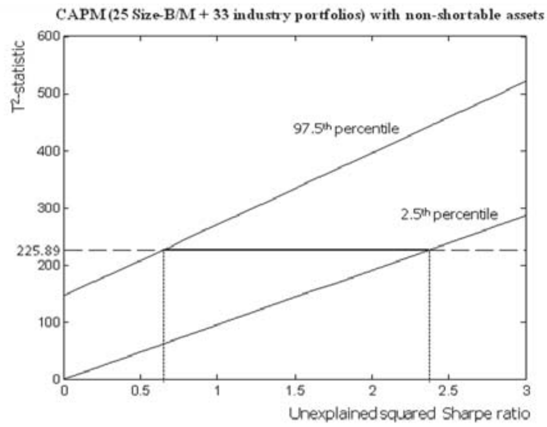
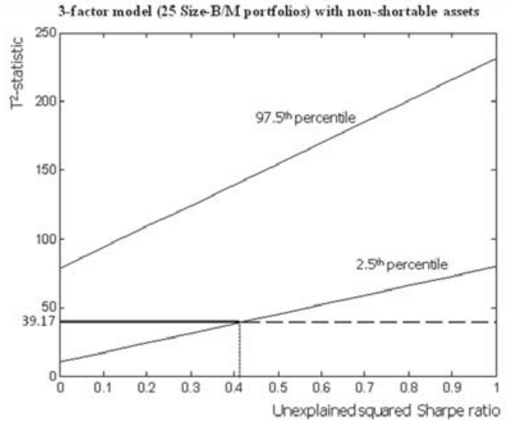



**Figure.4.2. Sample distribution of the $T^2$ statistic and confidence interval for q.**

Below figures provides a test of three-factor model using monthly returns on Fama and French's 25 size-B/M portfolios (shortable or non-shortable) and 25 size-B/M + 33ind. The smaple distribution of the $T^2$ statistic, for a given value of the ture unexplained squared Sharpe ratio($T^2$-related), q , is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q , given the sample F statistic, is found by slicing along the y-axis (fixing F then scanning across).



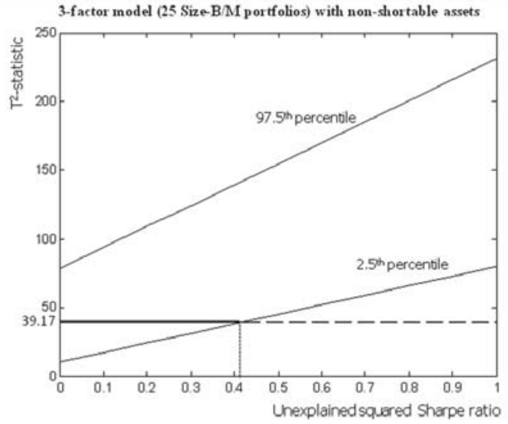
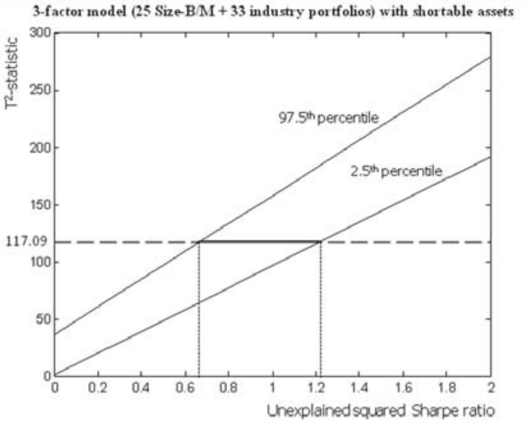
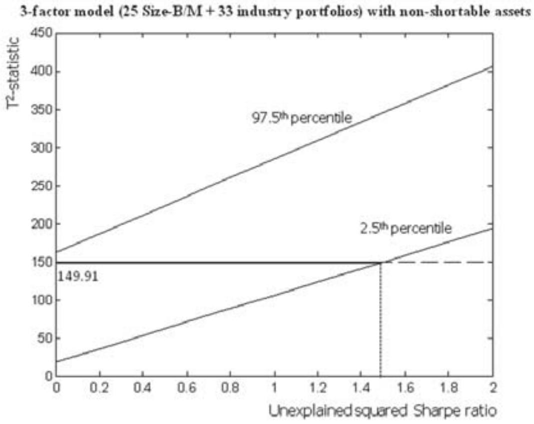



**Figure.4.2(continued). Sample distribution of the $T^2$ statistic and confidence interval for q.**

Below figures provides a test of three-factor model using monthly returns on Fama and French's 25 size-B/M portfolios (shortable or non-shortable) and 25 size-B/M + 33ind. The sample distribution of the $T^2$ statistic, for a given value of the ture unexplained squared Sharpe ratio($T^2$-related), q , is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q , given the sample F statistic, is found by slicing along the y-axis (fixing F then scanning across).



The wider and higher confidence interval of $q$ from non-shortable portfolios indicates that the CAPM considerably underperforms when explaining non-shortable portfolios' returns than shortable portfolios' returns. The same can be said in regards to the bottom graphs of Figure 4.1, where the regressants now become 25 size-B/M plus 33 industry portfolios.

Figure 4.2 pertains to the three-factor model. The confidence intervals of $q$ from the regressions using non-shortable portfolios as the regressants are always wider and higher than those from the regressions using shortable portfolios as the regressants. Adding 33 industry portfolios to the LHS of the model does not quantitatively change these results. In summary, the cross-sectional regression analysis, backed by the new asset-pricing test approach suggested by Lewellen, Nagel and Shanken (2010), reinforces the conclusion reached in the time-series regression analysis: The CAPM and the Fama-French three-factor model fare much worse in the shorting-banned market than in the short-permitted market.

### 4.6 Summary and Conclusion

This chapter addresses the second question posed in Chapter 1: Do short-selling restrictions make asset pricing models perform differently? To this end, I utilise the unique short-selling setting of the Hong Kong stock market to examine asset-pricing models' performance/validity when the assumption of no short-sale constraints is disregarded. The models I test include the theoretical CAPM and the standard empirical Fama-French three-factor model.

Applying the conventional time-series analysis and the improved cross-sectional tests, I find that the CAPM and the Fama-French three-factor model fare significantly worse in capturing the time variation in, and the cross-section of, expected returns on stocks when their short-selling is forbidden than when it is permitted.

Specifically, the conventional time-series analysis demonstrates that the two models for stocks without short-sale constraints have significantly higher $R^2$ and adjusted $R^2$ than for stocks that are banned from short selling. This result suggests that the two models are much less capable of explaining the time variation in stock returns if short-sale constraints are present than if they are absent. This result is generally supported by other statistics used to evaluate the performance of the models, including the absolute values of alphas, the GRS F-statistic and its core component SR($a$), which is the unexplained Sharpe ratio.

In the second pass of the Fama-MacBeth method, I apply Lewellen, Nagel and Shanken's (2010) prescriptions when carrying out the cross-sectional testing. That is, I expand the cross-sectional space of regressants by adding 33 industry portfolios, report the p-values of the $T^2$ statistics based on simulations, and resort to the confidence interval of q. The cross-sectional regression tests support the results from the first pass of Fama-MacBeth method. All the statistics point in one direction: Short-selling restrictions do limit/reduce the applicability of the CAPM and the Fama-French three-factor models. The implication is that practitioners, and academics alike, need to be cautious about applying the extant asset-pricing models to circumstances where short-sale restrictions are present in various forms. A further and logical implication is that a new asset-pricing model is called for that takes into account an additional factor due to the risk induced by short-sale constraints. What that risk factor will be, and whether adding it to the existing multifactor models would make them workable in the markets with short-sale constraints, are the questions left to be answered in Chapter 5.

# Chapter 5 Short-sales Constraints: Another Risk Factor for Asset-pricing Models

## 5.1 Introduction

This chapter evaluates whether short-sale constraints constitute an additional risk factor to be included in asset-pricing models for explaining stock returns where, and when, the constraints are present. I define the risk factor as the difference between the return on a portfolio of non-shortable stocks and the return on a portfolio of shortable stocks, denoted by NMS (Non-shortable Minus Shortable), and refer to it hereafter as the "no-shorting factor". This new factor is analogous to the well-known size factor (SMB, long in small caps and short in big caps), value factor (HML, long in value stocks and short in growth stocks) and momentum factor (WML, long in prior-month winners and short in prior-month losers). Why should short-sale constraints (NMS) constitute a risk factor? Take the value factor (HML) from the Fama-French (FF) three-factor model as an example. It is a risk factor because value stocks (characterised by a high book-to-market equity ratio) are believed to have higher risk of financial distress[23] and, hence, higher expected returns than growth stocks (characterised by a low book-to-market equity ratio). Similarly, I propose that non-shortable stocks have higher risk and, hence, higher expected excess returns than shortable stocks, for the three reasons given below.

The first is related to the well-known over-pricing of a non-shortable stock and disagreements between investors about the stock's value. For convenience, I will refer to the

[23] Fama and French (1995) find that stocks with high BE/ME tend to be stocks that have persistently low earnings, and stocks with low BE/ME tend to be stocks that have persistently high earnings. Intuitively, for example, if a person/company has spent, say, $1,000,000 to purchase a firm, the book value is always $1,000,000. Suppose the person/company then issues/sells shares of the firm in the stock market with the market value becoming $800,000, leading to a high B/M ratio (1,000,000/800,000 = 1.25). In this case, the raised amount of funds is less than the spent amount of funds by $200,000, certainly causing financial distress.

risk simply as the "overvaluation risk". Short-sale constraints prevent the stock from impounding negative information into, or reflecting pessimistic opinions in, its prices, leading to overvaluation. Once the constraints are lifted, however, its prices will decline, with constraint-induced upward price biases being corrected (Berkman et al., 2009; Diether et al., 2009; Boehmer & Wu, 2009). If there is overcorrection, the price drops would be even greater, overshooting the fundamental value. The higher the overvaluation, the worse the situation will be. Thus, the uncertainty in the short-selling status of already constrained stocks is a risk for investors (whether informed, or uninformed) holding them, relative to those investing in shortable stocks, without significant and persistent overvaluation.

The second reason has to do with the low liquidity of non-shortable stocks relative to that of shortable stocks. In other words, this liquidity risk is induced by short-sale constraints; I will refer to it as "the constraint-induced liquidity risk".[24] A short-selling ban reduces the speed of price discovery by preventing informed investors to trade on bad news, thereby increasing the information asymmetry component of the bid-ask spread and reducing the liquidity of non-shortable stocks (Diamond & Verrecchia, 1987). Many empirical studies have provided evidence in support of the theory (See literature review in Section 5.2.2 for more details). A drop in liquidity could be particularly detrimental to investors during a crisis when investors are in greater need of liquidity. Thus, investors would require higher returns as compensation for taking on the risk of losses resulting from liquidity dry-up due to a short-selling ban.

[24] In this study, I focus on this constraint-induced liquidity risk and do not consider a separate liquidity risk factor induced by other reasons than short-sale constraints, as conceptually such "other reasons" should be shared among both non-shortable and shortable stocks. In addition, Fama and French (1992) argue that liquidity need not be specifically measured.

The third reason concerns the speed of price discovery itself. For convenience, I will refer to the related risk as the “constraint-induced information risk”. Theory predicts that short-sale constraints lower the speed of price discovery for constrained stocks, and investors will view such a speed slowdown as a loss of information efficiency, which entails risk. They will, therefore, require higher expected returns from the stocks. The empirical literature provides evidence that non-shortable stocks do have a lower price discovery/adjustment speed than shortable stocks (See literature review in Section 5.2.2 for more details).

Based on the above considerations, I attempt to augment the Fama-French three-factor model with an additional risk factor for equity markets that practice short-sale constraints. Specifically, I conjecture that returns on the portfolios of long in non-shortable, and short in shortable, stocks one such risk factor; referred to as the no-shorting factor; that shall be priced in the augmented asset pricing model. Following Fama and French (1993) who treat respectively the size factor and the value factor as a whole, I take the no-shorting factor as synthesising the above-discussed “overvaluation risk”, “constraint-induced liquidity risk” and “constraint-induced information risk”. In other words, if a risk premium is detected, this implies that investors require it to compensate for taking on the synthesised risk. Testing the conjecture, or investigating, whether the no-shorting factor pays a significant risk premium, I do three things. First, I run a time-series regression to see whether the no-shorting factor explains time-series variation in stock returns. Second, I conduct the two-step Fama-MacBeth (Fama & MacBeth, 1973) regression to determine whether the no-shorting factor also explains the cross-section of stock returns. Third, I adopt the approach suggested by Lewellen, Nagel and Shanken (2010) by reporting the T-square statistics, the unexplained squared

Sharpe ratios and their confidence intervals to assess the performance of my new factor model.

As noted in Chapter 4, all asset-pricing models make simplifying assumptions. For one, the CAPM assumes no short-sale restrictions. In the real world market, however, regulators do prohibit the short-sales of risky assets, fearing, for example, the abuse of short-selling for downward price manipulation. It is widely observed that regulators often impose short-sale restrictions to prevent falling stocks/markets from crashing. According to Bris et al. (2007), out of 46 countries, 21[25] do not allow and/or practice short sales due to either restrictive regulations, or huge costs, on shorting stocks. In fact, during the recent financial crisis period from 2007 to 2009, even many of those 25 countries that used to allow short-sales did impose short-selling bans on the entire market, sectors, or individual stocks, from time to time, including the US and most European countries (See Chapter 4 for more information about short-selling bans during the 2007-2009 financial crises).

Before ascertaining whether the existing asset-pricing models need modification, there is, however, yet another question to answer: Does the assumption that assets are freely shortable significantly impair the performance of the models when applied to the assets/markets facing short-sale restrictions? If not, devoting efforts to modify the models would become trivial and unnecessary. Using unique short-selling regulations on the Hong Kong stock market, the previous chapter (Chapter 4) has provided strong evidence that the presence of short-sale constraints significantly jeopardises the validity of the theoretical

[25] They are Argentina, Brazil, Chile, China, Colombia, Finland, Greece, Hungary, Indonesia, Israel, New Zealand, Pakistan, Peru, the Philippines, Poland, South Korea, Spain, Taiwan, Turkey, Venezuela and Zimbabwe. The other 25 countries that allow and practice short-sales are Australia, Austria, Belgium, Canada, the Czech Republic, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, Luxembourg, Malaysia, Mexico, the Netherlands, Norway, Portugal, Singapore, South Africa, Sweden, Switzerland, Thailand, the United Kingdom and the United States. See Table 1 in Bris, Goetzmann and Zhu (2007) for detailed descriptions of the 46 countries.

CAPM and the empirical Fama-French three-factor model. Specifically, the conventional tests show lower average R-squares, higher GRS statistics,[26] greater absolute intercepts and greater unexplained Sharpe ratios where the CAPM and three-factor models work with non-shortable stocks than where they work with shortable stocks. In addition, the LNS enhanced approaches (Lewellen, Nagel & Shanken, 2010) obtain similar evidence: The two models employing non-shortable stocks' data have greater confidence intervals of q (representing the $T^2$-related[27] unexplained Sharpe ratio) than when employing shortable stocks' data. My results based on both the conventional test statistics and the enhanced approaches reinforce each other. They suggest that asset-pricing models work better for shortable assets than for non-shortable assets. This should not be surprising, since the models' assumption of no short-selling restrictions pre-restrict their applicability to markets without such restrictions.

Previous studies in the literature can also lead us to the above conclusion. Fama and French (1998) find that the CAPM and their three-factor model have strong explanatory power for 13[28] developed international countries/markets, but fail to explain the risk variation of returns in emerging markets. It is worth noting that the 13 markets do ***not*** have short-selling restrictions, while almost all emerging markets prohibit, or partly prohibit, short-selling activities. Griffin (2002) confirms that the Fama-French three-factor model is largely country specific, especially in the US, Japan, the UK and Canada. Again, these four countries had free short-selling regulations and short-sales were very active[29] in the period studied by the author. Since Griffin (2002) there have been an increasing number of empirical studies

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[26] The GRS F statistic tests whether all portfolios' time-series intercepts (α) are equal to zero (Gibbons, Ross & Shanken, 1989).

[27] The cross-sectional $T^2$ statistic tests whether the weighted sum of squared pricing errors are all equal to zero (Shanken, 1985).

[28] The 13 developed markets countries' are the US, Japan, the UK, France, Germany, Italy, the Netherlands, Belgium, Switzerland, Sweden, Australia, Hong Kong and Singapore.

[29] Borrowing and lending stocks are well developed in the Canadian stock market and account for a large amount.

applying the CAPM and the Fama-French three-factor model to emerging countries/markets that restrict short-selling, but few of them have obtained evidence in line with Fama and French (1998) for the 13 developed countries. Thus, one will naturally attribute the performance differences of the CAPM and three-factor models between developed markets and developing markets to the presence of short-selling restrictions.

In summary, the regular and prevalent observations of short-selling restrictions and the evidence of poor performances of the existing asset-pricing models in such restrictive markets constitute a call for relaxing the assumption and augmenting the models accordingly. This call has not yet gained due attention in the literature. So, in this chapter, I devote my efforts to filling this void. Specifically, I augment the extant asset-pricing models with the no-shorting factor, in order to improve their performances. As in the previous two chapters, the unique Hong Kong short-selling regulation allows me to divide all Hong Kong listing stocks into shortable and non-shortable groupings according to a designated short-selling list, and then construct the no-shorting factor by take the differences between the returns to the portfolios of non-shortable stocks and the returns to the portfolios of shortable stocks.

The present study yields three main findings. First, the no-shorting factor has significant power in explaining both time-series and cross-sectional variation in stock returns. Second, adding the no-shorting factor to the one factor (CAPM), three-factor and four-factor models, significantly improves their overall performances. Third, however, the no-shorting factor makes the momentum factor, constructed either as the Carhart momentum or as the Fama-French momentum, unimportant in explaining return variation in the Hong Kong stock market.

This study makes two contributions to the asset-pricing literature. First, it demonstrates, for the first time in the literature, that the assumption of no restrictions on short sales of any assets can be relaxed. This does not mean that one can ignore the assumption, as has been the case in the literature. The existing asset-pricing models are “constrained” by the assumption that they work within the environment of no short-selling restrictions. Relaxing the assumption by allowing for the presence of short-sale constraints, the resultant augmented asset-pricing model will work just as well in the environment of short-selling restrictions. Moreover, the augmented models also nest the existing models, in that, where short sales are allowed and practiced, the former collapses to the latter.

Second, this study expands the extant set of risk factors with a new one that mimics the factor of short-sale constraints. Creating the new factor has three implications. The first is that it enables me to address the question of how to allow for the presence of short-sale constraints and how to modify asset-pricing models accordingly. The second is related to the persistent higher returns on non-shortable stocks than on shortable stocks. Prior work fails to provide explanations, but my new factor can offer one: The return difference could be due to a risk premium required by investors holding non-shortable stocks, hence bearing some undiversifiable risk (such as the overvaluation risk, the low-liquidity risk, and the low-speed risk, as noted above). The third implication is that, when it comes to the markets where short sales are not allowed, there is an additional pattern in average returns that all the existing factor models cannot explain. This extra anomaly is caused by the short-selling restrictions.

The rest of this chapter is organised as follows: Section 5.2 summarises the relevant literature. Section 5.3 describes the data and methodology, followed by Section 5.4 where empirical results are presented and discussed. Section 5.5 concludes.

## 5.2 Literature Review

This section surveys the relevant literature. My study is related mainly to two streams of the literature: (1) Theoretical and empirical studies on asset-pricing models and risk factors; and (2) research on the impacts of short sales and short-selling restrictions on asset-pricing and market efficiency.

### *5.2.1 Evolution of Asset-pricing Factor Models*

Since Treynor (1961, 1962), Sharpe (1964), Lintner (1965), Mossin (1966) and Black (1972) developed the Capital Asset Pricing Model (CAPM), a single factor model, it has been widely used in both academia and industry. Early empirical studies find, however, that the CAPM cannot explain several market anomalies[30], including firm size (Banz, 1981), the book-to-market ratio (Stattman, 1980), the earnings-to-price ratio (Basu, 1983), firm leverage (Bhandrari, 1988), long-term return reversals (De Bondt & Thaler, 1985, 1987) and momentum returns (Jegadeesh & Titman, 1993).

Addressing some of these anomalies (size, leverage, E/P and B/M), Fama and French (1992), compare their explanatory powers together with betas in cross-sectional regressions. They find that size and B/M have the strongest relation to returns, while other variables (including beta) have none. Then, in a follow-up study, Fama and French (1993) expand the single factor CAPM by adding the size factor (SMB) and the value factor (HML). Using the model, the authors show that the two additional factors can capture the cross-sectional differences in expected returns on stocks and bonds beyond what the CAPM predicts. For

[30] According to Schwert (2003), market anomalies refer to empirical results that are not consistent with the maintained theories of asset pricing behaviour, such as the CAPM.

instance, the three-factor model is able to explain more than 90% (OLS $R^2$) of cross-sectional changes in expected returns, while the CAPM can only capture 70%, for the US stock market data that they examine. The subsequent research on various stock markets, thus, switched from the CAPM to the Fama-French three-factor model. Their results indicate that the latter is able to explain, on average, 96% (an average OLS $R^2$) of the cross-sectional variations in expected returns.[31] The successes of the Fama-French three-factor model have, therefore, made it increasingly popular among academics and practitioners. Fama and French (1993, 1996) suggest that the size and value factors proxy for the priced distress factor. In particular, pursuing value strategies that buy a portfolio of stocks with persistently low sales and earnings records (i.e., high distress) and sell a portfolio of stocks with persistently high sales and earnings records (i.e., low distress) is fundamentally riskier and, therefore, requires compensation for bearing this risk. DeBondt and Thaler (1987), Lakonishok, Shleifer and Vishny (1994) and Haugen (1995) offer another reason for the value premium, based on the overreaction hypothesis. The search for the reasons why the size premium exists has, however, been unsuccessful (see, e.g., Chan & Chen, 1991; Perez-Quiroz & Timmermann, 2000; Lettau & Ludvigson, 2001).

Fama and French (1996) concede that their three-factor model is unable to explain the well-documented momentum effect. In view of this, Carhart (1997) adds a fourth factor to the model to reflect momentum. The author finds that the momentum factor also plays a significant role in explaining expected returns, suggesting that momentum is yet another important market anomaly that the CAPM and the Fama-French three-factor model fail to capture. There are several different explanations for the existence of the momentum. Barberis, Shleifer and Vishny (1998) use behavioural models to show that investor underreaction, or

[31] Fama and French (1992, 1993, 1996, 2002) and Gaunt (2004).

overreaction, to firm specific news is a possible explanation of momentum anomaly. Daniel, Hirshleifer and Subrahmanyam (1998) and Barberis et al. (1998) suggest that investors failing to incorporate new information into their investment under the irrational theory may lead to the momentum phenomenon. Hong and Stein (1999) and Chordia and Shivkumar (2002) attribute momentum to macroeconomic factors.

Amihud and Mendelson (1986) pioneer the studies on the role of liquidity in asset-pricing models and find that liquidity, which was previously regarded as a firm specific characteristic, is related to the cross-section of asset returns. Several researchers also suggest that liquidity variation and uncertainty constitutes some undiversifiable systematic risk, which needs to be compensated for (Chordia, Roll & Subrahmanyam, 2001; Hasbrouck & Seppi, 2001; Huberman & Halka, 2001). Amihud (2002) and Bekaert, Harvery and Lundblad (2003) find evidence that liquidity has predictive power for stocks' future returns. Acharya and Pedersen (2005) incorporate transaction cost, which is a very important determinant of liquidity, into the CAPM framework and reveal that the liquidity-adjusted asset pricing model performs better in explaining return variations. Pastor and Stambaugh (2003) use a five-factor model, adjusting for Fama-French's three factors and the momentum factor. Their results imply that sensitivity to market-wide shifts in liquidity may also be a priced risk factor, since stocks with a high "liquidity beta" have high average returns. This liquidity factor appears to be distinct from the market, size, value and momentum, hence it is an independent source of risk. Liquidity betas are, however, highly unstable and there is substantial variation in the corresponding premium.

In fact, most of the factors in the above-reviewed multi-factor models, such as the market portfolio, SMB and HML, behave in the way that the risk factors from the Arbitrage

Pricing Theory (APT) model would behave (these risk factors are systematic and cannot be diversified away).[32] The APT model hinges on the premise that arbitrage opportunities should not be present in efficient financial markets and that, in order to prevent arbitrage, an asset's expected returns must depend (linearly) on its sensitivity to a sufficient number (n) of systematic risks (Ross, 1976a, 1976b). The absence of arbitrage opportunities is possible only if market participants are able to take offsetting positions in close economic substitutes in order to enforce the law of one price. The chief obstacles to arbitrage in these cases are short-sale constraints. Thus, where short sales are practiced, there is no need to include the no-shorting factor defined above as the n+1$^{th}$ common factor. Many asset markets in the real world are, however, inefficient because of short-selling restrictions among all market frictions. As such, the no-shorting factor should be added to the model so that arbitrage opportunities across assets will vanish. Without doing so, the validity of the above-reviewed multi-factor asset-pricing models when applied to markets with short-selling restrictions would be impaired by the presence of arbitrage opportunities.

### *5.2.2 Short-selling Restriction and Market Quality*

In Section 5.1, I asked why short-sale constraints should constitute a risk factor and offered reasons based on a very limited number of previous studies. Here, I provide a more detailed review, but only of those studies directly relevant to the question, as reviewing the extensive literature on short-sale constraints is both infeasible and unnecessary.

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[32] Consider, for example, the time-series averages of $SMB_t$ and $HML_t$. They can be interpreted as the average risk premiums for the two risk factors, which correspond to two $\lambda$'s from the APT model $E(R_i) = R_f + \sum_j^n \beta_{i,j}\lambda_j$ .

The overvaluation risk involves both overpricing of non-shortable stocks and disagreements among investors about the stocks' value: Without the latter two, the former would be non-existent. A pioneering work noting the two aspects is Miller (1977). The author reasons that, when investors have heterogeneous beliefs about the value of an asset and its short-selling is not allowed, the equilibrium price of the asset will reflect the opinions of the more optimistic investors, leading to overpricing. Since Miller (1977), many researchers have explored the overpricing effects of short-selling constraints. Boehme et al. (2006) use lending fees, while Figlewski (1981), Asquith and Meulbroek (1995), Woolridge and Dickinson (1994) and Desai et al. (2002) use short interest. These studies lead to either conflicting results as to whether Miller's overpricing exists, because they look at only one of the two conditions (short-sale constraints and divergent investor opinions) for overvaluation; or the result that the Miller effect does exist, but only if the two conditions are taken into account simultaneously (Boehme et al., 2006). There is little doubt that the results that allow for both conditions, instead of just one, should be taken more seriously.

As Chapter 5's focus of augmenting the multi-factor models with the no-shorting factor follows logically from the findings of Chapter 4, it is useful to also include my own study in this literature survey. Chapter 3 of this thesis documents that short-selling restrictions affect asset prices by inducing permanent higher returns on non-shortable stocks than on shortable stocks, rather than just causing temporary share price overvaluation. In the Hong Kong stock market, from January 1994 to December 2009, non-shortable stocks outperform shortable stocks by 15 basis points per month on average. This difference is statistically significant and remains robust even after controlling for firms' characteristics (the size and book-to-market effects and the liquidity effect, among others) and the market risk. These findings substantially advance those of Chang et al. (2007), who document a significant positive discrepancy in returns of the same stocks between when they are not allowed to be sold short and when they are. They show that the average daily discrepancy is 0.55% in raw returns and 0.64% in risk-adjusted returns. Chang et al. (2007) attribute the significant price drops after the lifting of short-selling restrictions to Miller's (1977) overpricing effect. They do not, however, explore the possibility that, as long as stocks remain without short-selling constraints, their returns are lower than if they remain under short-selling restrictions. Despite this difference between my permanent overvaluation evidence and their temporary overvaluation evidence, both imply a common point that changes in the valuation of a stock depends on, among other things, changes in the short-selling regime, which cannot be precisely predicted. The unpredictable part of the changes then represents the risk that the investors of non-shortable stocks have to bear.

Now, I turn to the literature that examines constraint-induced liquidity risk. Diamond and Verrecchia (1987) develop a theoretical framework for analysing how short-selling restrictions reduce the liquidity of the affected stocks. Boehmer et al. (2009) and Kolasinski, Reed and Thornock (2010) are two examples of empirical studies of the US stock market. The former study, using spreads and price impacts to measure liquidity, concludes that liquidity is significantly deteriorated for stocks subject to the short-selling ban. The latter study reaches a similar conclusion in their empirical study of the effect of the June 2008 emergency order on the 19 stocks restricted for short-selling. Marsh and Payne (2012) provide UK evidence by showing that as soon as the short-selling ban applies to financial stocks, their liquidity declines, which is reflected by their bid-ask spreads widening. Beber and Pagano (2013) examine the impacts of short-selling bans on liquidity, price discovery and stock prices of 30 countries that responded to the 2007-2009 financial crises by imposing bans, or constraints. The study demonstrates that short-selling bans and constraints have led to a statistically and economically significant liquidity disruption, especially for small stocks. In fact, it is not difficult to understand the negative relation between short-sale constraints and liquidity results. As Autore, Billingsley and Kovacs (2011) note, short-sellers are liquidity providers. Thus, their absence (from non-shortable stocks) could lower liquidity and increase trade spreads. All the above reviewed studies suggest that evidence does exist for short-sale constraints to induce less liquidity, which is a risk borne by investors in non-shortable stocks.

Next, I turn to an examination of studies on the link between short-selling restrictions and the speed of price discovery. Diamond and Verrecchia's (1987) theoretical study predicts that short-selling restrictions prevent negative information from being impounded in stock prices and so reduce the speed of price discovery.  Bai et al. (2006) also theorise that short-sale constraints lower the speed of price discovery. These theoretical hypotheses have received strong support from empirical studies. Bris et al. (2007) report that prices impound negative information faster in the equity markets that allow investors to practice short sales. Several subsequent studies; for example, Saffi and Sigurdsson (2010), Boehmer and Wu (2010), and Chen and Rhee (2010); produce results that basically conform with Bris et al. (2007). In particular, Chen and Rhee (2010), like my study, also employ data from the Hong Kong market. They present evidence that short sales contribute to market efficiency by increasing the speed of price adjustment to both firm-specific and market-wide information, and both private and public information. If short sellers are also primary information providers, in addition to being liquidity providers, then their absence could hinder price discovery as one of the major functions of capital markets. Thus, the findings of the above reviewed articles are intuitively plausible. Bai et al. (2006) argue, however, that the slowdown of price discovery due to short-sale constraints increases risk, because less informative prices make less informed investors feel more uncertain about what the suppressed *negative* information is. The constrained stocks must then offer higher returns (by lowering current prices) as compensation, such that these investors will be willing to buy them.

Apart from the overvaluation risk, the constraint-induced liquidity risk and the constraint-induced information risk, market crashes are another risk that short-sale constraints may lead to. Several studies have examined links between short-sale constraints and market crashes. Hong and Stein (2003) and Scheinkman and Xiong (2003) associate market crashes with revisions of expectations: Informed investors are constrained from short selling, so their accumulated negative information will not be manifested until the market begins to drop, which further aggravates the market decline and results in a crash. Bai et al.'s (2006) model also implies that short-sale constraints can be a potential cause of market crashes: Market crashes arise from a sudden surge in uncertainty as perceived by less informed investors, rather than a change in asset value as perceived by investors.

I can now draw conclusions from the literature survey conducted in Section 5.2. The existing asset-pricing models have evolved from the single-factor model to the multi-factor model to take into account more and more CAPM anomalies, and have achieved intended successes. One of their limitations is, however, the unrealistic assumption of no limit to arbitrage such as short sales. This assumption should make them work well where it holds, but not where it fails to hold. Short-sale constraints are increasingly widely present in both developed and emerging markets, especially since the recent drastic financial crises. Thus, ignoring the assumption and continuing to apply the existing models indistinguishably to any markets is also increasingly questionable. Studies on the effects of short-sale constraints on markets, or individual assets, suggest that short-sale constraints entail risk via overpricing assets, lowering liquidity, impairing informational efficiency and possibly leading to market crashes. Considered together, these points motivate my conjecture that short-sale constraints *per se* are a systematic, un-diversifiable risk factor. Therefore, the work reported in the remaining sections attempts to improve the validity of the existing standard multi-factor asset-pricing model by incorporating the conjecture. This is a two-in-one goal derived from, and justified by, the literature surveys in Sections 5.2.1 and 5.2.2.

## 5.3 Data, Risk Factor Construction and Methodology

I have seen, from Chapters 3 and 4, that the uniqueness of Hong Kong's regulations on short-sales provides an ideal laboratory for exploring the differences in stock pricing behaviour and in the performances of asset-pricing models, the differences being due to two opposite short-selling statuses. In fact, the designated short-selling list also enables me to construct the no-shorting risk factor. According to the designated short-selling list, at any point in time, a stock stays either on the list, or off the list. I can, therefore, differentiate individual stocks' short-selling statuses: If a stock is on the list, I refer to it as "shortable"; if a stock is off the list, I refer to it as "non-shortable". The detailed description of the Hong Kong designated short-selling list has already been given in Chapter 2. This chapter adopts the same sample period of addition/deletion stocks in the Hong Kong stock market as in Chapter 4. The changes of the designated short-selling list are provided by Table 2.1 in Chapter 2.

To construct risk factors[33] and form portfolios, I collect the following data for each individual stock traded on the HKSE; closing prices, market value (ME), book value (BE), and the number of shares outstanding. I also obtain the monthly Hong Kong 3-month Treasury bill rate (T-bill) as a proxy for the risk-free rate. All of the above data come from the Datastream database.

In constructing the size and book-to-market risk factors, I follow Fama and French (1992, 1993). Specifically, I sort all the stocks listed on the HKSE at the end of June of each year t based on their market value (ME) and classify them into the two size groups: Stocks with ME above (below) the cross-sectional median are classified as big (small) stocks and denoted as B (S). Meanwhile, I rank all the stocks based on their book-to-market ratios (BM) and classify them into one of the three BM groups: Stocks with the highest (lowest) 33% BM are classified as high (low) book-to-market stocks and denoted as H (L), with the remaining 33% classified as medium book-to-market stocks and denoted as M. These independent 2×3 sorts allow me to construct six size and book-to-market portfolios (S/L, S/M, S/H, B/L, B/M and B/H) from the intersections of the two size and the three book-to-market groups. For example, the S/L portfolio contains the stocks in the small-size group that are also in the low book-to-market group, and the B/H portfolio contains the big-size stocks that also have high book-to-market ratios. I calculate monthly value-weighted returns on the six portfolios from July of year t to June of year t+1, and reform the portfolios at June of each year. To be included in the test, a firm must have closing prices for December of year t-1 and June of year t, and book equity for year t-1.

[33] Risk factors for the Hong Kong stock market are not available from the Data Library website of Professor Kenneth French. So, I construct all of them, adopting the approach proposed by Fama and French (1992, 1993, 1996).

Below are the details[34] of each risk factor to be used in this study. The size factor is represented by the portfolio returns denoted as SMB (small minus big), meant to mimick the risk factor in returns related to size. The SMB returns are calculated as the difference, each month, between the simple average of the returns on the three small-stock portfolios (S/L, S/M, and S/H) and the simple average of the returns on the three big-stock portfolios (B/L, B/M, and B/H):

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

In short, SMB is the difference between returns on small-stock portfolios and returns on big-stock portfolios. This difference is largely free of the influence of BE/ME, focusing instead on the different return behaviours of small and big stocks.

The BE/ME factor is represented by the portfolio returns denoted as HML (high minus low), meant to mimick the risk factor in returns related to book-to-market equity. The HML returns are calculated as the difference, each month, between the simple average of the returns on the two high-BE/ME portfolios (S/H and B/H) and the simple average of the returns on the two low-BE/ME (S/L and B/L) portfolios:

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

HML is largely free of the size effect in returns, and focuses on the different return behaviours of high-BE/ME and low-BE/ME stocks.

[34] The constructions of the market, size and book-to-market factors are the same as in Chapter 4, however, in Chapter 5 I construct two more factors; namely, the momentum and no-shorting factors.

True mimicking portfolios for the common risk factors in returns will minimise the variance of firm-specific factors. The six size-BE/ME portfolios in SMB and HML are value-weighted, to be in the spirit of minimising variance and reducing estimation bias[35]. More importantly, use of value-weighted components results in mimicking portfolios that capture the different return behaviours of small and big stocks, or high-BE/ME and low-BE/ME stocks, in a way that corresponds to realistic investment opportunities.

I proxy the market factor by excess market returns denoted as RM-RF. RM is the returns on the value-weighted portfolio of the all shares in the Hong Kong market, and RF is the Hong Kong 3-month Treasury bill rates (T-bill).

I use two alternative measures for the momentum factor WML; The Carhart momentum factor MOM_CARH, and the Fama-French momentum factor MOM_FF. MOM_CARH represents the portfolio returns constructed following Carhart (1997). The winner (loser) portfolio W (L) consists of firms with the top (bottom) 33% returns in the past 11 months prior to month t-1, and the momentum factor is simply the difference between equally-weighted portfolio returns of W and those of L:

$$MOM\_CARH = Winner\_PROTFOLIO - Loser\_PORTFOLIO$$

I construct the Fama-French momentum factor (available on Kenneth French's website for many stock markets, but not for Hong Kong) in the following way: It uses the intersections of two value-weighted size portfolios and three value-weighted portfolios formed on prior returns (all Hong Kong stock returns in the past eleven months prior to month t-1). This momentum factor is the simple difference between the average return on the

[35] Asparouhova, Bessembinder and Kalcheva (2012) point out that equally-weighted returns of portfolios constructed based on firm characteristics could produce estimation bias.

two top prior return portfolios and the average return on the two bottom prior return portfolios:

$$MOM\_FF = \frac{(S/Top - S/Bottom) + (B/Top - B/Bottom)}{2}$$

The no-shorting factor NMS is the difference in returns between the portfolio of non-shortable stocks and the portfolio of shortable stocks, meant to mimick the risk factor related to short-sale constraints. The factor is constructed as follows. Using the same rebalancing scheme as for the 25 size/BM portfolios, SMB and HML, I sort all stocks based on whether or not they are on the shorting list at the end of June of each year t, and classify them into each of the two portfolios; shortable, and non-shortable. I then hold the two portfolios for 12 months (as I do for size/BM, SMB and HML portfolios), and calculate their respective monthly value-weighted returns. The shorting factor is then equal to non-shortable portfolio returns less shortable portfolios returns, and is denoted as NMS12. The constituent stocks in the shortable, the non-shortable and, hence the NMS12 portfolio, do not change between the end of June of year t and the end of June of year t+1. For comparison purposes, I also consider the 1-month holding period for the no-shorting factor portfolio, which is denoted as NMS1. Specifically, in each month, I classify all stocks into shortable and non-shortable portfolios, according to whether or not they are on the short-selling list in that month, and calculate their respective monthly value-weighted returns. NMS1 is then equal to the difference between the two portfolios’ returns, so the constituent stocks in the two portfolios and, hence, in NMS1 may change from month to month. Since the rebalancing period of NMS1 is different from, while NMS12 has the same rebalancing period as, that for the size/BM portfolios, SMB and HML, I will discuss the results involving NMS12 in the main text, while leaving the results involving NMS1 to the appendix of this chapter.

To examine the explanatory power of the no-shorting risk factor for variation in stock returns, I employ the Fama-Macbeth (Fama & MacBeth, 1973) two-pass regression method. The first pass runs the time-series regressions, as Fama and French (1992, 1993) do. By regressing each of 25 size-B/M portfolio returns on five common factors (including the no-shorting factor NMS) over the sample period, I can obtain direct evidence of whether NMS causes the 25 portfolio returns to vary together, in addition to their variations explained by the other four factors. The regression model is:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + s_p SMB_t + h_p HML_t + m_p MOM_t + n_p NMS_t + \varepsilon_{pt} \qquad (5.1)$$

where the dependent variables $R_{pt} - R_{ft}$ are excess returns on 25 size-B/M portfolios (i.e., $p$ =1, 2,…, 25), formed on size and the book-to-market ratio of stocks[36]; $R_{mt} - R_{ft}$ are the excess returns on the market portfolio; $SMB_t$ is the size factor; $HML_t$ is the value (book-to-market) factor; $MOM_t$ is either the Carhart momentum factor (MOM_CARTH), or the Fama-French momentum factor (MOM_FF); and $NMS_t$ is the no-shorting factor. $\alpha_p$ is the intercept measuring abnormal returns. $\beta_p$, $s_p$, $h_p$, $m_p$ and $n_p$ are the slope coefficients, which measure the sensitivity of the return on portfolio $p$ to their respectively associated factors. If $NMS_t$ is a risk factor and helps explain stock returns, I expect its loading $n_p$ to be statistically significant, and the adjusted $R^2$ to be higher than if $NMS_t$ was not included in Equation (5.1). As in Chapter 4, I employ conventional statistics (such as the adjusted $R^2$ and the GRS F) to compare the performances of the FF three-factor model, the FF four-factor model (with

[36] In Chapter 4, I form 25 size-B/M portfolios respectively for shortable and non-shortable stocks. In this chapter, I do so for all stocks without dividing them into the two groups.

MOM_FF added), the Carhart four-factor model (with MOM_CARTH included) and my five-factor model with the no-shorting factor added.

The second pass runs cross-sectional regressions, through which I examine how well the average premiums for the five proxy risk factors explain the cross-section of average returns on stocks.

## 5.4 Empirical Results: Time-series Regression Analysis

Table 5.1 presents the means and standard deviations of the dependent variables; returns on the 25 size-B/M portfolios of *all* stocks in the Hong Kong stock market. The summary statistics indicate that small firms have higher returns than large firms, and high book-to-market stocks have higher returns than low book-to-market stocks. Specifically, firms with the smallest size and the highest B/M ratios have the largest return, at 6.10% per month for the raw return and 3.00% for the risk-adjusted return. Firms with the biggest size and the lowest B/M ratios have almost the lowest return, at 0.80% per month for the raw return and -2.30% for the risk-adjusted return. Furthermore, the stock returns of small firms generally have higher standard deviations than the stock returns of large firms, which is consistent with the notion that small firms are riskier than large firms and so investors demand a higher rate of return from the former as compensation for bearing extra risk.

**Table 5.1 Summary statistics of monthly excess returns for 25 portfolios formed on size and B/M, Jan 1999 – Feb 2012**

At the end of June of each year I construct 25 size-B/M portfolios of all stocks (containing both shortable and non-shortable stocks). The size breakpoints are the 20th, 40th, 60th and 80th percentiles of market capitalisation. The B/M quintile breakpoints are the 20th, 40th, $60^{th}$ and 80th percentiles of the book-to-market ratio. The intersections of the 5x5 independent size and B/M sorts for those stocks produce 25 monthly value-weighted size-B/M portfolios. The risk free rate is the monthly Hong Kong 3-month Treasury bill rate.

Summary statistics for dependent returns (monthly)

Book-to-Market Equity (BE/ME) Quintiles

Raw Return

| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Means | | | | | | Standard Deviations | | | |
| Small | 0.056 | 0.044 | 0.035 | 0.045 | 0.061 | Small | 0.200 | 0.164 | 0.162 | 0.148 | 0.208 |
| 2 | 0.017 | 0.023 | 0.024 | 0.021 | 0.030 | 2 | 0.169 | 0.129 | 0.190 | 0.119 | 0.117 |
| 3 | 0.012 | 0.006 | 0.013 | 0.020 | 0.017 | 3 | 0.158 | 0.113 | 0.115 | 0.117 | 0.133 |
| 4 | 0.006 | 0.010 | 0.009 | 0.016 | 0.017 | 4 | 0.110 | 0.095 | 0.110 | 0.106 | 0.108 |
| Big | 0.008 | 0.009 | 0.006 | 0.010 | 0.012 | Big | 0.079 | 0.087 | 0.089 | 0.098 | 0.117 |

Excess Return

| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Means | | | | | | Standard Deviations | | | |
| Small | 0.027 | 0.015 | 0.003 | 0.014 | 0.030 | Small | 0.203 | 0.163 | 0.167 | 0.154 | 0.211 |
| 2 | -0.013 | -0.008 | -0.007 | -0.010 | -0.001 | 2 | 0.173 | 0.135 | 0.193 | 0.125 | 0.122 |
| 3 | -0.019 | -0.025 | -0.018 | -0.011 | -0.014 | 3 | 0.162 | 0.119 | 0.121 | 0.123 | 0.138 |
| 4 | -0.025 | -0.021 | -0.023 | -0.016 | -0.014 | 4 | 0.115 | 0.101 | 0.117 | 0.113 | 0.115 |
| Big | -0.023 | -0.022 | -0.025 | -0.022 | -0.019 | Big | 0.083 | 0.093 | 0.096 | 0.104 | 0.124 |

Table 5.2 sets out the descriptive statistics of the five risk factors; market, size, book-to-market, no-shorting (with two measures), and momentum (with two measures). Averaging over the sample period from January 1994 to December 2012, the market portfolio underperforms risk-free assets, so I can see a negative excess market return of -1.309% (t-statistic = -2.360). Small stocks outperform big stocks, resulting in a statistically significant average return of 2.10% on the size portfolio (t-statistic = 2.80). Stocks with high book-to-market ratios generate higher returns than stocks with low book-to-market ratios. Hence, there is a statistically significant average return on the value portfolio of 1.50% (t-statistic = 3.47). Winning stocks perform insignificantly differently than losing stocks, whether based on the Carhart (1997) measure, or on the Fama-French measure. Finally, stocks with a short-selling ban generate a significantly higher return than stocks without the ban. There is an average return on the shorting-status portfolio of 1.2% (t-statistic = 2.62) for NMS1, and 1.1% (t-statistic = 2.29) for NMS12. One can see that the no-shorting factor's average return is quite similar to the size factor's and the value factor's average return in terms of economic and statistical significance.

Table 5.3 reports the correlation coefficients across all the risk factors to be used as independent variables in the asset-pricing tests. The market factor ($R_m - R_f$) is highly correlated with the momentum factors (*MOM_CARH*, or *MOM_FF*), but not correlated with the size factor (*SMB*), B/M factor (*HML*) and the two no-shorting factors (*NMS1 and NMS12*). The size factor (*SMB*) is not correlated with the market factor ($R_m - R_f$), the value factor (*HML*) and the Carhart momentum factor (*MOM_CARH*), but is highly correlated with the no-shorting factor (*NMS1*), and moderately correlated with the *NMS12* and the Fama-French momentum factor (*MOM_FF*). The value factor (*HML*) is correlated with the two no-shorting factors (*NMS1 & NMS12*) in different levels, as well as with the two momentum factors (*MOM_CARH* or *MOM_FF*). The no-shorting factor with a 1 month holding period (*NMS1*) is correlated with the 12 month holding period no-shorting factor *(NMS12)*, but is not correlated with the momentum factors (*MOM_CARH*, or *MOM_FF*). The no-shorting factor with a 12 month holding period (*NMS12*) is not correlated with the two momentum factors. The two momentum factors are highly correlated with each other, with the coefficient (0.841) being close to 1.

**Table 5.2 Summary statistics for risk factors, Jan 1999 – Feb 2012**

Market is the value-weighted market factor with dividends of all Hong Kong stocks; SMB, HML and MOM_Carh/MOM_FF are the risk factors associated with firm size and book-to-market and momentum, respectively. I construct the market risk factor by using all Hong Kong shares. The all-share index is value-weighted.

I break all Hong Kong stocks into two size groups based on the breakpoints for the bottom 50% (Small) and top 50% (Big) of the ranked values of ME. I also break all Hong Kong stocks into three book-to-market equity groups based on the breakpoints for the bottom 33% (Low), middle 33% (Medium) and top 33% (High) of the ranked values of BE/ME. Then I construct six portfolios (S/L, S/M, S/H, B/L, B/M, B/H) from the intersections of the two ME and three BE/ME groups. For example, the S/L portfolio contains the stocks in the small-ME group that are also in the low-BE/ME group, the B/H portfolio contains the big-ME stocks that are also in the low-BE/ME group and the B/H portfolio contains the big-ME stocks that also have high BE/MEs. Monthly value-weighted returns on the six portfolios are calculated from July of year t to June of t+1, and the portfolios are reformed in June of t+1. I calculate returns beginning in July of year t to ensure that book equities for year t-1 are known. Size risk factor (SMB) is the average of the returns on the small-stock portfolios minus the returns on the big-stock portfolios:

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

Likewise, B/M risk factor (HML) is the average of the returns on the high-B/M portfolios minus the returns on the low-B/M portfolios:

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

The Carhart momentum factor is defined as the equally-weighted winner portfolio constituting of firms with the top 30% eleven-month returns lagged one month minus the equally-weighted loser portfolio constituting of bottom 30% eleven-month returns lagged one month. WML is the simple average of the returns on the winner-stock portfolios minus the returns on the loser-stock portfolios.

*MOM_CARH = Winner_PROTFOLIO – Loser_PORTFOLIO*

The Fama-French momentum factor is constructed as intersections of two value-weight size portfolios and three value-weight prior (2-12) return portfolios. The momentum factor is the simple difference of the average return on the two top prior return portfolios and the average return on the two bottom prior return portfolios.

$$MOM\_FF = \frac{(S/Top - S/Bottom) + (B/Top - B/Bottom)}{2}$$

The short-selling-restriction risk factor NMS1 is the value-weighted monthly returns on non-shortable portfolios held for one month less the value-weighted monthly returns on shortable portfolios held for one month.

*NMS1 = Nonshortable_PORTFOLIO(with a 1-month-holding period) – Shortable_PORTFOLIO( with a 1-month holding period)*

The short-selling-restriction risk factor NMS12 is the value-weighted monthly returns on non-shortable portfolios held for 12 months (from July of year t to June of year t+1) minus the value-weighted monthly returns on shortable portfolios held for 12 months (from July of year t to June of year t+1).

*NMS12 = Nonshortable_PORTFOLIO(with a 12-month holding period) – Shortable_PORTFOLIO(with a 12-month holding period)*

| | $R_m$ - $R_f$ | *SMB* | *HML* | *NMS1* | *NMS12* | *MOM_CARH* | *MOM_FF* |
|---|---|---|---|---|---|---|---|
| Mean | -0.013 | 0.021 | 0.015 | 0.012 | 0.011 | 0.000 | -0.010 |
| t-value for mean | -2.360 | 2.800 | 3.470 | 2.620 | 2.290 | -0.070 | -1.860 |
| Median | -0.009 | 0.007 | 0.011 | 0.013 | 0.008 | 0.006 | 0.000 |
| Maxium | 0.153 | 0.668 | 0.266 | 0.255 | 0.319 | 0.125 | 0.181 |
| Minimum | -0.186 | -0.267 | -0.118 | -0.232 | -0.163 | -0.302 | -0.267 |
| Standard Deviations | 0.068 | 0.092 | 0.054 | 0.056 | 0.063 | 0.059 | 0.067 |
| No. Obs | 158 | 158 | 158 | 158 | 158 | 158 | 158 |

**Table 5.3 Correlation coefficients matrix of independent variables, sample period is from January 1999 to February 2012**

| Pearson Correlation Coefficients Matrix Prob > │r│ under $H_0$: $\rho = 0$ | | | | | | | |
|---|---|---|---|---|---|---|---|
| | *$R_m - R_f$* | *SMB* | *HML* | *NMS1* | *NMS12* | *MOM_CARH* | *MOM_FF* |
| *$R_m - R_f$* | | 0.005<br>*0.946* | 0.118<br>*0.139* | -0.079<br>*0.321* | -0.017<br>*0.833* | -0.241<br>*0.002* | -0.340<br>*<.0001* |
| *SMB* | | | -0.058<br>*0.470* | 0.623<br>*<.0001* | 0.137<br>*0.085* | 0.107<br>*0.180* | 0.143<br>*0.073* |
| *HML* | | | | 0.261<br>*0.001* | 0.137<br>*0.085* | 0.290<br>*0.000* | -0.357<br>*<.0001* |
| *NMS1* | | | | | 0.741<br>*<.0001* | -0.112<br>*0.161* | -0.117<br>*0.144* |
| *NMS_12* | | | | | | 0.002<br>*0.985* | -0.037<br>*0.645* |
| *MOM_CARH* | | | | | | | 0.841<br>*<.0001* |
| *MOM_FF* | | | | | | | |

Italic numbers are *p*-values of the correlation coefficients.

Now I turn to the formal empirical tests. My first task is to test the ability of the no-shorting factor to explain the time-series return variation. In so doing, I begin with the well-established asset-pricing models, namely the one-factor CAPM and the Fama-French three-factor model, as well as the Carhart four-factor model, or the Fama-French four-factor model. Then, I augment each of them with the no-shorting factor measured by NMS12, to determine the additional contribution of this new risk factor to the explanation of stock returns. The results are reported in Table 5.4 through Table 5.6 (The results associated with NMS1 will appear in the Appendix to this chapter).

**Table 5.4 Panel A: Time-series regressions based on the CAPM to explain monthly excess returns of 25 size-B/M portfolios, Jan 1999 – Feb 2012.**

The regression model: $R_{pt} - R_{ft} = \alpha_p + \beta_p \left( R_{mt} - R_{ft} \right) + \varepsilon_{pt}$

Book-to-Market Equity (BE/ME) Quintiles

| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $a_p$ | | | | | | $t(a_p)$ | | |
| Small | 0.060 | 0.041 | 0.046 | 0.061 | 0.051 | Small | 4.718 | 3.162 | 3.913 | 3.611 | 4.455 |
| 2 | 0.021 | 0.018 | 0.013 | 0.029 | 0.033 | 2 | 1.989 | 2.360 | 1.803 | 3.315 | 2.584 |
| 3 | 0.011 | 0.011 | 0.011 | 0.026 | 0.018 | 3 | 0.972 | 1.454 | 2.083 | 2.798 | 2.429 |
| 4 | 0.002 | 0.010 | 0.010 | 0.015 | 0.015 | 4 | 0.330 | 2.201 | 1.982 | 2.687 | 2.592 |
| Big | 0.002 | 0.003 | 0.001 | 0.005 | 0.009 | Big | 0.613 | 0.968 | 0.343 | 1.066 | 1.344 |
| | | | $\beta_\pi$ | | | | | | $t(\beta_\pi)$ | | |
| Small | 1.028 | 1.036 | 0.939 | 1.169 | 0.968 | Small | 5.556 | 6.437 | 7.587 | 5.399 | 6.009 |
| 2 | 1.203 | 0.919 | 1.005 | 1.060 | 1.008 | 2 | 6.856 | 8.174 | 7.557 | 7.688 | 4.775 |
| 3 | 1.289 | 0.803 | 0.987 | 1.042 | 0.877 | 3 | 5.914 | 8.862 | 13.418 | 8.144 | 10.632 |
| 4 | 1.322 | 0.972 | 1.082 | 1.021 | 0.995 | 4 | 11.947 | 15.924 | 14.231 | 12.844 | 11.790 |
| Big | 0.992 | 0.896 | 1.158 | 1.020 | 1.426 | Big | 21.746 | 22.659 | 15.332 | 15.284 | 15.137 |
| | | | $R^2$ | | | | | | Adj $R^2$ | | |
| Small | 0.165 | 0.210 | 0.270 | 0.157 | 0.188 | Small | 0.160 | 0.205 | 0.265 | 0.152 | 0.183 |
| 2 | 0.232 | 0.300 | 0.268 | 0.275 | 0.128 | 2 | 0.227 | 0.295 | 0.263 | 0.270 | 0.122 |
| 3 | 0.183 | 0.335 | 0.536 | 0.298 | 0.420 | 3 | 0.178 | 0.331 | 0.533 | 0.294 | 0.416 |
| 4 | 0.478 | 0.619 | 0.565 | 0.514 | 0.471 | 4 | 0.474 | 0.617 | 0.562 | 0.511 | 0.468 |
| Big | 0.752 | 0.767 | 0.601 | 0.600 | 0.595 | Big | 0.750 | 0.765 | 0.599 | 0.597 | 0.592 |

**Table 5.4 Panel B: Time-series regressions based on the CAPM augmented with the no-shorting factor with a 12-month holding period to explain monthly excess returns of 25 size-B/M portfolios, Jan 1999 – Feb 2012.**

The regression model: $R_{pt} - R_{ft} = \alpha_p + \beta_p \left(R_{mt} - R_{ft}\right) + n_p NMS12_t + \varepsilon_{pt}$

Book-to-Market Equity (BE/ME) Quintiles

| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $\alpha_\pi$ | | | | | | t($a_p$) | | | |
| Small | 0.044 | 0.028 | 0.029 | 0.049 | 0.036 | Small | 4.148 | 2.388 | 3.207 | 3.025 | 3.839 |
| 2 | 0.005 | 0.009 | 0.003 | 0.014 | 0.014 | 2 | 0.641 | 1.356 | 0.551 | 2.478 | 1.465 |
| 3 | -0.001 | 0.001 | 0.003 | 0.014 | 0.007 | 3 | -0.078 | 0.172 | 0.876 | 1.865 | 1.244 |
| 4 | -0.008 | 0.004 | 0.004 | 0.008 | 0.007 | 4 | -1.624 | 1.154 | 0.948 | 1.724 | 1.497 |
| Big | 0.004 | 0.004 | 0.003 | 0.003 | 0.004 | Big | 1.173 | 1.323 | 0.682 | 0.711 | 0.677 |
| | | $\beta_\pi$ | | | | | | t($\beta_\pi$) | | | |
| Small | 1.051 | 1.220 | 1.312 | 1.338 | 1.012 | Small | 6.960 | 7.286 | 10.126 | 5.726 | 7.592 |
| 2 | 1.058 | 0.932 | 0.816 | 0.993 | 0.923 | 2 | 9.625 | 9.866 | 9.756 | 11.982 | 6.611 |
| 3 | 0.955 | 1.019 | 0.996 | 1.097 | 1.173 | 3 | 6.805 | 11.167 | 17.440 | 9.860 | 14.701 |
| 4 | 1.183 | 1.068 | 1.050 | 1.030 | 1.032 | 4 | 16.702 | 19.231 | 16.830 | 15.587 | 15.699 |
| Big | 0.965 | 1.007 | 0.875 | 0.997 | 1.432 | Big | 22.317 | 22.859 | 15.436 | 15.464 | 15.952 |
| | | $n_p$ | | | | | | t($n_p$) | | | |
| Small | 1.445 | 1.125 | 1.481 | 1.014 | 1.313 | Small | 8.910 | 6.255 | 10.638 | 4.039 | 9.166 |
| 2 | 1.396 | 0.825 | 0.882 | 1.286 | 1.691 | 2 | 11.827 | 8.125 | 9.810 | 14.446 | 11.277 |
| 3 | 1.009 | 0.909 | 0.624 | 0.981 | 0.998 | 3 | 6.691 | 9.265 | 10.172 | 8.207 | 11.636 |
| 4 | 0.909 | 0.496 | 0.519 | 0.597 | 0.759 | 4 | 11.943 | 8.323 | 7.738 | 8.404 | 10.737 |
| Big | -0.148 | -0.098 | -0.120 | 0.139 | 0.395 | Big | -1.183 | -1.072 | -0.964 | 2.008 | 4.100 |
| | | $R^2$ | | | | | | Adj $R^2$ | | | |
| Small | 0.448 | 0.369 | 0.578 | 0.238 | 0.473 | Small | 0.441 | 0.361 | 0.572 | 0.228 | 0.467 |
| 2 | 0.596 | 0.509 | 0.548 | 0.691 | 0.521 | 2 | 0.591 | 0.503 | 0.543 | 0.687 | 0.515 |
| 3 | 0.366 | 0.572 | 0.722 | 0.511 | 0.691 | 3 | 0.358 | 0.566 | 0.718 | 0.505 | 0.687 |
| 4 | 0.728 | 0.737 | 0.686 | 0.666 | 0.697 | 4 | 0.725 | 0.733 | 0.682 | 0.662 | 0.693 |
| Big | 0.767 | 0.773 | 0.611 | 0.610 | 0.635 | Big | 0.764 | 0.770 | 0.606 | 0.605 | 0.630 |

Table 5.4 provides evidence about the role that the no-shorting factor NMS12 plays in explaining stock returns. Panel A of the table reports the results of time-series regressions of the 25 size-B/M portfolio returns on the market risk factor, while Panel B presents the regression results with the NMS12 factor added into the model. Comparing the regression results in the two panels, one can make the following observations: (1) After adding NMS12 to the CAPM, 23 out of 25 alphas become closer to zero, in terms of both economic magnitude and statistical significance. In particular, among all the 23 reduced t-statistics of alphas, 9 fall from a 90% significance level, or higher, to become insignificant, and 2 fall from the 99% significance level to the 90%; (2) 22 out of the 25 coefficients on NMS12 are statistically significantly positive, with the risk sensitivities ranging from 0.139 to 1.691; (3) all of the 25 adjusted $R^2$s increase significantly, and some of them are more than doubled; and (4) the increased explanatory power, as reflected by an increased adjusted $R^2$, could come from two sources. One is the explanatory power added by NMS12 *per se*. The other is the enhanced explanatory power of the market risk factor owing to the addition of NMS12; after NMS12 is added into the model, all of the 25 t-statistics of the β coefficients are increased. To sum up, augmenting the CAPM with the no-shorting risk factor significantly increases the ability of the model to explain the time-series variation in the size/BM portfolio returns.

Similar results appear in Table 5.5, where comparisons are made between the Fama-French three-factor model and its extension with the no-shorting factor added. The model augmented with NMS12 produces higher adjusted $R^2$s in 22 out of 25 regressions than the model without. Among the 25 coefficients ($n_p$) on NBS12, 22 are positive and most of them are significant at a higher than 99% level. Also, the addition of the NMS factor enhances the explanatory power of the market factor, with 21 out of the 25 $\beta_p$ coefficients increasing.

**Table 5.5 Panel A: Time-series regressions based on the Fama-French three-factor model to explain monthly excess returns on 25 size-B/M portfolios, Jan 1999 – Feb 2012.**

The regression model: $R_{pt} - R_{ft} = \alpha_p + \beta_p \left( R_{mt} - R_{ft} \right) + s_p SMB_t + h_p HML_t + \varepsilon_{pt}$

| Book-to-Market Equity (BE/ME) Quintiles | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
| | | | $\alpha_\pi$ | | | | | | t($\alpha_\pi$) | | |
| Small | 0.034 | 0.015 | 0.021 | 0.009 | 0.017 | Small | 3.349 | 1.216 | 2.182 | 0.677 | 1.932 |
| 2 | -0.007 | 0.002 | -0.007 | 0.000 | 0.005 | 2 | -0.927 | 0.233 | -1.109 | -0.036 | 0.591 |
| 3 | -0.022 | -0.004 | 0.000 | -0.001 | -0.009 | 3 | -2.570 | -0.625 | 0.040 | -0.082 | -2.007 |
| 4 | -0.011 | 0.000 | 0.000 | 0.001 | -0.001 | 4 | -1.915 | 0.049 | -0.102 | 0.147 | -0.144 |
| Big | 0.006 | 0.005 | -0.002 | 0.000 | 0.001 | Big | 1.878 | 1.478 | -0.603 | -0.107 | 0.093 |
| | | | $\beta_\pi$ | | | | | | t($\beta_\pi$) | | |
| Small | 1.005 | 1.137 | 1.258 | 1.155 | 0.901 | Small | 7.305 | 6.842 | 9.658 | 6.227 | 7.284 |
| 2 | 0.981 | 0.874 | 0.743 | 0.906 | 0.881 | 2 | 9.112 | 8.838 | 8.747 | 12.653 | 7.150 |
| 3 | 0.843 | 0.977 | 0.962 | 0.993 | 1.077 | 3 | 7.101 | 10.186 | 14.966 | 9.354 | 17.054 |
| 4 | 1.160 | 1.039 | 1.010 | 0.972 | 0.969 | 4 | 15.416 | 18.452 | 15.292 | 14.389 | 13.679 |
| Big | 0.983 | 1.012 | 0.840 | 0.962 | 1.398 | Big | 22.693 | 22.729 | 17.356 | 15.526 | 15.191 |
| | | | $s_p$ | | | | | | t($s_p$) | | |
| Small | 1.159 | 0.758 | 1.020 | 1.191 | 0.912 | Small | 11.502 | 6.225 | 10.691 | 8.765 | 10.061 |
| 2 | 0.961 | 0.461 | 0.512 | 0.914 | 1.317 | 2 | 12.182 | 6.356 | 8.226 | 17.419 | 14.585 |
| 3 | 0.847 | 0.565 | 0.322 | 0.573 | 0.703 | 3 | 9.745 | 8.034 | 6.843 | 7.369 | 15.192 |
| 4 | 0.587 | 0.324 | 0.254 | 0.294 | 0.377 | 4 | 10.640 | 7.853 | 5.250 | 5.947 | 7.264 |
| Big | -0.080 | -0.065 | -0.152 | -0.018 | 0.173 | Big | -2.523 | -1.981 | -4.278 | -0.407 | 2.561 |
| | | | $h_p$ | | | | | | t($h_p$) | | |
| Small | 0.156 | 0.636 | 0.244 | 1.679 | 0.887 | Small | 0.904 | 3.047 | 1.495 | 7.212 | 5.708 |
| 2 | 0.507 | 0.439 | 0.589 | 0.633 | 0.056 | 2 | 3.748 | 3.531 | 5.522 | 7.037 | 0.364 |
| 3 | 0.958 | 0.254 | 0.230 | 0.891 | 0.804 | 3 | 6.428 | 2.110 | 2.846 | 6.682 | 10.145 |
| 4 | 0.042 | 0.198 | 0.325 | 0.489 | 0.522 | 4 | 0.442 | 2.808 | 3.922 | 5.768 | 5.868 |
| Big | -0.150 | -0.032 | 0.409 | 0.349 | 0.280 | Big | -2.756 | -0.567 | 6.735 | 4.490 | 2.425 |
| | | | $R^2$ | | | | | | Adj $R^2$ | | |
| Small | 0.551 | 0.391 | 0.582 | 0.530 | 0.556 | Small | 0.542 | 0.380 | 0.574 | 0.520 | 0.547 |
| 2 | 0.613 | 0.462 | 0.535 | 0.769 | 0.627 | 2 | 0.613 | 0.462 | 0.535 | 0.769 | 0.627 |
| 3 | 0.547 | 0.528 | 0.648 | 0.555 | 0.807 | 3 | 0.547 | 0.528 | 0.648 | 0.555 | 0.807 |
| 4 | 0.693 | 0.730 | 0.649 | 0.651 | 0.649 | 4 | 0.693 | 0.730 | 0.649 | 0.651 | 0.649 |
| Big | 0.767 | 0.769 | 0.717 | 0.640 | 0.616 | Big | 0.767 | 0.769 | 0.717 | 0.640 | 0.616 |

**Table 5.5 Panel B: Time-series regressions based on the Fama-French three-factor model augmented with the no-shorting factor with a 12-month holding period to explain monthly excess returns on 25 size-B/M portfolios, Jan 1999 – Feb 2012.**

The regression model: $R_{pt} - R_{ft} = \alpha_p + \beta_p \left( R_{mt} - R_{ft} \right) + s_p SMB_t + h_p HML_t + n_p NMS12_t + \varepsilon_{pt}$

Book-to-Market Equity (BE/ME) Quintiles

| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $a_p$ | | | | | | t($a_p$) | | | |
| Small | 0.034 | 0.017 | 0.024 | 0.001 | 0.019 | Small | 3.375 | 1.376 | 2.576 | 0.056 | 2.109 |
| 2 | -0.005 | 0.005 | -0.004 | 0.001 | 0.007 | 2 | -0.611 | 0.687 | -0.696 | 0.278 | 0.757 |
| 3 | -0.024 | -0.002 | 0.003 | 0.002 | -0.008 | 3 | -2.764 | -0.232 | 0.740 | 0.261 | -1.824 |
| 4 | -0.008 | 0.001 | 0.002 | 0.003 | 0.003 | 4 | -1.503 | 0.341 | 0.432 | 0.719 | 0.583 |
| Big | 0.005 | 0.005 | -0.002 | 0.001 | 0.003 | Big | 1.722 | 1.394 | -0.548 | 0.267 | 0.422 |
| | | $\beta_\pi$ | | | | | | t($\beta_\pi$) | | | |
| Small | 1.010 | 1.157 | 1.291 | 1.069 | 0.917 | Small | 7.303 | 6.968 | 10.160 | 6.455 | 7.431 |
| 2 | 1.007 | 0.905 | 0.771 | 0.923 | 0.896 | 2 | 9.579 | 9.572 | 9.543 | 13.145 | 7.281 |
| 3 | 0.826 | 1.005 | 0.992 | 1.020 | 1.085 | 3 | 6.984 | 10.903 | 17.252 | 9.849 | 17.235 |
| 4 | 1.189 | 1.051 | 1.034 | 0.998 | 1.003 | 4 | 16.925 | 18.974 | 16.775 | 15.905 | 16.093 |
| Big | 0.978 | 1.009 | 0.841 | 0.979 | 1.420 | Big | 22.574 | 22.560 | 17.293 | 16.299 | 15.774 |
| | | $s_p$ | | | | | | t($s_p$) | | | |
| Small | 1.081 | 0.479 | 0.569 | 2.387 | 0.685 | Small | 5.838 | 2.153 | 3.344 | 10.765 | 4.146 |
| 2 | 0.597 | 0.028 | 0.123 | 0.686 | 1.105 | 2 | 4.237 | 0.223 | 1.137 | 7.293 | 6.701 |
| 3 | 1.081 | 0.168 | -0.090 | 0.205 | 0.584 | 3 | 6.823 | 1.360 | -1.173 | 1.478 | 6.921 |
| 4 | 0.192 | 0.157 | -0.090 | -0.069 | -0.103 | 4 | 2.043 | 2.121 | -1.094 | -0.823 | -1.237 |
| Big | -0.013 | -0.031 | -0.177 | -0.252 | -0.131 | Big | -0.224 | -0.525 | -2.713 | -3.136 | -1.088 |
| | | $h_p$ | | | | | | t($h_p$) | | | |
| Small | 0.126 | 0.527 | 0.068 | 2.146 | 0.798 | Small | 0.686 | 2.393 | 0.405 | 9.776 | 4.876 |
| 2 | 0.364 | 0.270 | 0.437 | 0.544 | -0.026 | 2 | 2.614 | 2.151 | 4.081 | 5.841 | -0.162 |
| 3 | 1.049 | 0.099 | 0.069 | 0.747 | 0.758 | 3 | 6.689 | 0.812 | 0.900 | 5.442 | 9.075 |
| 4 | -0.112 | 0.133 | 0.191 | 0.347 | 0.334 | 4 | -1.206 | 1.818 | 2.333 | 4.173 | 4.045 |
| Big | -0.124 | -0.019 | 0.399 | 0.258 | 0.162 | Big | -2.153 | -0.316 | 6.187 | 3.241 | 1.354 |
| | | $n_p$ | | | | | | t($n_p$) | | | |
| Small | 0.136 | 0.489 | 0.792 | -2.099 | 0.397 | Small | 0.499 | 1.496 | 3.165 | -1.436 | 1.634 |
| 2 | 0.639 | 0.758 | 0.682 | 0.401 | 0.372 | 2 | 3.085 | 4.071 | 4.288 | 2.898 | 1.534 |
| 3 | -0.410 | 0.696 | 0.724 | 0.646 | 0.209 | 3 | -1.758 | 3.830 | 6.393 | 3.169 | 1.683 |
| 4 | 0.692 | 0.292 | 0.604 | 0.638 | 0.842 | 4 | 5.003 | 2.679 | 4.974 | 5.158 | 6.860 |
| Big | -0.118 | -0.058 | 0.044 | 0.410 | 0.533 | Big | -1.379 | -0.660 | 0.462 | 3.466 | 3.006 |
| | | $R^2$ | | | | | | Adj $R^2$ | | | |
| Small | 0.552 | 0.400 | 0.608 | 0.630 | 0.563 | Small | 0.540 | 0.385 | 0.597 | 0.620 | 0.552 |
| 2 | 0.642 | 0.524 | 0.593 | 0.786 | 0.639 | 2 | 0.633 | 0.512 | 0.582 | 0.780 | 0.630 |
| 3 | 0.565 | 0.578 | 0.727 | 0.590 | 0.814 | 3 | 0.553 | 0.566 | 0.720 | 0.580 | 0.809 |
| 4 | 0.741 | 0.747 | 0.704 | 0.709 | 0.737 | 4 | 0.735 | 0.740 | 0.696 | 0.701 | 0.730 |
| Big | 0.774 | 0.774 | 0.723 | 0.673 | 0.645 | Big | 0.768 | 0.768 | 0.716 | 0.664 | 0.635 |

Table 5.6 compares the performances of the four-factor model and its extension with the no-shorting factor added, where the momentum factor is in either the Carhart measure, or the Fama-French measure. Panels A and B use the Carhart momentum factor. They convey several messages worth noting. First, compared with Panel A of Table 5.5, Panel B of Table 5.6 indicates that the momentum factor does not play an important role in the asset-pricing model, as almost all of the 25 momentum coefficients ($m_p$) are negative and some are highly significant, while many of the adjusted $R^2$s do not increase.

Second, the no-shorting factor increases the explanatory power of the model in the following ways (see Panel B of Table 5.6): It increases the explanatory power of the market risk factor by increasing 21 out of the 25 beta coefficients and the t-statistics of 20 out of the 25 beta coefficients ($\beta_p$); 21 out of the 25 $n_p$ coefficients are positive and most of them are statistically significant; and 21 out of the 25 adjusted $R^2$s are increased. Panels C and D of Table 5.6 use the Fama-French momentum factor. As the Carhart momentum factor is highly correlated with the Fama-French momentum factor, it is not surprising that, in particular, the results presented in Panel D are very similar to those in Panel B of Table 5.6, enabling me to conclude that the no-shorting factor increases the explanatory power of the augmented four factor model.

**Table 5.6 Panel A: Time-series regressions based on the Carhart four-factor model to explain monthly excess returns on 25 size-B/M portfolios, Jan 1999 – Feb 2012.**

The regression model: $R_{pt} - R_{ft} = \alpha_p + \beta_p \left( R_{mt} - R_{ft} \right) + s_p SMB_t + h_p HML_t + m_p MOM\_CARH_t + \varepsilon_{pt}$

Book-to-Market Equity (BE/ME) Quintiles

| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $a_p$ | | | | | | $t(a_p)$ | | |
| Small | 0.034 | 0.015 | 0.021 | 0.009 | 0.018 | Small | 3.368 | 1.224 | 2.254 | 0.673 | 1.935 |
| 2 | -0.007 | 0.002 | -0.007 | 0.000 | 0.005 | 2 | -0.933 | 0.260 | -1.110 | -0.028 | 0.598 |
| 3 | -0.022 | -0.004 | 0.000 | -0.001 | -0.009 | 3 | -2.580 | -0.632 | 0.060 | -0.076 | -2.001 |
| 4 | -0.010 | 0.000 | 0.000 | 0.001 | -0.001 | 4 | -1.952 | 0.081 | -0.083 | 0.162 | -0.141 |
| Big | 0.006 | 0.005 | -0.002 | 0.000 | 0.001 | Big | 1.929 | 1.480 | -0.602 | -0.101 | 0.098 |
| | | | $\beta_\pi$ | | | | | | $t(\beta_\pi)$ | | |
| Small | 0.961 | 1.094 | 1.173 | 1.252 | 0.880 | Small | 6.841 | 6.429 | 9.009 | 6.687 | 6.927 |
| 2 | 0.909 | 0.804 | 0.701 | 0.884 | 0.851 | 2 | 8.459 | 8.173 | 8.154 | 12.076 | 6.740 |
| 3 | 0.793 | 0.892 | 0.918 | 0.972 | 1.062 | 3 | 6.572 | 9.538 | 14.332 | 8.921 | 16.420 |
| 4 | 1.108 | 0.983 | 0.955 | 0.938 | 0.960 | 4 | 14.782 | 18.184 | 14.733 | 13.730 | 13.198 |
| Big | 0.958 | 1.004 | 0.841 | 0.948 | 1.383 | Big | 21.984 | 21.981 | 16.914 | 14.927 | 14.641 |
| | | | $s_p$ | | | | | | $t(s_p)$ | | |
| Small | 1.173 | 0.772 | 1.048 | 1.159 | 0.919 | Small | 11.623 | 6.317 | 11.200 | 8.615 | 10.075 |
| 2 | 0.984 | 0.484 | 0.526 | 0.921 | 1.327 | 2 | 12.749 | 6.849 | 8.513 | 17.528 | 14.631 |
| 3 | 0.864 | 0.592 | 0.337 | 0.581 | 0.707 | 3 | 9.965 | 8.810 | 7.327 | 7.420 | 15.216 |
| 4 | 0.604 | 0.342 | 0.272 | 0.306 | 0.380 | 4 | 11.210 | 8.819 | 5.840 | 6.223 | 7.264 |
| Big | -0.072 | -0.062 | -0.152 | -0.014 | 0.178 | Big | -2.296 | -1.894 | -4.258 | -0.303 | 2.615 |
| | | | $h_p$ | | | | | | $t(h_p)$ | | |
| Small | 0.089 | 0.569 | 0.113 | 1.830 | 0.853 | Small | 0.496 | 2.630 | 0.684 | 7.689 | 5.285 |
| 2 | 0.395 | 0.329 | 0.524 | 0.598 | 0.009 | 2 | 2.893 | 2.632 | 4.793 | 6.427 | 0.059 |
| 3 | 0.880 | 0.123 | 0.160 | 0.857 | 0.782 | 3 | 5.742 | 1.035 | 1.970 | 6.192 | 9.508 |
| 4 | -0.039 | 0.111 | 0.240 | 0.437 | 0.508 | 4 | -0.410 | 1.619 | 2.915 | 5.026 | 5.499 |
| Big | -0.189 | -0.043 | 0.412 | 0.327 | 0.257 | Big | -3.405 | -0.746 | 6.509 | 4.054 | 2.141 |
| | | | $m_p$ | | | | | | $t(m_p)$ | | |
| Small | -0.236 | -0.235 | -0.460 | 0.529 | -0.117 | Small | -1.413 | -1.161 | -2.968 | 2.375 | -0.778 |
| 2 | -0.390 | -0.384 | -0.229 | -0.123 | -0.164 | 2 | -3.052 | -3.283 | -2.234 | -1.408 | -1.094 |
| 3 | -0.271 | -0.459 | -0.243 | -0.118 | -0.077 | 3 | -1.885 | -4.122 | -3.192 | -0.913 | -1.004 |
| 4 | -0.283 | -0.306 | -0.298 | -0.185 | -0.046 | 4 | -3.172 | -4.756 | -3.860 | -2.271 | -0.533 |
| Big | -0.135 | -0.041 | 0.009 | -0.077 | -0.081 | Big | -2.615 | -0.748 | 0.150 | -1.024 | -0.718 |
| | | | $R^2$ | | | | | | Adj $R^2$ | | |
| Small | 0.557 | 0.397 | 0.605 | 0.546 | 0.557 | Small | 0.545 | 0.381 | 0.594 | 0.534 | 0.546 |
| 2 | 0.642 | 0.507 | 0.558 | 0.777 | 0.637 | 2 | 0.633 | 0.494 | 0.547 | 0.771 | 0.627 |
| 3 | 0.566 | 0.583 | 0.676 | 0.566 | 0.812 | 3 | 0.555 | 0.572 | 0.667 | 0.554 | 0.807 |
| 4 | 0.718 | 0.769 | 0.686 | 0.669 | 0.656 | 4 | 0.710 | 0.763 | 0.678 | 0.660 | 0.647 |
| Big | 0.781 | 0.774 | 0.722 | 0.649 | 0.625 | Big | 0.776 | 0.768 | 0.715 | 0.640 | 0.615 |

**Table 5.6 Panel B: Time-series regressions based on the Carhart four-factor model augmented with the no-shorting factor with a 12-month holding period to explain monthly excess returns on 25 size-B/M portfolios, Jan 1999 – Feb 2012.**

The regression model: $R_{pt} - R_{ft} = \alpha_p + \beta_p \left(R_{mt} - R_{ft}\right) + s_p SMB_t + h_p HML_t + m_p MOM\_CARH_t + n_p NMS12_t + \varepsilon_{pt}$

| Book-to-Market Equity (BE/ME) Quintiles | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
| | | $a_p$ | | | | | | | $t(a_p)$ | | |
| Small | 0.034 | 0.017 | 0.024 | 0.001 | 0.019 | Small | 3.380 | 1.373 | 2.622 | 0.064 | 2.103 |
| 2 | -0.005 | 0.005 | -0.004 | 0.001 | 0.007 | 2 | -0.635 | 0.695 | -0.710 | 0.275 | 0.754 |
| 3 | -0.024 | -0.002 | 0.003 | 0.002 | -0.008 | 3 | -2.800 | -0.256 | 0.750 | 0.259 | -1.825 |
| 4 | -0.008 | 0.001 | 0.002 | 0.003 | 0.003 | 4 | -1.551 | 0.348 | 0.438 | 0.719 | 0.581 |
| Big | 0.005 | 0.005 | -0.002 | 0.001 | 0.003 | Big | 1.750 | 1.390 | -0.545 | 0.264 | 0.420 |
| | | $\beta_\pi$ | | | | | | | $t(\beta_\pi)$ | | |
| Small | 0.966 | 1.117 | 1.211 | 1.149 | 0.899 | Small | 6.826 | 6.555 | 9.486 | 6.836 | 7.080 |
| 2 | 0.939 | 0.840 | 0.734 | 0.903 | 0.869 | 2 | 8.903 | 8.885 | 8.937 | 12.554 | 6.873 |
| 3 | 0.770 | 0.925 | 0.953 | 1.004 | 1.072 | 3 | 6.410 | 10.226 | 16.566 | 9.426 | 16.581 |
| 4 | 1.142 | 0.995 | 0.983 | 0.970 | 1.003 | 4 | 16.234 | 18.628 | 16.173 | 15.194 | 15.621 |
| Big | 0.951 | 1.001 | 0.844 | 0.968 | 1.410 | Big | 21.839 | 21.772 | 16.837 | 15.684 | 15.220 |
| | | $s_p$ | | | | | | | $t(s_p)$ | | |
| Small | 1.114 | 0.508 | 0.628 | 2.328 | 0.699 | Small | 5.981 | 2.268 | 3.739 | 10.534 | 4.186 |
| 2 | 0.647 | 0.077 | 0.150 | 0.700 | 1.125 | 2 | 4.662 | 0.616 | 1.388 | 7.396 | 6.768 |
| 3 | 1.122 | 0.227 | -0.062 | 0.217 | 0.593 | 3 | 7.100 | 1.910 | -0.815 | 1.547 | 6.970 |
| 4 | 0.227 | 0.198 | -0.053 | -0.048 | -0.103 | 4 | 2.452 | 2.818 | -0.664 | -0.572 | -1.220 |
| Big | 0.007 | -0.025 | -0.178 | -0.244 | -0.124 | Big | 0.120 | -0.419 | -2.707 | -3.010 | -1.016 |
| | | $h_p$ | | | | | | | $t(h_p)$ | | |
| Small | 0.067 | 0.473 | -0.039 | 2.254 | 0.773 | Small | 0.357 | 2.093 | -0.230 | 10.106 | 4.591 |
| 2 | 0.273 | 0.182 | 0.388 | 0.518 | -0.064 | 2 | 1.951 | 1.448 | 3.558 | 5.423 | -0.379 |
| 3 | 0.974 | -0.009 | 0.016 | 0.726 | 0.741 | 3 | 6.111 | -0.075 | 0.210 | 5.136 | 8.630 |
| 4 | -0.176 | 0.059 | 0.122 | 0.309 | 0.334 | 4 | -1.881 | 0.832 | 1.518 | 3.646 | 3.920 |
| Big | -0.160 | -0.030 | 0.402 | 0.244 | 0.148 | Big | -2.771 | -0.492 | 6.049 | 2.976 | 1.205 |
| | | $m_p$ | | | | | | | $t(m_p)$ | | |
| Small | -0.231 | -0.211 | -0.421 | 0.421 | -0.097 | Small | -1.371 | -1.041 | -2.778 | 2.110 | -0.645 |
| 2 | -0.359 | -0.347 | -0.194 | -0.102 | -0.146 | 2 | -2.866 | -3.087 | -1.986 | -1.196 | -0.970 |
| 3 | -0.294 | -0.425 | -0.207 | -0.085 | -0.067 | 3 | -2.062 | -3.957 | -3.021 | -0.670 | -0.868 |
| 4 | -0.248 | -0.292 | -0.268 | -0.152 | -0.002 | 4 | -2.971 | -4.606 | -3.705 | -2.006 | -0.023 |
| Big | -0.143 | -0.044 | 0.011 | -0.056 | -0.053 | Big | -2.760 | -0.806 | 0.190 | -0.765 | -0.481 |
| | | $n_p$ | | | | | | | $t(n_p)$ | | |
| Small | 0.104 | 0.460 | 0.733 | -2.041 | 0.384 | Small | 0.381 | 1.402 | 2.984 | -1.304 | 1.570 |
| 2 | 0.589 | 0.710 | 0.656 | 0.386 | 0.352 | 2 | 2.900 | 3.904 | 4.143 | 2.789 | 1.445 |
| 3 | -0.450 | 0.637 | 0.696 | 0.635 | 0.199 | 3 | -1.467 | 3.657 | 6.278 | 3.095 | 1.601 |
| 4 | 0.658 | 0.252 | 0.567 | 0.617 | 0.842 | 4 | 4.857 | 2.446 | 4.841 | 5.019 | 6.810 |
| Big | -0.137 | -0.064 | 0.046 | 0.402 | 0.526 | Big | -1.639 | -0.726 | 0.475 | 3.383 | 2.946 |
| | | $R^2$ | | | | | | | Adj $R^2$ | | |
| Small | 0.557 | 0.405 | 0.627 | 0.640 | 0.565 | Small | 0.543 | 0.385 | 0.614 | 0.628 | 0.550 |
| 2 | 0.661 | 0.552 | 0.603 | 0.788 | 0.642 | 2 | 0.650 | 0.537 | 0.590 | 0.781 | 0.630 |
| 3 | 0.577 | 0.617 | 0.743 | 0.591 | 0.815 | 3 | 0.563 | 0.604 | 0.734 | 0.578 | 0.809 |
| 4 | 0.756 | 0.778 | 0.728 | 0.716 | 0.737 | 4 | 0.748 | 0.770 | 0.719 | 0.707 | 0.728 |
| Big | 0.785 | 0.775 | 0.723 | 0.674 | 0.645 | Big | 0.778 | 0.767 | 0.714 | 0.663 | 0.633 |

**Table 5.6 Panel C: Time-series regressions based on the Fama-French four-factor model to explain monthly excess returns on 25 size-B/M portfolios, Jan 1999 – Feb 2012.**

The regression model: $R_{pt} - R_{ft} = \alpha_p + \beta_p \left( R_{mt} - R_{ft} \right) + s_p SMB_t + h_p HML_t + m_p MOM\_FF_t + \varepsilon_{pt}$

| | Book-to-Market Equity (BE/ME) Quintiles | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
| | | $a_p$ | | | | | | t($a_p$) | | | |
| Small | 0.032 | 0.013 | 0.019 | 0.016 | 0.017 | Small | 3.183 | 1.088 | 1.952 | 1.224 | 1.835 |
| 2 | -0.011 | -0.001 | -0.010 | -0.002 | 0.004 | 2 | -1.414 | -0.183 | -1.573 | -0.339 | 0.391 |
| 3 | -0.025 | -0.009 | -0.002 | -0.001 | -0.011 | 3 | -2.829 | -1.335 | -0.504 | -0.181 | -2.275 |
| 4 | -0.012 | -0.002 | -0.004 | -0.002 | -0.002 | 4 | -2.254 | -0.480 | -0.857 | -0.383 | -0.399 |
| Big | 0.006 | 0.005 | -0.002 | -0.002 | -0.001 | Big | 1.728 | 1.400 | -0.569 | -0.376 | -0.106 |
| | | $\beta_\pi$ | | | | | | t($\beta_\pi$) | | | |
| Small | 0.966 | 1.095 | 1.196 | 1.370 | 0.881 | Small | 6.634 | 6.221 | 8.707 | 7.235 | 6.718 |
| 2 | 0.869 | 0.782 | 0.659 | 0.857 | 0.827 | 2 | 7.841 | 7.636 | 7.511 | 11.429 | 6.357 |
| 3 | 0.770 | 0.837 | 0.886 | 0.969 | 1.037 | 3 | 6.180 | 8.750 | 13.516 | 8.613 | 15.652 |
| 4 | 1.104 | 0.973 | 0.905 | 0.893 | 0.928 | 4 | 14.037 | 16.931 | 13.907 | 12.952 | 12.462 |
| Big | 0.970 | 1.006 | 0.842 | 0.924 | 1.357 | Big | 21.162 | 21.308 | 16.413 | 14.204 | 13.969 |
| | | $s_p$ | | | | | | t($s_p$) | | | |
| Small | 1.171 | 0.771 | 1.039 | 1.125 | 0.918 | Small | 11.488 | 6.257 | 10.811 | 8.487 | 9.999 |
| 2 | 0.995 | 0.489 | 0.538 | 0.929 | 1.334 | 2 | 12.836 | 6.816 | 8.766 | 17.690 | 14.648 |
| 3 | 0.869 | 0.607 | 0.346 | 0.581 | 0.715 | 3 | 9.967 | 9.066 | 7.540 | 7.375 | 15.407 |
| 4 | 0.604 | 0.344 | 0.286 | 0.319 | 0.389 | 4 | 10.980 | 8.548 | 6.278 | 6.599 | 7.471 |
| Big | -0.076 | -0.063 | -0.152 | -0.007 | 0.185 | Big | -2.376 | -1.902 | -4.245 | -0.153 | 2.727 |
| | | $h_p$ | | | | | | t($h_p$) | | | |
| Small | 0.106 | 0.581 | 0.164 | 1.958 | 0.861 | Small | 0.579 | 2.622 | 0.949 | 8.208 | 5.209 |
| 2 | 0.361 | 0.320 | 0.480 | 0.570 | -0.014 | 2 | 2.589 | 2.476 | 4.342 | 6.028 | -0.084 |
| 3 | 0.864 | 0.073 | 0.131 | 0.860 | 0.753 | 3 | 5.503 | 0.609 | 1.583 | 6.065 | 9.023 |
| 4 | -0.032 | 0.114 | 0.190 | 0.387 | 0.469 | 4 | -0.321 | 1.572 | 2.316 | 4.456 | 5.000 |
| Big | -0.166 | -0.039 | 0.413 | 0.301 | 0.227 | Big | -2.874 | -0.658 | 6.382 | 3.667 | 1.852 |
| | | $m_p$ | | | | | | t($m_p$) | | | |
| Small | -0.128 | -0.140 | -0.207 | 0.718 | -0.066 | Small | -0.811 | -0.732 | -1.385 | 3.491 | -0.464 |
| 2 | -0.374 | -0.306 | -0.282 | -0.162 | -0.181 | 2 | -3.110 | -2.754 | -2.961 | -1.991 | -1.280 |
| 3 | -0.241 | -0.465 | -0.255 | -0.080 | -0.131 | 3 | -1.781 | -4.475 | -3.585 | -0.658 | -1.817 |
| 4 | -0.189 | -0.218 | -0.348 | -0.263 | -0.136 | 4 | -2.217 | -3.491 | -4.928 | -3.511 | -1.679 |
| Big | -0.042 | -0.019 | 0.009 | -0.125 | -0.138 | Big | -0.834 | -0.372 | 0.168 | -1.772 | -1.309 |
| | | $R^2$ | | | | | | Adj $R^2$ | | | |
| Small | 0.553 | 0.394 | 0.587 | 0.564 | 0.556 | Small | 0.541 | 0.378 | 0.576 | 0.553 | 0.545 |
| 2 | 0.643 | 0.497 | 0.569 | 0.779 | 0.638 | 2 | 0.633 | 0.484 | 0.557 | 0.774 | 0.628 |
| 3 | 0.565 | 0.591 | 0.681 | 0.565 | 0.814 | 3 | 0.554 | 0.580 | 0.673 | 0.553 | 0.809 |
| 4 | 0.708 | 0.754 | 0.703 | 0.683 | 0.662 | 4 | 0.701 | 0.748 | 0.695 | 0.675 | 0.653 |
| Big | 0.773 | 0.773 | 0.722 | 0.654 | 0.628 | Big | 0.767 | 0.767 | 0.715 | 0.645 | 0.618 |

**Table 5.6 Panel D: Time-series regressions based on the Fama-French four-factor model augmented with the no-shorting factor with a 12-month holding period to explain monthly excess returns on 25 size-B/M portfolios, Jan 1999 – Feb 2012.**

The regression model: $R_{pt} - R_{ft} = \alpha_p + \beta_p \left( R_{mt} - R_{ft} \right) + s_p SMB_t + h_p HML_t + m_p MOM\_FF_t + n_p NMS12_t + \varepsilon_{pt}$

Book-to-Market Equity (BE/ME) Quintiles

| Size | Low | 2 | 3 | 4 | High | Size | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $a_p$ | | | | | | t($a_p$) | | | |
| Small | 0.033 | 0.016 | 0.023 | 0.006 | 0.019 | Small | 3.188 | 1.276 | 2.397 | 0.499 | 2.048 |
| 2 | -0.008 | 0.002 | -0.006 | 0.000 | 0.005 | 2 | -1.064 | 0.324 | -1.084 | 0.021 | 0.572 |
| 3 | -0.027 | -0.006 | 0.001 | 0.002 | -0.010 | 3 | -3.154 | -0.917 | 0.280 | 0.258 | -2.067 |
| 4 | -0.009 | -0.001 | -0.001 | 0.001 | 0.002 | 4 | -1.714 | -0.190 | -0.291 | 0.249 | 0.497 |
| Big | 0.005 | 0.004 | -0.002 | 0.000 | 0.002 | Big | 1.490 | 1.275 | -0.489 | 0.068 | 0.290 |
| | | $\beta_\pi$ | | | | | | t($\beta_\pi$) | | | |
| Small | 0.973 | 1.131 | 1.255 | 1.219 | 0.912 | Small | 6.590 | 6.372 | 9.255 | 7.020 | 6.908 |
| 2 | 0.910 | 0.836 | 0.706 | 0.886 | 0.852 | 2 | 8.262 | 8.369 | 8.300 | 11.875 | 6.491 |
| 3 | 0.729 | 0.881 | 0.938 | 1.020 | 1.051 | 3 | 5.858 | 9.346 | 15.582 | 9.210 | 15.713 |
| 4 | 1.155 | 0.991 | 0.944 | 0.938 | 0.993 | 4 | 15.459 | 17.215 | 15.108 | 14.289 | 14.907 |
| Big | 0.959 | 1.000 | 0.846 | 0.954 | 1.397 | Big | 20.793 | 20.927 | 16.266 | 14.917 | 14.527 |
| | | $s_p$ | | | | | | t($s_p$) | | | |
| Small | 1.117 | 0.504 | 0.603 | 2.242 | 0.691 | Small | 5.817 | 2.183 | 3.420 | 9.934 | 4.022 |
| 2 | 0.691 | 0.096 | 0.186 | 0.721 | 1.148 | 2 | 4.822 | 0.737 | 1.678 | 7.439 | 6.724 |
| 3 | 1.174 | 0.289 | -0.038 | 0.205 | 0.617 | 3 | 7.258 | 2.356 | -0.485 | 1.420 | 7.098 |
| 4 | 0.225 | 0.215 | -0.003 | -0.011 | -0.094 | 4 | 2.314 | 2.876 | -0.041 | -0.127 | -1.083 |
| Big | 0.005 | -0.023 | -0.182 | -0.229 | -0.109 | Big | 0.084 | -0.370 | -2.684 | -2.749 | -0.868 |
| | | $h_p$ | | | | | | t($h_p$) | | | |
| Small | 0.090 | 0.502 | 0.034 | 2.291 | 0.793 | Small | 0.474 | 2.194 | 0.195 | 10.246 | 4.662 |
| 2 | 0.270 | 0.202 | 0.375 | 0.508 | -0.069 | 2 | 1.906 | 1.573 | 3.416 | 5.286 | -0.410 |
| 3 | 0.955 | -0.022 | 0.016 | 0.748 | 0.724 | 3 | 5.957 | -0.178 | 0.208 | 5.239 | 8.408 |
| 4 | -0.145 | 0.075 | 0.104 | 0.289 | 0.325 | 4 | -1.506 | 1.018 | 1.286 | 3.417 | 3.784 |
| Big | -0.142 | -0.027 | 0.404 | 0.234 | 0.139 | Big | -2.385 | -0.442 | 6.027 | 2.845 | 1.122 |
| | | $m_p$ | | | | | | t($m_p$) | | | |
| Small | -0.117 | -0.082 | -0.112 | 0.475 | -0.017 | Small | -0.718 | -0.420 | -0.750 | 2.490 | -0.115 |
| 2 | -0.308 | -0.221 | -0.205 | -0.117 | -0.140 | 2 | -2.542 | -2.013 | -2.195 | -1.429 | -0.973 |
| 3 | -0.307 | -0.396 | -0.172 | 0.001 | -0.110 | 3 | -2.245 | -3.820 | -2.597 | 0.010 | -1.490 |
| 4 | -0.107 | -0.190 | -0.285 | -0.191 | -0.031 | 4 | -1.302 | -3.001 | -4.153 | -2.652 | -0.422 |
| Big | -0.059 | -0.028 | 0.016 | -0.077 | -0.074 | Big | -1.166 | -0.527 | 0.274 | -1.096 | -0.703 |
| | | $n_p$ | | | | | | t($n_p$) | | | |
| Small | 0.092 | 0.459 | 0.750 | -1.921 | 0.391 | Small | 0.330 | 1.366 | 2.922 | -0.848 | 1.565 |
| 2 | 0.524 | 0.676 | 0.606 | 0.357 | 0.320 | 2 | 2.512 | 3.576 | 3.760 | 2.528 | 1.286 |
| 3 | -0.524 | 0.548 | 0.660 | 0.647 | 0.168 | 3 | -1.226 | 3.072 | 5.793 | 3.085 | 1.326 |
| 4 | 0.652 | 0.221 | 0.497 | 0.566 | 0.831 | 4 | 4.612 | 2.031 | 4.205 | 4.558 | 6.586 |
| Big | -0.140 | -0.068 | 0.050 | 0.381 | 0.505 | Big | -1.600 | -0.757 | 0.509 | 3.148 | 2.777 |
| | | $R^2$ | | | | | | Adj $R^2$ | | | |
| Small | 0.553 | 0.401 | 0.609 | 0.644 | 0.563 | Small | 0.539 | 0.381 | 0.596 | 0.633 | 0.549 |
| 2 | 0.657 | 0.536 | 0.605 | 0.788 | 0.642 | 2 | 0.646 | 0.521 | 0.592 | 0.781 | 0.630 |
| 3 | 0.579 | 0.615 | 0.739 | 0.590 | 0.816 | 3 | 0.565 | 0.602 | 0.730 | 0.577 | 0.810 |
| 4 | 0.744 | 0.761 | 0.734 | 0.721 | 0.737 | 4 | 0.736 | 0.753 | 0.725 | 0.712 | 0.728 |
| Big | 0.776 | 0.774 | 0.723 | 0.675 | 0.646 | Big | 0.769 | 0.767 | 0.714 | 0.664 | 0.634 |

The above time-series analysis provides some evidence that the no-shorting risk factor has certain power in explaining the time-series variation in returns, and also enhances the importance of the market risk factor in various multi-factor asset-pricing models. The next, and perhaps more important, question I have to address is how well the no-shorting factor can help explain the cross-section of average stock returns. To this end, I perform Fama-MacBeth second-pass regressions and present the results in Section 5.5, to which I now turn.

## 5.5 Empirical Results: Cross-sectional Regression Analysis

As discussed in Chapter 4, Lewellen et al. (2010) argue that conventional cross-section tests, mainly relying on the point estimates and their statistical significances, often lead to overstated conclusions. As remedies, they offer several suggestions to improve/correct the conventional approaches. In this section, therefore, I adopt the Lewellen et al. (2010) approach, following their suggestions, to further investigate the explanatory powers of the four asset-pricing models augmented with the no-shorting factor.

Their first suggestion is to expand the dimensionality of the cross-section beyond the 25 size-B/M portfolios. The 25 test portfolios are sorted by size and B/M ratios. This sorting procedure results in their strong factor structure; i.e., there is a strong relation between loadings on the size and B/M factors (SMB and HML), and expected returns. Hence, Lewellen et al. (2010) suggest adding portfolios formed on other characteristics to the LHS assets. Such portfolios should not be systematically related to the size and B/M characteristics of the 25 size-B/M portfolios. In this study, I consider Hong Kong's 33 industry portfolios when expanding the cross-sectional space. Note that the test portfolios *of interest* are still the 25 size-BM portfolios, not 58 portfolios.

Their second suggestion is to use the GLS cross-sectional $R^2$ instead of the OLS $R^2$ mentioned in the preceding section. As the GLS $R^2$ is determined by the proximity of the mimicking portfolios to the minimum-variance boundary, it has a useful economic interpretation in terms of the relative mean-variance efficiency of a model's factor-mimicking portfolios" (Lewellen et al., 2010). Additionally, the GLS $R^2$ is a more stringent hurdle than the OLS $R^2$. As such, I mainly rely on the GLS $R^2$, while also reporting the OLS $R^2$.

The most important suggestion of Lewellen et al. (2010) is to report confidence intervals for the GLS $R^2$ and for the weighted sum of squared pricing errors (represented by the $T^2$ statistic). As they argue, when though there are high sampling errors in the asset-pricing statistics, it is insufficient to rely only on the point estimates and their *p*-values. The confidence interval shows the range of true parameters that are consistent with the data. Thus, it not only reveals the high sampling errors by showing a wide range of parameters, but also avoids taking a stand on the right null hypothesis. Therefore, to reflect the true parameters that are consistent with the data, I report confidence intervals for the OLS adjusted $R^2$ and the GLS cross-sectional $R^2$, as well as Shanken's (1985) $T^2$ with simulated p-value. I obtain the various confidence intervals via simulations with 40,000 replications in each case, following the procedures detailed in Lewellen et al. (2010).

I also compute the main component, q, shared by the GLS $R^2$ and the $T^2$, which is interpreted as the unexplained squared Sharpe ratio, or the distance a model's mimicking portfolios are from the minimum variance boundary, measured as the difference between the maximum generalised squared Sharpe ratio and that attainable from the mimicking portfolios[37]. In general, the smaller the unexplained squared Sharpe ratio, the better the model's performance in explaining expected returns.

My analysis is conducted in the following way: I run cross-sectional regressions for the one- and three-factor models and for the two, four-factor models in their standard versions, before adding NMS12 to each of them for further regressions, to evaluate whether NMS12 carries a significant risk premium. Meanwhile, I let the dependent variables in each model either be 25 size/BM portfolios, or be 58 portfolios (made up of 25 size/BM and 33 industry portfolios, as discussed above). The results of the 16 cross-sectional regressions appear in Table 5.7. Panel A of the table concerns 8 regressions with 25 size-B/M portfolios as the dependent variables, while Panel B of the table pertains to another 8 regressions with 58 portfolios as the dependent variables.

One can see that the cross-sectional test results in Table 5.7 provide conclusions that greatly strengthen those drawn from the time-series test results in Tables 5.4 through 5.6. Let us take a look at Panel A first. Adding NMS12 to the one-factor CAPM increases the overall explanatory power of the model, with the GLS $R^2$ rising from 0.009 to 0.041. The portfolio NMS12 is priced positively, with a coefficient of 0.016 at the 99% significance level. Adding NMS12 to the FF three-factor model, and to the two momentum-augmented four-factor models, increases the GLS $R^2$ from 0.141 to 0.182, from 0.153 to 0.183, and from 0.195 to 0.204, respectively. Moreover, the risk premiums on the no-shorting factor are all significantly positive, as evidenced by the coefficient estimates for NMS12 being 0.019, 0.020 and 0.020, respectively, and with t-values being 2.99, 3.18 and 3.16, respectively. Furthermore, augmenting the four models with the no-shorting factor does not qualitatively

[37] See Lewellen, Nagel and Shanken (2010) for the definitions of the GLS $R^2$ and the $T^2$.

affect the significances of the risk premiums on the SMB and HML factors, while the market risk premium ($R_m$ - $R_f$) of the CAPM remains insignificant regardless of whether or not NMS12 is included. Panel A of Table 5.7 also suggests that momentum does not play an important role in explaining cross-sectional return variations for the Hong Kong stock market.

Panel B of Table 5.7 basically confirms the results in Panel A, although the full set of 58 portfolios is now used in the tests. The coefficients on NMS12 are all positive, and three of them are significant at a higher than 5% level, with one at the 10% level. The GLS $R^2$ also increases in each of the four models, as a result of NMS12 being added.

It may be noted that the OLS adjusted $R^2$ in Panel A of Table 5.7 seems to indicate that there are better performances for only three no-shorting-factor augmented models, and not for the Fama-French three-factor model augmented with NMS12 (as the OLS adjusted $R^2$ falls from 0.473 to 0.460). Similarly, the OLS adjusted $R^2$ Panel B seems to be against the four-factor model containing the Fama-French momentum factor. In fact, however, the OLS $R^2$ should not be taken seriously. Lewellen et al. (2010) point out that "if a market proxy is nearly mean-variance efficient, the GLS R2 is nearly one but the OLS R2 can, in principle, be anything". Referring back to footnote 16 in Chapter 4, one can see that the GLS $R^2$ now only depends on the unexplained squared Sharpe ratio $q$, as the four models I consider here have the same LHS variables. Thus, it makes both statistical and economic sense to resort to the GLS $R^2$, not the OLS $R^2$, for inference.

**Table 5.7 The Fama-MacBeth two-pass regressions of factor models (with NMS12 as the no-shorting factor)**

This table reports the coefficient estimates from the Fama-MacBeth two-pass regressions for the CAPM, the Fama-French three-factor model, the Carhart four-factor model and the Fama-French four-factor model, as well as their respective augmented versions with the no-shorting factor added. The OLS $R^2$ is the adjusted $R^2$. NMS12 represents the no-shorting factor with a holding period of 12 months.

| Panel A: The LHS test assets are the 25 size/BM portfolios | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Intercept | Rm - Rf | SMB | HML | MOM_CARH | MOM_FF | NMS12 | GLS $R^2$ | OLS $R^2$ |
| Coefficient | 0.027 | -0.021 | | | | | | 0.009 | -0.023 |
| t-value | 0.84 | -0.72 | | | | | | | |
| Coefficient | -0.033 | 0.024 | | | | | 0.016** | 0.041 | 0.366 |
| t-value | -1.65 | 1.12 | | | | | 2.58 | | |
| Coefficient | -0.014 | 0.003 | 0.020** | 0.013** | | | | 0.141 | 0.473 |
| t-value | -0.68 | 0.14 | 2.60 | 2.56 | | | | | |
| Coefficient | -0.016 | 0.003 | 0.020** | 0.015*** | | | 0.019*** | 0.182 | 0.460 |
| t-value | -0.78 | 0.12 | 2.63 | 3.06 | | | 2.99 | | |
| Coefficient | -0.001 | -0.007 | 0.020** | 0.010 | 0.016 | | | 0.153 | 0.465 |
| t-value | -0.02 | -0.36 | 2.56 | 2.11 | 1.21 | | | | |
| Coefficient | 0.007 | -0.016 | 0.020** | 0.012** | 0.030* | | 0.020*** | 0.183 | 0.481 |
| t-value | 0.33 | -0.76 | 2.57 | 2.48 | 1.88 | | 3.18 | | |
| Coefficient | -0.006 | -0.002 | 0.020** | 0.011*=* | | 0.011 | | 0.195 | 0.465 |
| t-value | -0.32 | -0.09 | 2.55 | 2.24 | | 0.88 | | | |
| Coefficient | -0.002 | -0.009 | 0.020** | 0.013** | | 0.024 | 0.020*** | 0.204 | 0.496 |
| t-value | -0.08 | -0.43 | 2.56 | 2.68 | | 1.64 | 3.16 | | |

*,**,*** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

**Table 5.7 The Fama-MacBeth two-pass regressions of factor models (with NMS12 as the no-shorting factor) (Continued)**

This table reports the coefficient estimates from the Fama-MacBeth two-pass regressions for the CAPM, the Fama-French three-factor model, the Carhart four-factor model and the Fama-French four-factor model, as well as their respective augmented versions with the no-shorting factor added. The OLS $R^2$ is the adjusted $R^2$. NMS12 represents the no-shorting factor with a holding period of 12 months.

| Panel B: The LHS test assets are the 25 size/BM portfolios + 33 industry portfolios | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Intercept | Rm - Rf | SMB | HML | MOM_CARH | MOM_FF | NMS12 | GLS $R^2$ | OLS $R^2$ |
| Coefficient | 0.013 | -0.008 | | | | | | 0.007 | -0.018 |
| t-value | 1.74 | -1.15 | | | | | | | |
| Coefficient | 0.013 | -0.012 | | | | | 0.008* | 0.014 | 0.361 |
| t-value | 1.69 | -1.71 | | | | | 1.84 | | |
| Coefficient | 0.012 | -0.013* | 0.011 | 0.007 | | | | 0.044 | 0.483 |
| t-value | 1.57 | -1.89 | 1.35 | 1.38 | | | | | |
| Coefficient | 0.013 | -0.013* | 0.012 | 0.006 | | | 0.004* | 0.055 | 0.495 |
| t-value | 1.94 | -1.82 | 1.46 | 1.12 | | | 2.01 | | |
| Coefficient | 0.014 | -0.014* | 0.011 | 0.007 | 0.007 | | | 0.056 | 0.504 |
| t-value | 1.26 | -2.03 | 1.34 | 1.31 | 0.77 | | | | |
| Coefficient | 0.014 | -0.013* | 0.011 | 0.005 | 0.005 | | 0.004** | 0.065 | 0.503 |
| t-value | 1.25 | -1.88 | 1.45 | 1.1 | 0.48 | | 2.09 | | |
| Coefficient | 0.015 | -0.140 | 0.010 | 0.007 | | 0.012 | | 0.068 | 0.526 |
| t-value | 1.58 | -2.01 | 1.32 | 1.33 | | 1.42 | | | |
| Coefficient | 0.015 | -0.013* | 0.011 | 0.006 | | 0.010 | 0.004** | 0.072 | 0.517 |
| t-value | 1.53 | -1.91 | 1.42 | 1.15 | | 1.14 | 2.10 | | |

*,**,*** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5.8 presents the additional cross-sectional test results following Lewellen et al.'s (2010) suggestions that focus on confidence intervals of several statistics. Panel A of the table concerns the regressions for the CAPM and Fama-French three-factor models, while Panel B of the Table is devoted to regressions for the Carhart and Fama-French four-factor models. There, I compare the statistics and their confidence intervals between the standard with the augmented one-, three-, four-factor models with the no-shorting factor NMS12 added.

Consider the CAPM first (see Panel A of Table 5.8). The confidence intervals for the OLS $R^2$ and the GLS $R^2$ all rise, from [-0.043, 0.292] to [0.118, 0.715] and from [0.000, 0.416] to [0.012, 0.481], respectively, due to the addition of the no-shorting factor to the model. Take the confidence intervals for the GLS $R^2$, for example. Without the no-shorting factor, there is a 95% chance that the standard CAPM's GLS $R^2$ will fall between 0.000 and 0.416. With the no-shorting factor added, the standard CAPM's GLS $R^2$ has a 95% chance of falling between 0.012 and 0.481. Turning to the $T^2$ statistic, one can see that it drops from 96.985 to 77.807, and its p-value increases from 0.000 to 0.056, after adding the no-shorting factor to the standard CAPM. This means that the augmented CAPM cannot reject the null of no pricing errors at the 5% level, while the standard CAPM can at a higher than 1% level. The more interesting observation is that the 95% confidence interval for the q statistic falls sharply from [0.257, 0.728] to [0.000, 0.537] as the CAPM turns from its standard version to its augmented version. That is, the CAPM's unexplained squared Sharpe ratio has a 95% chance of taking a value between 0.257 and 0.728, but the augmented CAPM's unexplained squared Sharpe ratio has a 95% chance of taking a value between 0.000 and 0.537. I view this as the most convincing evidence that adding the no-shorting factor to the CAPM makes it better-performed.

**Table 5.8 Additional cross-sectional tests for factor models based on the Lewellen et al. (2010) approach (with NMS12 as the no-shorting factor)**

The table reports the cross-sectional regression results with 25 size-B/M portfolios used alone, or together with 33 industry portfolios, as the test assets. The OLS $R^2$ is an adjusted $R^2$. The cross-sectional $T^2$ statistic tests whether pricing errors in a cross-sectional regression are all zero, with simulated *p*-values in brackets; *q* is the distance that a model's mimicking portfolios are from the minimum-variance frontier, measured as the difference between the maximum generalised squared Sharpe ratio and that attainable from the mimicking portfolios. 95% confidence intervals for the true OLS $R^2$s, GLS $R^2$s and *q* are reported in brackets next to their sample estimates. Confidence intervals are obtained by simulations with 40,000 replications. Coefficient estimates and their t-values are computed according to Shanken and Zhou (2007). NMS12 represents the no-shorting factor with a holding period of 12 months. RHS stands for "right hand side". The sample period used for regressions is from January 1999 to February 2012, with 158 monthly observations.

**40,000 replications**

| Panel A: The one- and three-factor models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| CAPM (25 size-B/M) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf | -0.023 | [-0.043, 0.292] | 0.010 | [0.000, 0.416] | 96.985 | [p=0.000] | 0.673 | [0.257, 0.728] |
| RHS: Rm_Rf, NMS12 | 0.366 | [0.118, 0.715] | 0.041 | [0.012, 0.481] | 77.807 | [p=0.056] | 0.600 | [0.000, 0.537] |
| | | | | | | | | |
| CAPM (25 + 33 ind.) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf | -0.018 | [-0.018, 0.099] | 0.007 | [0.000, 0.038] | 300.543 | [p=0.000] | 1.902 | [1.287, 1.968] |
| RHS: Rm_Rf, NMS12 | 0.361 | [0.195, 0.587] | 0.014 | [0.001, 0.093] | 175.964 | [p=0.000] | 1.302 | [0.394, 1.139] |
| | | | | | | | | |
| FF3F (25 size-B/M) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf, SMB, HML | 0.473 | [0.253, 0.790] | 0.141 | [0.035, 0.462] | 82.993 | [p=0.005] | 0.584 | [0.078, 0.609] |
| RHS:: Rm_Rf, SMB, HML, NMS12 | 0.460 | [0.259, 0.800] | 0.182 | [0.051, 0.505] | 66.406 | [p=0.210] | 0.560 | [0.000, 0.396] |
| | | | | | | | | |
| FF3F (25 + 33 ind.) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf, SMB, HML | 0.483 | [0.334, 0.686] | 0.044 | [0.010, 0.141] | 249.270 | [p=0.000] | 1.830 | [0.840, 1.651] |
| RHS: Rm_Rf, SMB, HML, NMS12 | 0.495 | [0.357, 0.709] | 0.055 | [0.016, 0.162] | 165.399 | [p=0.000] | 1.250 | [0.231, 1.033] |

**Table 5.8 Additional cross-sectional tests for factor models based on the Lewellen et al. (2010) approach (with NMS12 as the no-shorting factor) (continued)**

The table reports the cross-sectional regression results with 25 size-B/M portfolios used alone, or together with 33 industry portfolios, as the test assets. The OLS $R^2$ is an adjusted $R^2$. The cross-sectional $T^2$ statistic tests whether pricing errors in a cross-sectional regression are all zero, with simulated *p*-values in brackets; *q* is the distance that a model's mimicking portfolios are from the minimum-variance frontier, measured as the difference between the maximum generalised squared Sharpe ratio and that attainable from the mimicking portfolios. 95% confidence intervals for the true OLS $R^2$s, GLS $R^2$s and *q* are reported in brackets next to their sample estimates. Confidence intervals are obtained by simulations with 40,000 replications. Coefficient estimates and their t-values are computed according to Shanken and Zhou (2007). NMS12 represents the no-shorting factor with a holding period of 12 months. RHS stands for "right hand side". The sample period used for regressions is from January 1999 to February 2012, with 158 monthly observations.

**40,000 replications**

| Panel B: The four-factor models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| CARH4F (25 size-B/M) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf, SMB, HML, MOM | 0.465 | [0.266, 0.801] | 0.153 | [0.049, 0.522] | 75.858 | [p=0.011] | 0.575 | [0.038, 0.586] |
| RHS: Rm_Rf, SMB, HML, MOM, NMS12 | 0.481 | [0.308, 0.825] | 0.183 | [0.075, 0.615] | 44.815 | [p=0.429] | 0.555 | [0.000, 0.267] |
| | | | | | | | | |
| CARH4F (25 + 33 ind.) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf, SMB, HML, MOM | 0.504 | [0.367, 0.710] | 0.056 | [0.017, 0.220] | 227.157 | [p=0.000] | 1.808 | [0.694, 1.513] |
| RHS: Rm_Rf, SMB, HML, MOM, NMS12 | 0.503 | [0.375, 0.716] | 0.065 | [0.024, 0.225] | 162.874 | [p=0.002] | 1.250 | [0.201, 1.000] |
| | | | | | | | | |
| FF4F (25 size-B/M) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf, SMB, HML, MOM | 0.465 | [0.264, 0.801] | 0.195 | [0.048, 0.498] | 75.744 | [p=0.013] | 0.547 | [0.030, 0.568] |
| RHS: Rm_Rf, SMB, HML, MOM, NMS12 | 0.496 | [0.326, 0.830] | 0.204 | [0.076, 0.604] | 57.523 | [p=0.287] | 0.552 | [0.000, 0.336] |
| | | | | | | | | |
| FF4F (25 + 33 ind.) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf, SMB, HML, MOM | 0.526 | [0.394, 0.724] | 0.068 | [0.019, 0.202] | 222.723 | [p=0.000] | 1.784 | [0.670, 1.477] |
| RHS: Rm_Rf, SMB, HML, MOM, NMS12 | 0.517 | [0.392, 0.727] | 0.072 | [0.025, 0.218] | 161.514 | [p=0.001] | 1.249 | [0.198, 0.987] |

The above analyses also apply to the models in Panel A of Table 5.8, where the full set of 58 portfolios are used as the test assets. The 95% confidence intervals for the OLS $R^2$ and the GLS $R^2$ all move up considerably, while the 95% confidence interval for q moves down significantly. Note that the $T^2$ statistic falls considerably from 300.543 to 175.964, although the p-value is still less than 0.000 due to 58 instead of 25 portfolios being used as the test assets. In sum, the NMS-augmented CAPM works better than the standard CAPM.

Next, consider the Fama-French three-factor model. According to Panel A of Table 5.8, with the no-shorting factor added to the model, the 95% confidence intervals for the OLS and the GLS $R^2$ move up to higher levels (although the sample OLS $R^2$ becomes smaller!), and the 95% confidence intervals for q move down to much lower levels. The p-value of the $T^2$ statistic rises from 0.005 to 0.210. This indicates that, augmented with the no-shorting factor, the Fama-French three-factor model with 25 size/BM portfolios as the test assets does not allow me to reject the null of no pricing errors in the model at the 20% significance level. When I expand the test assets to include 33 industry portfolios, the conclusion remains unchanged that adding NMS12 to the model makes it work better. Specifically, the last three rows in Panel A of Table 5.8 show that the confidence intervals for the OLS and the GLS $R^2$ rise to higher ranges, the $T^2$ statistic falls sharply (albeit still highly significant) and q's 95% confidence interval shifts substantially to the left.

Now turn to Panel B of Table 5.8 where two four-factor models, Carhart and Fama-French, are tested. Columns 2-4 and 6-8 are related to the Carhart four-factor model, and portray a picture similar to those shown in Panel A. One can observe that the 95% confidence intervals of the OLS and the GLS $R^2$ rise to higher levels in both the case of 25 size-BM portfolios, and the case of 58 portfolios, as the LHS variables, as a result of the no-shorting factor being included in the model. For the 25 size-B/M portfolios tested without the NMS factor, the $T^2$ statistic is significant at the 5% level, and with the new risk factor it becomes insignificant even at the 40% significance level. For the 58 test portfolios, there is also a large decline in the $T^2$ statistic from 227.157 to 162.874, though the latter is still significant at the 1% level. Again the most important statistic is q. After the four-factor model becomes a five-factor model, q's confidence interval declines notably, regardless of whether 25 size-B/M portfolios, or 58 portfolios, appear as the LHS variables. One may, therefore, conclude that my no-shorting factor can also greatly improve the applicability of the Carhart four-factor model.

The last model to look at is the Fama-French four-factor model, and its results are laid out in Panel B of Table 5.8. The points stated above in relation to the Carhart four-factor model all also apply here in relation to the Fama-French four-factor model: After I augment the model with the no-shorting factor, the confidence intervals of the OLR and the GLS $R^2$ move to the right; the p-values of the $T^2$ statistic fall; and the confidence interval for the q statistic moves to the left. These points hold true no matter which set of the test portfolios, 25 or 58, are placed in the left-hand side of the model. Like the Carhart four-factor model, the performance of the Fama-French four factor model will be enhanced if it is extended to include the no-shorting risk factor.

Graphical analysis is a more intuitive tool, as it delineates visual pictures about the benefits of adding the no-shorting factor to the existing asset-pricing models. Figures 5.1 through 5.4 plot confidence intervals of the true $T^2$-related q for, respectively, the CAPM, the Fama-French three-factor model, the Carhart four-factor model and the Fama-French four-factor model. As these figures lead to similar conclusions, albeit for different models, let me take Figure 5.4 as an example for illustration. Referring to the first two panels, the inclusion of the no-shorting factor moves the $T^2$ down from 75.74 to 57.52. As a result, the 95% confidence interval of the true *q* falls from [0.030, 0.568] to [0.000, 0.336]. In other words, allowing for the new factor, the Fama-French four-factor model will have a 95% chance that *q* will take a value between 0.000 and 0.336, while excluding the factor the model will give a 95% chance of *q* being equal to something between 0.030 and 0.568. The above results can be applied qualitatively to the last two panels of Figure 5.4, where 33 industry portfolios enter the set of test assets. With a given probability, the range of the *unexplained* squared Sharpe ratio becomes smaller: Allowing for the new risk factor NMS contributes to the ability of the augmented Fama-French four-factor model to reduce the distance that its mimicking portfolios are from the minimum-variance frontier.

**Figure 5.1 Sample distribution of the $T^2$ statistic and confidence interval for q: The CAPM**

This figure provides the results of the tests of the CAPM and the NMS-augmented CAPM using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS12 represents the no-shorting factor with a holding period of 12 months.

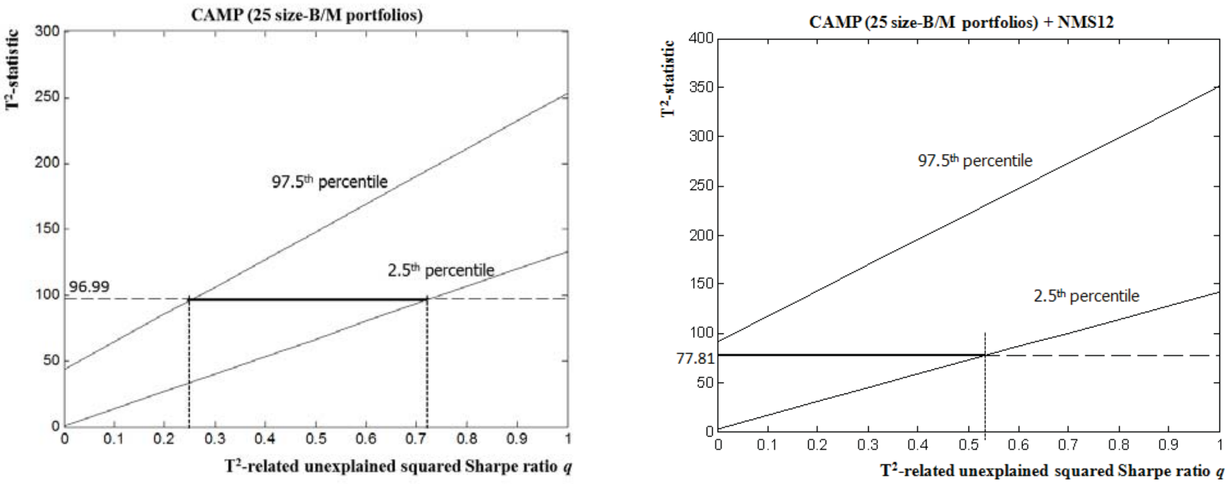


**Figure 5.1 Sample distribution of the $T^2$ statistic and confidence interval for q: The CAPM (continued)**

This figure provides the results of the tests of the CAPM and the NMS-augmented CAPM using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS12 represents the no-shorting factor with a holding period of 12 months.

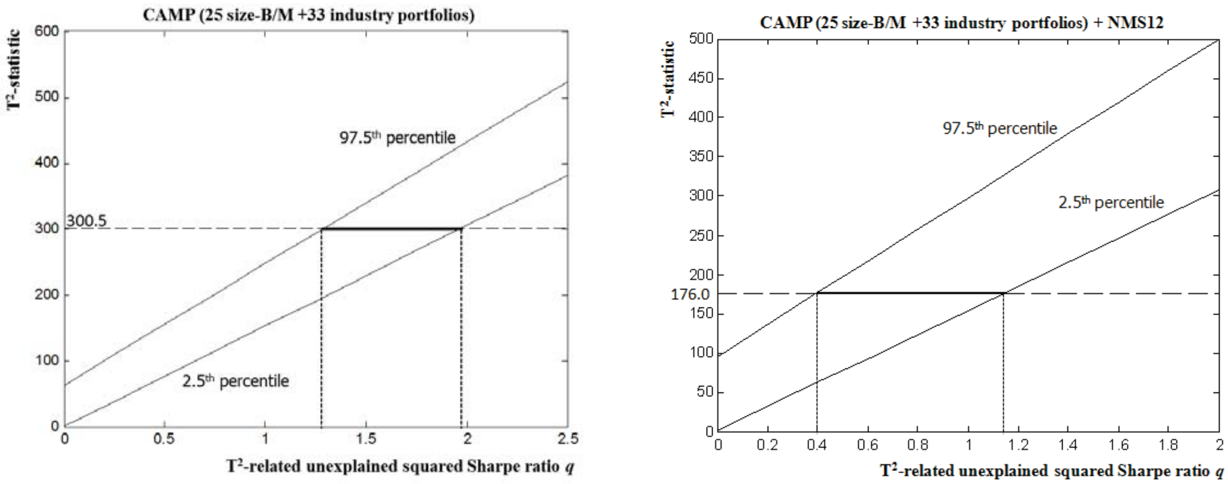


**Figure 5.2 Sample distribution of the $T^2$ statistic and confidence interval for q: The Fama-French three-factor model**

This figure provides the results of the tests of the Fama-French three-factor model and the NMS-augmented Fama-French three-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS12 represents the no-shorting factor with a holding period of 12 months.

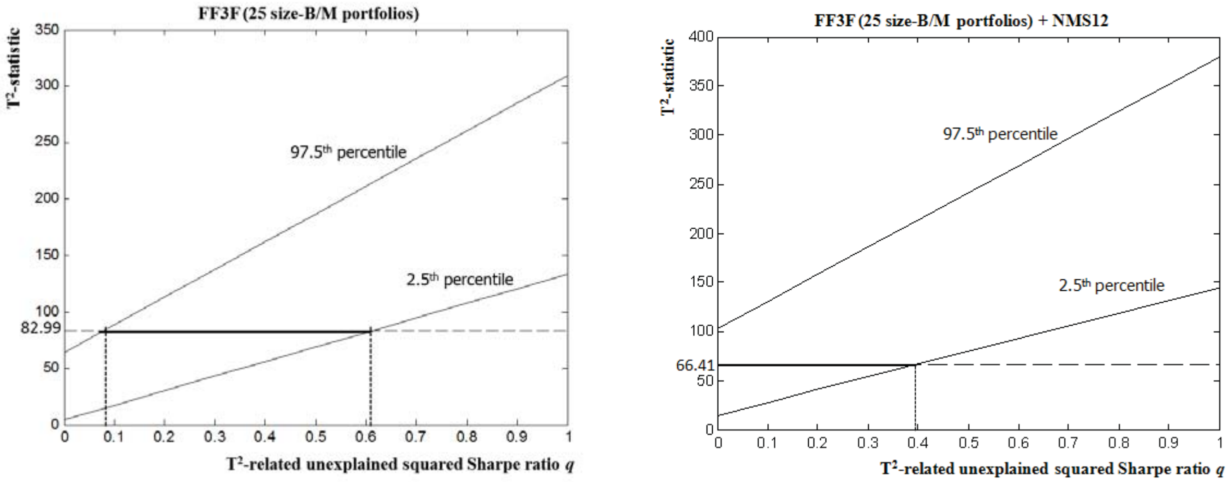


**Figure 5.2 Sample distribution of the $T^2$ statistic and confidence interval for q: The Fama-French three-factor model (continued)**

This figure provides the results of the tests of the Fama-French three-factor model and the NMS-augmented Fama-French three-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS12 represents the no-shorting factor with a holding period of 12 months.

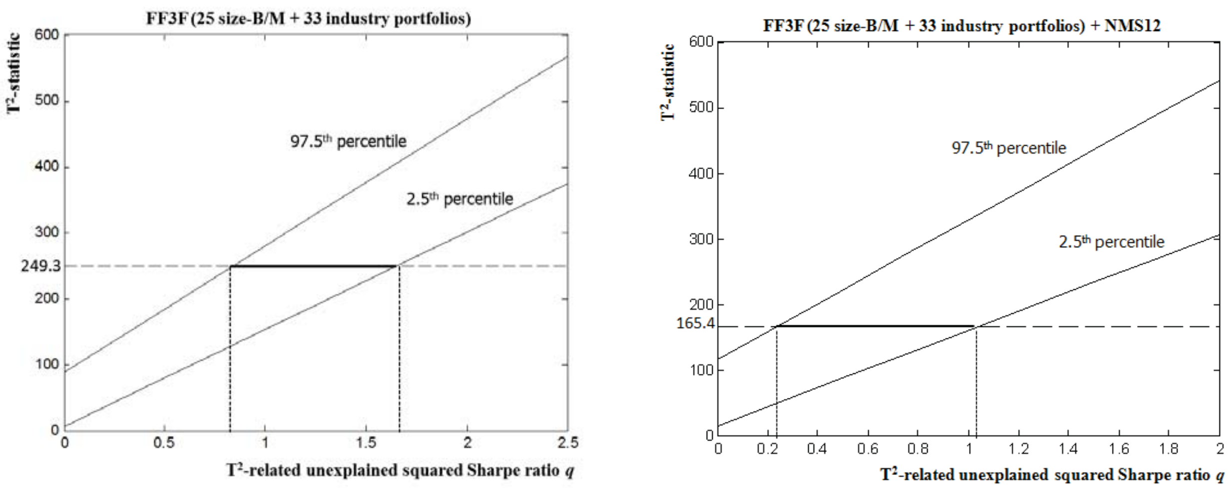
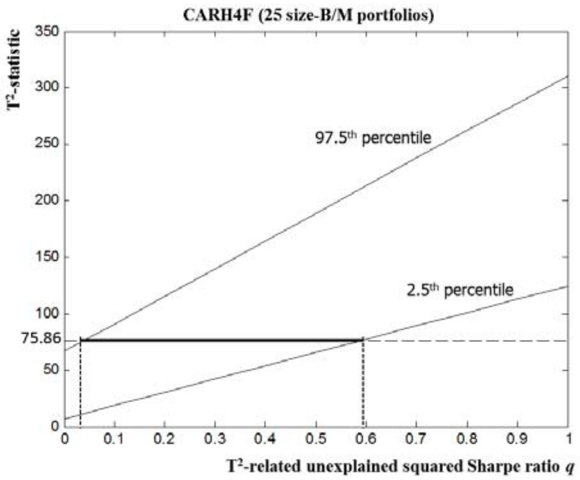


**Figure 5.3 Sample distribution of the $T^2$ statistic and confidence interval for q: The Carhart four-factor model**

This figure provides the results of the tests of the Carhart four-factor model and the NMS-augmented Carhart four-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS12 represents the no-shorting factor with a holding period of 12 months.



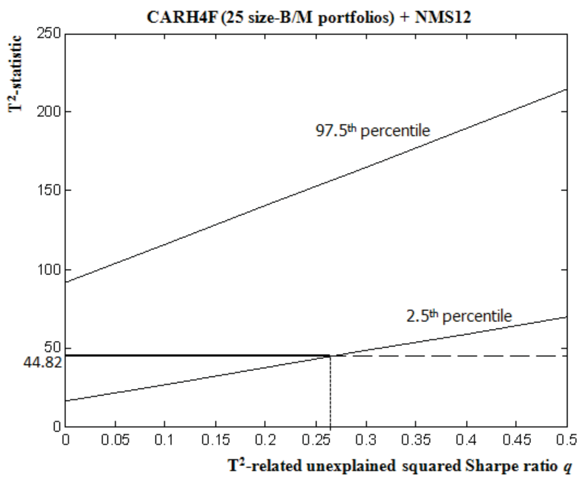
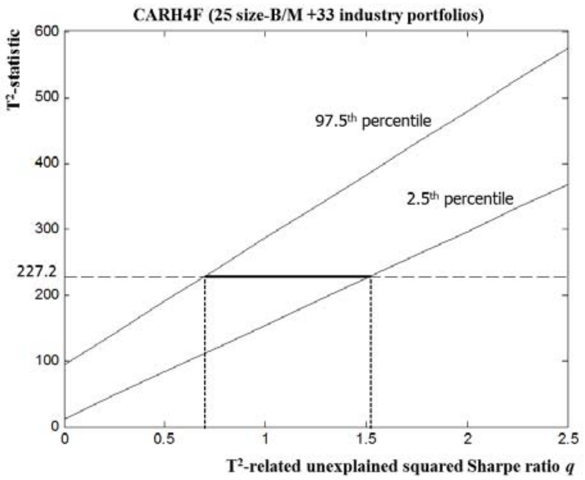



**Figure 5.3 Sample distribution of the $T^2$ statistic and confidence interval for q: The Carhart four-factor model (continued)**

This figure provides the results of the tests of the Carhart four-factor model and the NMS-augmented Carhart four-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS12 represents the no-shorting factor with a holding period of 12 months.



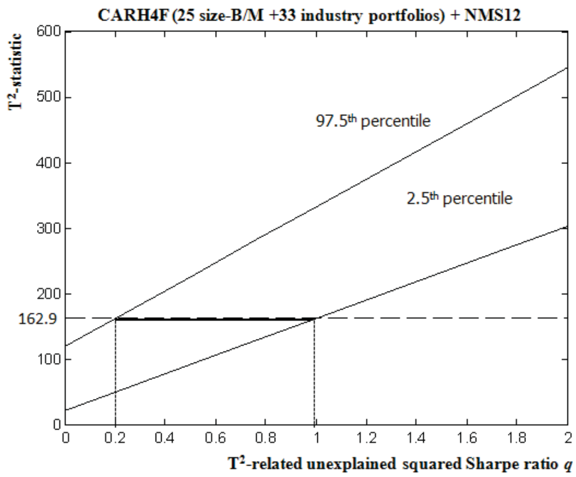
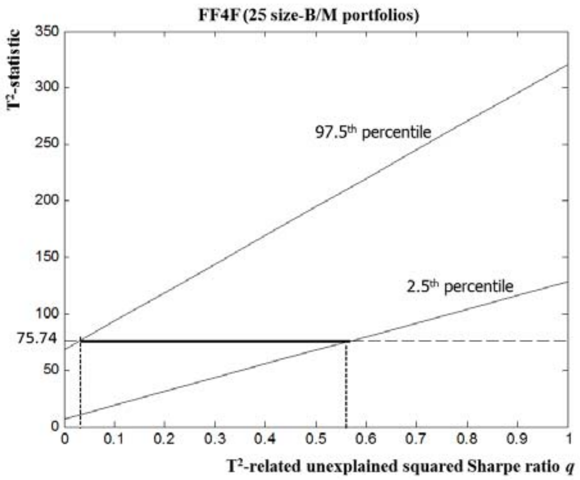



**Figure 5.4 Sample distribution of the $T^2$ statistic and confidence interval for q: The Fama-French four-factor model**

This figure provides the results of the tests of the Fama-French four-factor model and the NMS-augmented Fama-French four-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS12 represents the no-shorting factor with a holding period of 12 months.



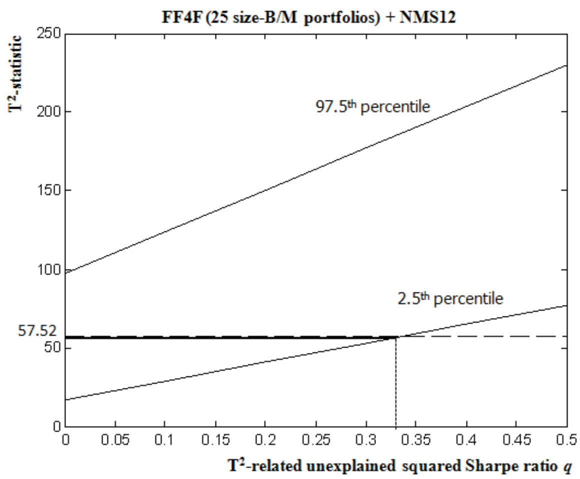
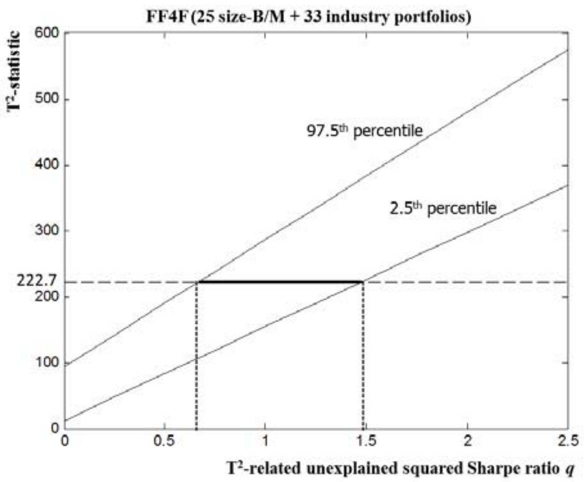
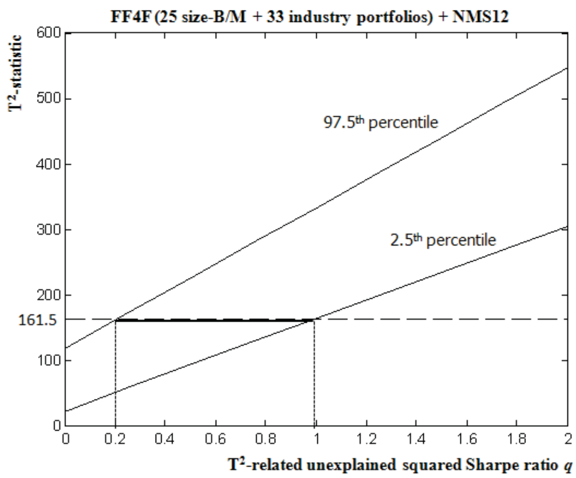



**Figure 5.4 Sample distribution of the $T^2$ statistic and confidence interval for q: The Fama-French four-factor model (continued)**

This figure provides the results of the tests of the Fama-French four-factor model and the NMS-augmented Fama-French four-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS12 represents the no-shorting factor with a holding period of 12 months.



## 5.5 Conclusion

All factor models of asset-pricing assume that asset markets are free of arbitrage-related friction and that participants can short-sell their assets freely. The problem is not so much with the assumption being unrealistic, but with the fact that researchers and practitioners have simply applied the models to any circumstances as if the absurdity of the underlying assumptions would not matter much. Two premises are needed to justify that one need not be too worried about the unrealisticness of the assumption. One is that short-sale constraints occur occasionally and/or in a negligible number of markets/circumstances. This is, however, not the case. Most security markets have imposed, or are imposing, restrictions on short-selling, though the constraints could vary from time to time and/or in the degree of severity. Even if in some markets regulators do not officially prohibit short-selling, the costs incurred in short-selling can be high enough to deter many, if not all, short-sellers, rendering a large number of assets not being practicable for short-selling.

The other premise is that it will make no significant difference if one ignores short-selling restrictions, however widely observed, when applying the existing factor models. Is this the case? I doubt that it is and, thus, attempt to prove this implicit prior belief wrong through thorough empirical research. The two preceding chapters have explored, respectively, how short-selling bans induce permanent overvaluation, and how shortable and non-shortable portfolios make different the performances of the existing asset-pricing models. Chapter 4 reports the finding that asset-pricing models work better for shortable than for non-shortable stocks. Then a logical question immediately follows: Will asset-pricing models work better if they take into account a risk factor related to short-sale restrictions. Therefore, to answer this question, in the present chapter I propose a no-shorting risk factor and augment the existing asset-pricing models with the factor. To justify the use of this risk factor, I review relevant studies in the literature and in the preceding two chapters of this dissertation. The justifications are as follow: Short-selling restrictions create overvaluation risk; constraint-induced liquidity risk; and constraint-induced information risk. Thus, investors holding non-shortable stocks will demand higher premiums as extra compensation, than those holding shortable stocks.

The interesting empirical results are summarised below. The no-shorting risk factor, constructed according to the short-selling status of stocks, has a significant power in explaining both time-series and cross-sectional variation in stock returns. The addition of the no-shorting risk factor to asset-pricing models considerably increases the overall performance of the models in three ways. First, most of the adjusted $R^2$s from the time-series regressions increase significantly and, in some cases, even more than double. Second, the risk factor itself has a significant loading, suggesting that it has strong power in explaining stock returns. Third, adding the risk factor into the asset-pricing models further enhances the importance of the market factor by increasing the statistical significance of the beta. In contrast, the momentum factor, either in the Carhart measure, or in the Fama-French measure, does not help explain the return variations for the Hong Kong Stock Market.

The study is conducted on the Hong Kong stock market, as its unique designated short-selling list makes it possible for me to construct various test portfolios, as well as the no-shorting risk factor. The findings of this study should be applicable to those markets with short-selling regulations similar to Hong Kong's.

**Appendix to Chapter 5**

In the main text of Chapter 5, I discuss the results related to the no-shorting factor measured by NMS12, which has a holding period of 12 months. It may be of interest to ask what would happen to the results if the holding period of the no-shorting factor is different, say one month (hereafter denoted as NMS1). This question is of practical relevance, since one could argue that investors can decide on the holding period of the no-shorting factor. Thus, in this appendix I only report the cross-sectional regression results related to NMS1, not the time-series regression results, to save space.

Let me begin with Panel A of Table A1. Adding NMS1 to the one-factor CAPM increases the overall explanatory power of the model, with the GLS $R^2$ rising from 0.010 to 0.053. The portfolio NMS1 is priced positively, with a coefficient of 0.018 at the 95% significance level. Adding NMS1 to the Fama-French three-factor model, and to the two momentum-augmented four-factor models, increases the GLS $R^2$ from 0.141 to 0.171, from 0.153 to 0.171, and from 0.195 to 0.199, respectively. Moreover, the risk premiums on the no-shorting factor are all significantly positive, except in the case of the Fama-French three-factor model where the risk premium is insignificantly positive. Panel B of Table A1 basically confirms the results in Panel A, although the full set of 58 portfolios is now used in the tests. The coefficients on NMS1 are all positive, and two of them are significant at the 5% level, with the other two significant at the 10% level. The GLS $R^2$ also increases in each of the four models, as a result of NMS1 being added.

**Table A1 The Fama-MacBeth two-pass regressions of factor models (with NMS1 as the no-shorting factor)**

This table reports the coefficient estimates from the Fama-MacBeth two-pass regressions for the CAPM, the Fama-French three-factor model, the Carhart four-factor model and the Fama-French four-factor model, as well as their respective augmented versions with the no-shorting factor added. The OLS $R^2$ is the adjusted $R^2$. NMS1 represents the no-shorting factor with a holding period of 1 month.

| Panel A: The LHS test assets are the 25 size/BM portfolios | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Intercept | Rm - Rf | SMB | HML | MOM_CARH | MOM_FF | NMS1 | GLS $R^2$ | OLS $R^2$ |
| Coefficient | 0.027 | -0.021 | | | | | | 0.010 | -0.023 |
| t-value | 0.84 | -0.72 | | | | | | | |
| Coefficient | -0.039 | 0.024 | | | | | 0.018** | 0.053 | 0.392 |
| t-value | -1.92 | 1.11 | | | | | 2.39 | | |
| Coefficient | -0.014 | 0.003 | 0.020** | 0.013** | | | | 0.141 | 0.473 |
| t-value | -0.68 | 0.14 | 2.60 | 2.56 | | | | | |
| Coefficient | -0.014 | 0.003 | 0.020** | 0.013** | | | 0.012 | 0.171 | 0.446 |
| t-value | -0.72 | 0.14 | 2.60 | 2.74 | | | 1.41 | | |
| Coefficient | -0.001 | -0.007 | 0.020** | 0.010** | 0.016 | | | 0.153 | 0.465 |
| t-value | -0.02 | -0.36 | 2.56 | 2.11 | 1.21 | | | | |
| Coefficient | -0.002 | -0.010 | 0.020** | 0.011** | 0.025 | | 0.016* | 0.171 | 0.448 |
| t-value | -0.09 | -0.47 | 2.53 | 2.27 | 1.41 | | 1.75 | | |
| Coefficient | -0.006 | -0.002 | 0.020** | 0.011** | | 0.011 | | 0.195 | 0.465 |
| t-value | -0.32 | -0.09 | 2.55 | 2.24 | | 0.88 | | | |
| Coefficient | -0.012 | -0.002 | 0.019** | 0.012** | | 0.021 | 0.020* | 0.199 | 0.459 |
| t-value | -0.66 | -0.11 | 2.51 | 2.47 | | 1.30 | 1.94 | | |

*,**,*** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

**Table A1 The Fama-MacBeth two-pass regressions of factor models (with NMS1 as the no-shorting factor) (continued)**

This table reports the coefficient estimates from the Fama-MacBeth two-pass regressions for the CAPM, the Fama-French three-factor model, the Carhart four-factor model and the Fama-French four-factor model, as well as their respective augmented versions with the no-shorting factor added. The OLS $R^2$ is the adjusted $R^2$. NMS1 represents the no-shorting factor with a holding period of 1 month.

Panel B: The LHS test assets are the 25 size/BM portfolios + 33 industry portfolios

| | Intercept | Rm - Rf | SMB | HML | MOM_CARH | MOM_FF | NMS1 | GLS $R^2$ | OLS $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| Coefficient | 0.013 | -0.008 | | | | | | 0.007 | -0.023 |
| t-value | 1.74 | -1.15 | | | | | | | |
| Coefficient | 0.011 | -0.012* | | | | | 0.009* | 0.014 | 0.392 |
| t-value | 1.26 | -1.73 | | | | | 1.80 | | |
| Coefficient | 0.012 | -0.013* | 0.011 | 0.007 | | | | 0.044 | 0.473 |
| t-value | 1.57 | -1.89 | 1.35 | 1.38 | | | | | |
| Coefficient | 0.015 | -0.013* | 0.012 | 0.006 | | | 0.002* | 0.053 | 0.446 |
| t-value | 1.25 | -1.82 | 1.49 | 1.30 | | | 1.91 | | |
| Coefficient | 0.014 | -0.014* | 0.011 | 0.007 | 0.007 | | | 0.056 | 0.465 |
| t-value | 1.26 | -2.03 | 1.34 | 1.31 | 0.77 | | | | |
| Coefficient | 0.016 | -0.013* | 0.012 | 0.006 | 0.005 | | 0.002* | 0.059 | 0.448 |
| t-value | 1.57 | -1.88 | 1.48 | 1.27 | 0.51 | | 2.02 | | |
| Coefficient | 0.015 | -0.140* | 0.010 | 0.007 | | 0.012 | | 0.068 | 0.465 |
| t-value | 1.58 | -2.01 | 1.32 | 1.33 | | 1.42 | | | |
| Coefficient | 0.016 | -0.013* | 0.011 | 0.006 | | 0.011 | 0.003* | 0.069 | 0.459 |
| t-value | 1.73 | -1.93 | 1.44 | 1.29 | | 1.20 | 2.06 | | |

*,**,*** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table A2 presents the additional cross-sectional test results following Lewellen et al.'s (2010) suggestions focusing on confidence intervals of several statistics. Panel A of the table focuses on the regressions for the CAPM and Fama-French three-factor models, while Panel B of the table is associated with regressions for the Carhart and Fama-French four-factor models. There, I compare the statistics and their confidence intervals between the standard with the augmented one-, three- and four-factor models with the no-shorting factor NMS1 added.

Consider the CAPM in Panel A of Table A2. The confidence intervals for the OLS $R^2$ and the GLS $R^2$ all increase, from [-0.043, 0.292] to [0.145, 0.723] and from [0.000, 0.416] to [0.009, 0.505], respectively, due to the addition of the no-shorting factor to the model. Take the confidence intervals for the GLS $R^2$ for example. Without the NMS1 factor, there is a 95% chance that the standard CAPM's GLS $R^2$ will fall between 0.000 and 0.416. With the no-shorting factor added, the standard CAPM's GLS $R^2$ has a 95% chance of falling between 0.009 and 0.505. Turning to the $T^2$ statistic, one can see that it drops from 96.985 to 81.908 and its p-value rises from 0.000 to 0.002 after adding the no-shorting factor to the standard CAPM. The more interesting observation is that the 95% confidence interval for the q statistic falls sharply from [0.257, 0.728] to [0.120, 0.588] as the CAPM turns from its standard version to its augmented version. That is, the CAPM's unexplained squared Sharpe ratio has a 95% chance of taking a value between 0.257 and 0.728, but the augmented CAPM's unexplained squared Sharpe ratio has a 95% chance of taking a value between 0.120 and 0.588.

The above analyses also apply to the CAPM with the full set of 58 portfolios being its test assets. The 95% confidence intervals for the OLS $R^2$ and the GLS $R^2$ all move up, while the 95% confidence interval for q moves down. Note that the $T^2$ statistic falls considerably, from 300.543 to 264.347, although the p-value is still less than 0.000 due to 58 instead of 25 portfolios being used as the test assets. In summary, the NMS1-augmented CAPM works better than the standard CAPM. If comparing Tables A1 and A2 with Tables 5.7 and 5.8, however, the NMS1-augmented CAPM is worse than the NMS12-augmented CAPM.

Next, consider the Fama-French three-factor model with 25 size-B/M portfolios on the LHS. According to Panel A of Table A2, with NMS1 added to the model, the 95% confidence intervals for the OLS and the GLS $R^2$ move up to higher levels, and the 95% confidence interval for q moves down to lower levels. The p-value of the $T^2$ statistic rises slightly from 0.005 to 0.009. When I expand the test assets to include 33 industry portfolios, the conclusion remains unchanged; that is, adding NMS1 to the model still makes it work slightly better. Specifically, the last three rows in Panel A of Table A2 show that the confidence intervals for the OLS and the GLS $R^2$ rise to higher ranges, the $T^2$ statistic falls a little bit and q's 95% confidence interval shifts slightly to the left. Again, if comparing Tables A1 and A2 with Tables 5.7 and 5.8, the NMS1-augmented Fama-French three-factor model is not as good as the NMS12-augmented Fama-French three-factor model.

Now turn to Panel B of Table A2 where two four-factor models, Carhart and Fama-French, are tested. Consider the Carhart four-factor model first. One can see that the 95% confidence intervals of the OLS and the GLS $R^2$ rise slightly to higher levels in both the case of 25 size-BM portfolios and the case of 58 portfolios as the LHS variables, as a result of the NMS1 factor being included in the model. For the 25 size-B/M portfolios tested, the $T^2$ statistic declines from 75.858 to 65.556, but for the 58 test portfolios, it rises slightly from 227.157 to 227.213. After the four-factor model becomes a five-factor model, q's confidence interval declines only slightly for both the 25 size-B/M portfolios tested and the 58 portfolios tested. One may, therefore, conclude that the no-shorting factor measured by NMS1 only slightly changes the applicability of the Carhart four-factor model.

The last model to look at is the Fama-French four-factor model. Based on Panel B of Table A2, the points stated above in relation to the Carhart four-factor model all apply here to the Fama-French four-factor model: The no-shorting factor measured by NMS1 does not much change the applicability of the Fama-French four-factor model.

Figures A1 through A4 plot confidence intervals of the true $T^2$-related q for, respectively, the CAPM, the Fama-French three-factor model, the Carhart four-factor model and the Fama-French four-factor model. The overall message conveyed by the four figures is that, if investors hold the no-shorting factor portfolio NMS for only one month, the benefit from adding it to the asset-pricing models will be rather limited. Holding NMS for 12 months is clearly more desirable. I will leave it to future research to uncover the “optimal” holding period of the NMS factor in the sense that it would enable the existing asset-pricing models to yield, for example, the smallest and lowest confidence interval for the unexplained squared Sharpe ratio q.

**Table A2 Additional cross-sectional tests for factor models based on the Lewellen et al. (2010) approach (with NMS1 as the no-shorting factor)**

The table reports the cross-sectional regression results with 25 size-B/M portfolios used alone, or together with 33 industry portfolios, as the test assets. The OLS $R^2$ is an adjusted $R^2$. The cross-sectional $T^2$ statistic tests whether pricing errors in a cross-sectional regression are all zero, with simulated *p*-values in brackets; *q* is the distance that a model's mimicking portfolios are from the minimum-variance frontier, measured as the difference between the maximum generalised squared Sharpe ratio and that attainable from the mimicking portfolios. 95% confidence intervals for the true OLS $R^2$s, GLS $R^2$s and *q* are reported in brackets next to their sample estimates. Confidence intervals are obtained by simulations with 40,000 replications. Coefficient estimates and their t-values are computed according to Shanken and Zhou (2007). NMS1 represents the no-shorting factor with a holding period of 1 month. RHS stands for "right hand side". The sample period used for the regressions is from January 1999 to February 2012, with 158 monthly observations.

**40,000 replications**

| Panel A: The one- and three-factor models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| CAPM (25 size-B/M) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf | -0.023 | [-0.043, 0.292] | 0.010 | [0.000, 0.416] | 96.985 | [p=0.000] | 0.673 | [0.257, 0.728] |
| RHS: Rm_Rf, NMS1 | 0.392 | [0.145, 0.7230] | 0.053 | [0.009, 0.505] | 81.908 | [p=0.002] | 0.643 | [0.120, 0.588] |
| | | | | | | | | |
| CAPM (25 + 33 ind.) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf | -0.018 | [-0.018, 0.099] | 0.007 | [0.000, 0.038] | 300.543 | [p=0.000] | 1.902 | [1.287, 1.968] |
| RHS: Rm_Rf, NMS1 | 0.366 | [0.199, 0.593] | 0.014 | [0.002, 0.101] | 264.347 | [p=0.000] | 1.888 | [0.993, 1.750] |
| | | | | | | | | |
| FF3F (25 size-B/M) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf, SMB, HML | 0.473 | [0.253, 0.790] | 0.141 | [0.035, 0.462] | 82.993 | [p=0.005] | 0.584 | [0.078, 0.609] |
| RHS: Rm_Rf, SMB, HML, NMS1 | 0.446 | [0.253, 0.790] | 0.171 | [0.024, 0.229] | 80.109 | [p=0.009] | 0.563 | [0.045, 0.589] |
| | | | | | | | | |
| FF3F (25 + 33 ind.) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| Rm_Rf+SMB+HML | 0.483 | [0.334, 0.686] | 0.044 | [0.010, 0.141] | 249.270 | [p=0.000] | 1.830 | [0.840, 1.651] |
| Rm_Rf+SMB+HML+NMS1 | 0.499 | [0.360, 0.710] | 0.053 | [0.018, 0.181] | 235.427 | [p=0.000] | 1.814 | [0.719, 1.559] |

**Table A2 Additional cross-sectional tests for factor models based on the Lewellen et al. (2010) approach (with NMS1 as the no-shorting factor) (continued)**

The table reports the cross-sectional regression results with 25 size-B/M portfolios used alone, or together with 33 industry portfolios, as the test assets. The OLS $R^2$ is an adjusted $R^2$. The cross-sectional $T^2$ statistic tests whether pricing errors in a cross-sectional regression are all zero, with simulated *p*-values in brackets; *q* is the distance that a model's mimicking portfolios are from the minimum-variance frontier, measured as the difference between the maximum generalised squared Sharpe ratio and that attainable from the mimicking portfolios. 95% confidence intervals for the true OLS $R^2$s, GLS $R^2$s and *q* are reported in brackets next to their sample estimates. Confidence intervals are obtained by simulations with 40,000 replications. Coefficient estimates and their t-values are computed according to Shanken and Zhou (2007). NMS1 represents the no-shorting factor with a holding period of 1 month. RHS stands for "right hand side". The sample period used for the regressions is from January 1999 to February 2012, with 158 monthly observations.

**40,000 replications (continued.)**

| Panel B: The four-factor models | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| CARH4F (25 size-B/M) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf, SMB, HML, MOM | 0.465 | [0.266, 0.801] | 0.153 | [0.049, 0.522] | 75.858 | [p=0.011] | 0.575 | [0.038, 0.586] |
| RHS: Rm_Rf, SMB, HML, MOM, NMS1 | 0.448 | [0.269, 0.811] | 0.171 | [0.066, 0.562] | 65.556 | [p=0.029] | 0.563 | [0.000, 0.550] |
| | | | | | | | | |
| CARH4F (25 + 33 ind.) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf, SMB, HML, MOM | 0.504 | [0.367, 0.710] | 0.056 | [0.017, 0.220] | 227.157 | [p=0.000] | 1.808 | [0.694, 1.513] |
| RHS: Rm_Rf, SMB, HML, MOM, NMS1 | 0.504 | [0.376, 0.716] | 0.059 | [0.024, 0.229] | 227.213 | [p=0.000] | 1.802 | [0.664, 1.526] |
| | | | | | | | | |
| FF4F (25 size-B/M) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| Rm_Rf, SMB, HML, MOM | 0.465 | [0.264, 0.801] | 0.195 | [0.048, 0.498] | 75.744 | [p=0.013] | 0.547 | [0.030, 0.568] |
| Rm_Rf, SMB, HML, MOM, NMS1 | 0.459 | [0.282, 0.816] | 0.199 | [0.067, 0.549] | 64.237 | [p=0.035] | 0.547 | [0.000, 0.505] |
| | | | | | | | | |
| FF4F (25 + 33 ind.) | OLS $R^2$ | | GLS $R^2$ | | $T^2$ | | q | |
| RHS: Rm_Rf, SMB, HML, MOM | 0.526 | [0.394, 0.724] | 0.068 | [0.019, 0.202] | 222.723 | [p=0.000] | 1.784 | [0.670, 1.477] |
| RHS: Rm_Rf, SMB, HML, MOM, NMS1 | 0.518 | [0.391, 0.726] | 0.069 | [0.024, 0.213] | 223.947 | [p=0.000] | 1.783 | [0.646, 1.494] |

**Figure A1 Sample distribution of the $T^2$ statistic and confidence interval for q: The CAPM**

This figure provides the results of the tests of the CAPM and the NMS-augmented CAPM using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS1 represents the no-shorting factor with a holding period of 1 month.

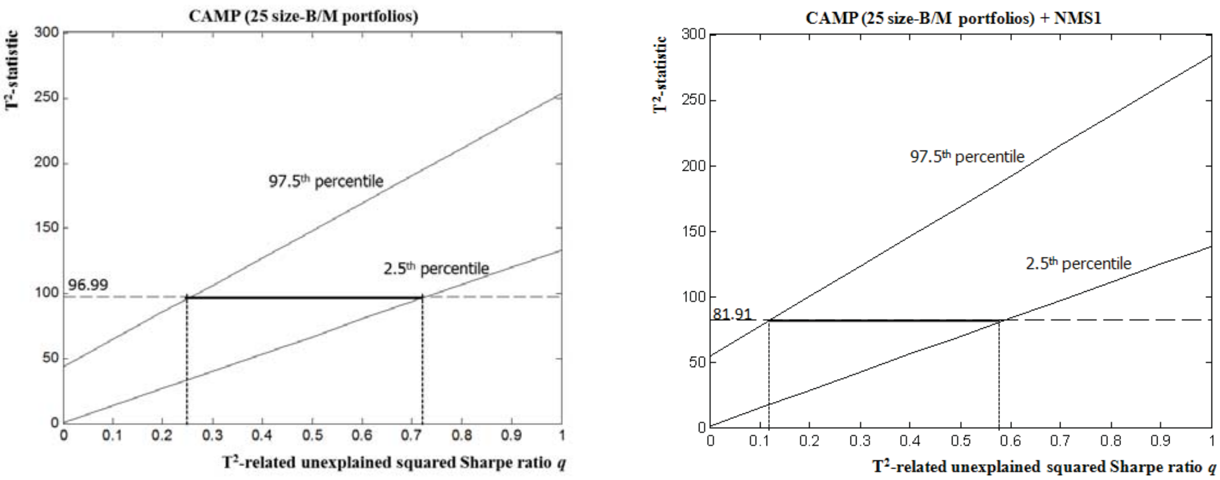
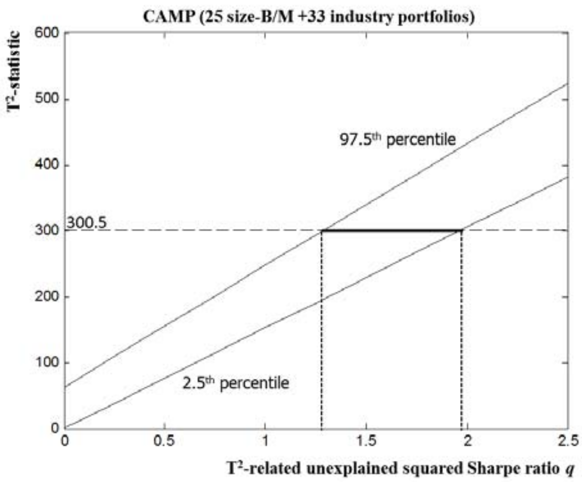


**Figure A1 Sample distribution of the $T^2$ statistic and confidence interval for q: The CAPM (continued)**

This figure provides the results of the tests of the CAPM and the NMS-augmented CAPM using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS1 represents the no-shorting factor with a holding period of 1 month.



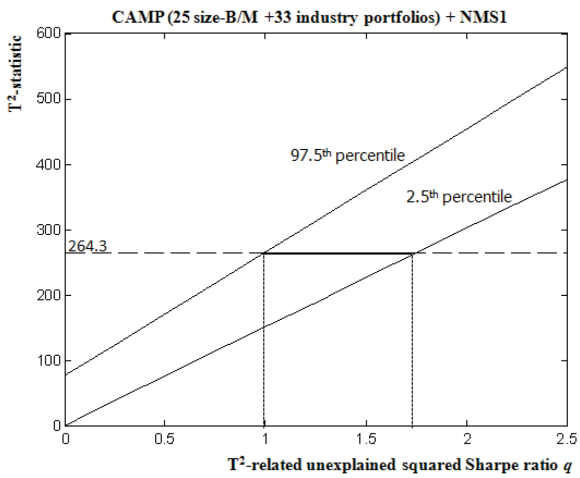
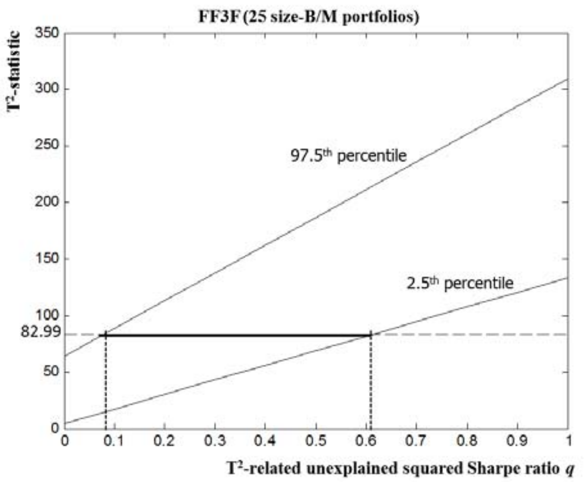



**Figure A2 Sample distribution of the $T^2$ statistic and confidence interval for q: The Fama-French three-factor model**

This figure provides the results of the tests of the Fama-French three-factor model and the NMS-augmented Fama-French three-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS1 represents the no-shorting factor with a holding period of 1 month.



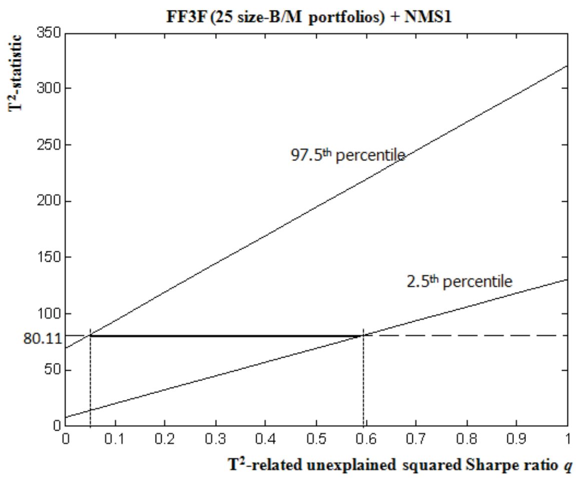
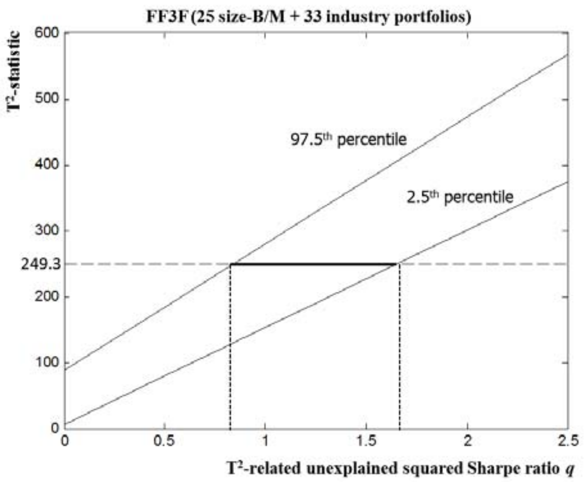



**Figure A2 Sample distribution of the $T^2$ statistic and confidence interval for q: The Fama-French three-factor model (continued)**

This figure provides the results of the tests of the Fama-French three-factor model and the NMS-augmented Fama-French three-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS1 represents the no-shorting factor with a holding period of 1 month.



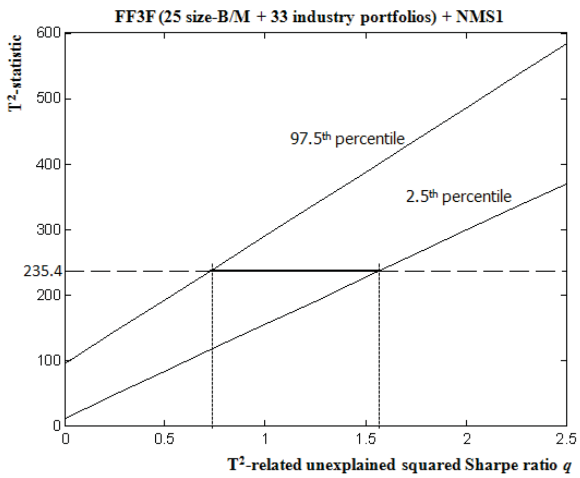
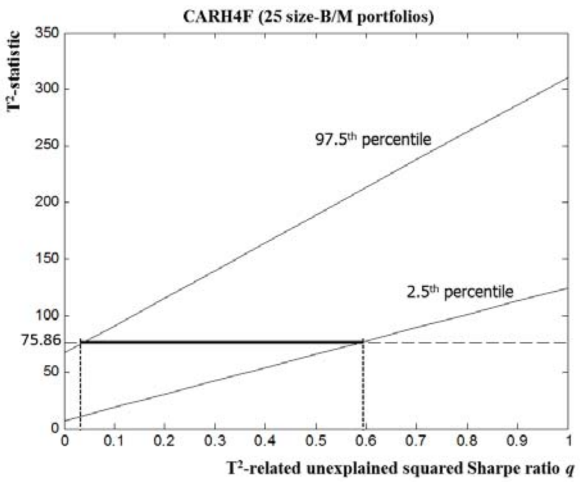



**Figure A3 Sample distribution of the $T^2$ statistic and confidence interval for q: The Carhart four-factor model**

This figure provides the results of the tests of the Carhart four-factor model and the NMS-augmented Carhart four-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS1 represents the no-shorting factor with a holding period of 1 month.



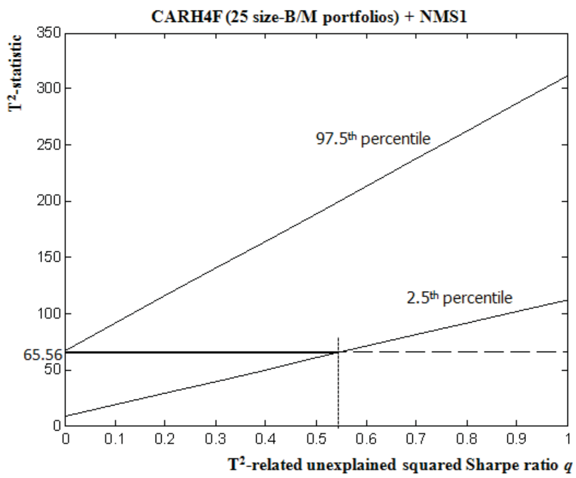
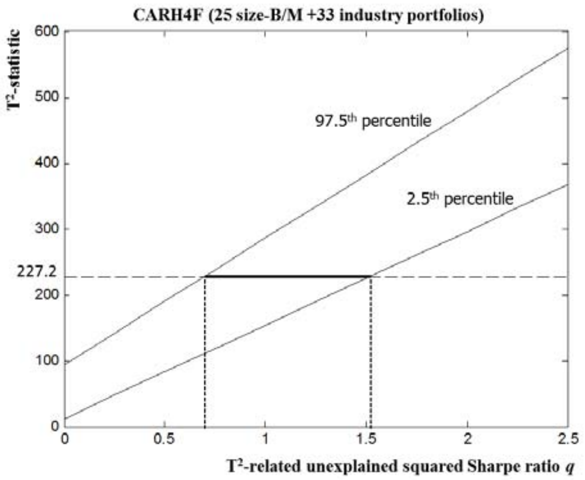



**Figure A3 Sample distribution of the $T^2$ statistic and confidence interval for q: The Carhart four-factor model (continued)**

This figure provides the results of the tests of the Carhart four-factor model and the NMS-augmented Carhart four-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS1 represents the no-shorting factor with a holding period of 1 month.



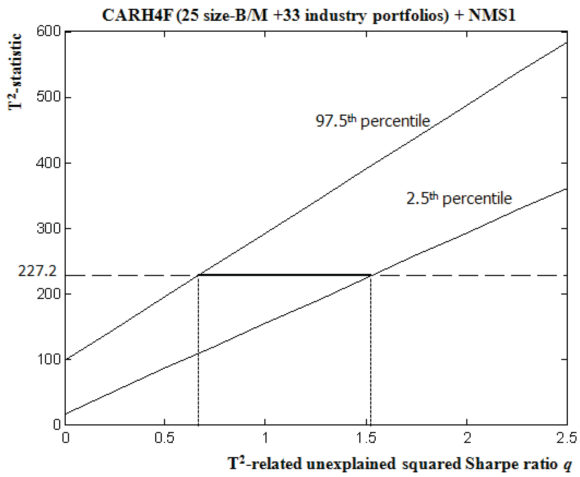



**Figure A4 Sample distribution of the $T^2$ statistic and confidence interval for q: The Fama-French four-factor model**

This figure provides the results of the tests of the Fama-French four-factor model and the NMS-augmented Fama-French four-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS1 represents the no-shorting factor with a holding period of 1 month.

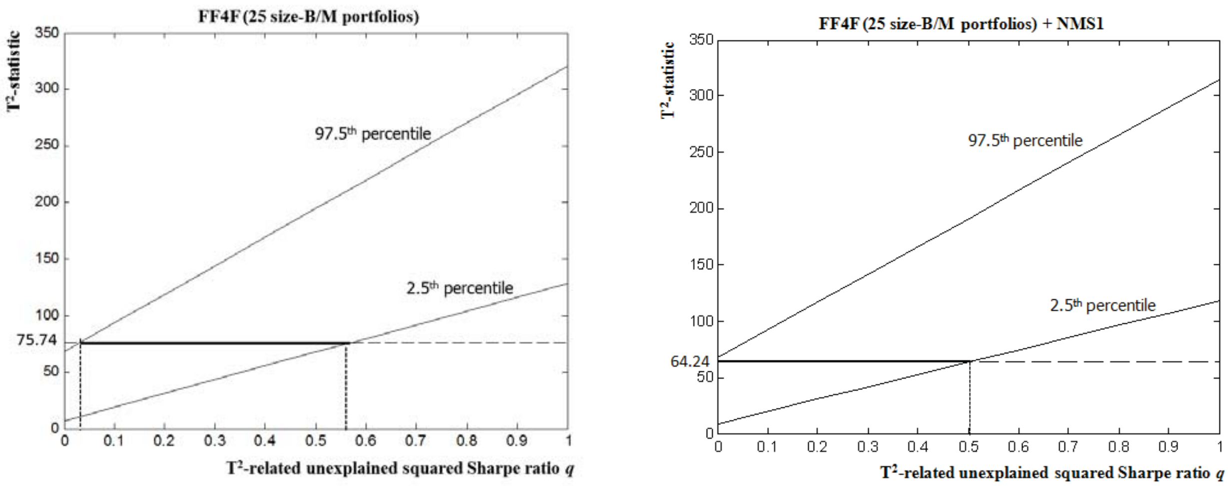
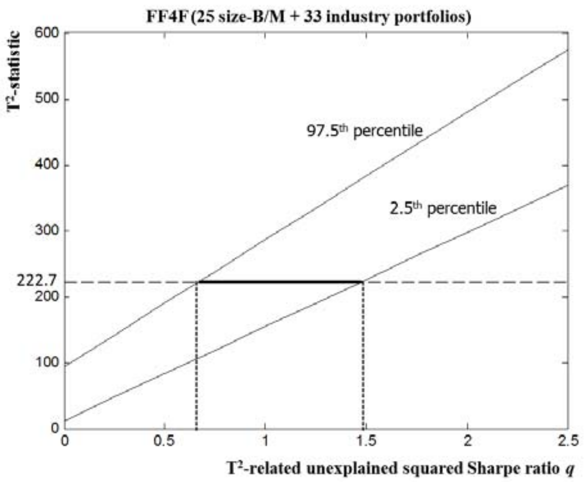
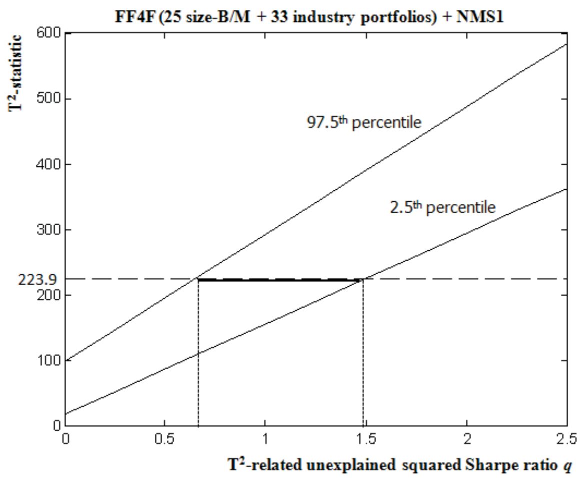


**Figure A4 Sample distribution of the $T^2$ statistic and confidence interval for q: The Fama-French four-factor model (continued)**

This figure provides the results of the tests of the Fama-French four-factor model and the NMS-augmented Fama-French four-factor model using monthly returns on 25 size-B/M portfolios, or on 25 size-B/M portfolios plus 33 industry portfolios, from January 1999 to February 2012. The sample distribution of the $T^2$ statistic, for a given value of the true unexplained squared Sharpe ratio, q, is found by slicing the graph along the x-axis (fixing q then scanning up to find percentiles of the sample distribution). A confidence interval for q, given the sample $T^2$ statistic, is found by slicing along the y-axis (fixing $T^2$ then scanning across). NMS1 represents the no-shorting factor with a holding period of 1 month.



# Chapter 6 Conclusions of the Thesis

Employing the designated short-selling list from the Hong Kong stock market, I explore three topics in this thesis. The first topic is concerned with whether short-sale constraints affect stock valuation by; (a) changing average abnormal returns, and (b) altering the effects of firm characteristics on stock returns. My attempt in (a) joins the empirical debate on Miller's (1977) overvaluation theory, since some questions are still left open from prior research on this issue. My attempt in (b) pioneers the study of the relation between short-sale constraints and the pricing of firm-specific risk factors.

Based on regime analysis not seen in previous studies of short-sale constraints, I uncover that a short-selling ban will cause the affected stocks to have higher mean abnormal returns throughout the entire period when the ban is being enforced. Among considered firm characteristics, I identify that firm size, illiquidity and dividend yields are affected by short-sale constraints in terms of their pricing behaviours. I find weak evidence suggests that, in the Hong Kong stock market, the effect of firm size on stock returns is more negative when the stock is banned for short-sales than when it is not. The size effect is interpreted as smaller firms paying a higher cost of capital, since they are often considered to be more financially distressed. If, however, investors cannot short the stocks of firms with smaller sizes the stocks will be more overpriced; i.e., the firms will pay an even higher cost of capital, other things being equal. The effect of contemporaneous illiquidity on stock returns in the Hong Kong stock market will be more strongly negative when the stock is not shortable than when it is shortable. A positive illiquidity shock predicts high future illiquidity, increasing risk and, hence, ex ante expected returns, by lowering contemporaneous prices. This should be reinforced by the presence of a short-sale restriction, as it represents increasing risk (i.e., the restriction lowers the speed of price discovery). On the other hand, however, if risk-averse investors cannot short the stock for hedging other risks (including the illiquidity risk) than the risk of slower price discovery, this will lead to excess demand for the stock and a rise in its prices. My results suggest that the former dominates the latter in the Hong Kong stock market. I also find moderate evidence shows that the negative relation between dividend yields and future returns becomes weak when stocks are constrained for short sales.

The second topic addresses one assumption underlying asset-pricing models: Short-sale restrictions are absent. In pursuing this topic, I attempt to show that it is problematic to apply the existing asset-pricing models to markets/assets where this assumption does not hold. My interest in this topic stems from the fact that so many markets, emerging and developed, have imposed short-sale restrictions constantly, or from time to time. The restrictions are part of the environment faced by a vast majority of practitioners who rely on the existing asset-pricing models for various purposes. In addition, the asset-pricing models have been applied by academic researchers indiscriminately to markets/assets without asking whether or not they are subject to short-sale constraints. Now is the time for both practitioners and academics to realise that it may be highly questionable to disregard the assumption that short-sale constraints are absent when applying the existing asset-pricing models. Chapter 4 is, therefore, devoted to this research endeavour.

In Chapter 4, I take both the conventional approach and Lewellen, Nagel and Shanken's (2010) enhanced approach to empirical investigation. Therein, I report that the CAPM and the Fama-French three-factor model fare significantly better in capturing the time-series and cross-section of expected returns on stocks when their short-selling is allowed than when it is not. These results are based on several statistics, such as the $R^2$, the adjusted

$R^2$, the GRS F, the cross-sectional $T^2$, the GLS $R^2$ and the *q* statistic, along with their confidence intervals. Short-sale restrictions, by worsening market efficiency, reduce the performance/validity of asset-pricing models that are supposed to work in frictionless markets. The results imply that it would produce biased estimates if applying the CAPM and the Fama-French three-factor model to stocks that are not allowed to be sold short. Showing these results only reveal the problem. A further step that naturally follows is to see whether there is a solution to the problem.

Therefore, as the third topic of this thesis, I explore, in Chapter 5, the possibility that constructing a new factor, which takes into account the risk-related short-selling restrictions and adding it to the existent asset-pricing model, might improve their performance/validity in the no-shorting market environment. Based on financial theories, I view the return discrepancy between shortable and non-shortable stocks as a risk premium to investors who hold non-shortable stocks. This not-shorting risk should be un-diversifiable, analogous to the SMB and HML factors in the Fama-French three-factor model. To make this conjecture testable, I thus construct a portfolio that mimics the no-shorting-related risk factor, again utilising the unique Hong Kong short-selling list. My test results show that the no-shorting risk factor has significant power in explaining both the time-series variation in stock returns and the cross-section of expected stock returns. This is reflected in the observation that adding the no-shorting factor to such asset-pricing models as the one-factor, the three-factor and the four-factor model, would significantly increase their overall performance, as compared to their original versions.

To summarise, this thesis fills three voids in the asset-pricing literature in general, and in the study of short-sale constraints in particular. The first regards the different pricing behaviours of stock characteristics across the shorting-ban and the no-shorting-ban regimes. The second concerns the poorer performance of the widely-adopted asset-pricing model in the shorting-ban regime than the no-shorting-ban regime. The third pertains to improving the applicability of these asset-pricing models in the short-ban regime.

Important implications for practitioners and academics can be derived from my findings in this thesis. As examples, practitioners (investors and companies) would learn the following: (1) Stocks banned for short sales earn higher average abnormal returns; (2) some firm characteristics are important in raising/lowering stock returns when the stocks change from being shortable to being non-shortable, and so need to be taken into account when pricing the stocks; and (3) augmenting the existing asset-pricing models with the shorting-restriction-rated factor would improve the accuracy of estimating the cost of equity capital in markets where short sales are restricted. Academics should learn that it is inappropriate to apply the existing asset-pricing models in research that involves assets and markets facing short-sale constraints. Extra endeavours to take into account the short-sale restrictions as an additional risk factor are required if one wishes to continue to employ these well-known models. An implication of my findings for further research then follows: Assets may demonstrate many different degrees of shortability, even if they are allowed to be sold short, due to, for example, different borrowing costs. Thus, it would be interesting to investigate how to construct a risk factor that captures the many different degrees of shortability in order to augment the existing asset-pricing models.

# Bibliography


Acharya, V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics, 77*, 375-410.

Aitken, M. J., Frino, A., McCorry, M.S., & Swan P. L. (1998). Short sales are almost instantaneously bad news: Evidence from the Australian Stock Exchange. *The Journal of Finance, 53*, 2205-2223.

Alexander, G.J., & Peterson, M.A. (2008). The effect of price tests on trader behaviour and market quality: An analysis of Reg SHO. *Journal of Financial Markets, 11*, 85-111.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets, 5*, 31-56.

Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid ask spread. *Journal of Financial Economics, 15*, 223-249.

Asparouhova, E., Bessembinder, H., & Kalcheva, I. (2013). Noisy prices and inference regarding returns. *The Journal of Finance*, Forthcoming.

Asquith, P., & Meulbroek, L. (1995). An empirical investigation of short interest. *Unpublished working paper*, Harvard University.

Autore, D., Billingsley, R., & Kovacs. T. (2011). The 2008 short sale ban: Liquidity, dispersion of opinion, and the cross-section of returns of US financial stocks. *Journal of Banking and Finance, 35*, 2252-2266.

Bai, Y., Chang, E.C., & Wang, J. (2006). Asset prices under short-sale constraints. Retrieved from http://www.fep.up.pt/investigacao/cempre/actividades/sem_fin/sem_fin_01_05/PAPERS_PDF/paper_sem_fin_23mar06.pdf

Ball, R. (1978). Anomalies in relationship between securities' yields and yield-surrogates. *Journal of Financial Economics, 6,* 103-126.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics, 9,* 3-18.

Barberis, N., Shleifer, A., & Vishny, R.W. (1998). A model of investor sentiment. *Journal of Financial Economics, 49,* 307-343.

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance, 32,* 663-682.

Basu, S. (1983). The relationship between earnings yield, market value and return for NYSE common stocks: Further evidence. *Journal of Financial Economics, 12,* 129-156.

Beber, A., & Pagano, M. (2013). Short-selling bans around the world: Evidence from the 2007-09 crisis. *The Journal of Finance, 68,* 343-381.

Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American Political Science Review, 89,* 634-647.

Bekaert, G., & Harvery,C.R. (2003). Emerging markets finance. *Journal of Empirical Finance, 10,* 3-55.

Bekaert, G., Harvey, C. R., & Lundblad, C. (2007). Liquidity and expected returns: Lessons from emerging markets. *The Review of Financial Studies, 20,* 1783-1831.

Berkman, H., Dimitrov, V., Jain, P.C., Koch, P.D., & Tice, S. (2009). Sell on the news: Differences of opinion, short-sales constraints, and returns around earnings announcement. *Journal of Financial Economics, 92,* 376-399.

Bhandrari, L.C. (1988). Debt/equity ratio and expected common stock returns: Empirical evidence. *The Journal of Finance, 43,* 507-528.

Black, F. (1972). Capital market equilibrium with restricted borrowing. *Journal of Business, 45*, 444-454.

Boehme, R.D., Danielsen, B. R., & Sorescu, S. M. (2006). Short-sale constraints, differences of opinion, and overvaluation. *Journal of Financial and Quantitative Analysis, 41,* 455-487.

Boehmer, E., Jones, C. & Zhang. X. (2009). Shackling short sellers: The 2008 shorting ban. *Working paper.*

Boehmer, E., & Wu. J. (2013). Short selling and the price discovery process. *The Review of Financial Studies, 26,* 287-322.

Boudoukh, J., Richardson, M. & Smith.T. (1993). Is the *ex ante* risk premium positive? A new approach to testing conditional asset pricing models. *Journal of Financial Economics, 34,* 387-408.

Boulton, T., & Braga-Alves, M. (2010). The skinny on the 2008 naked short-sale restrictions. *Journal of Financial Markets, 13,* 397-421.

Brennan, M.J., Chordia, T., & Subrahmanyam, A. (1998). Alternative factor specifications, security characteristics, and the cross-section of expected returns. *Journal of Financial Economics, 49,* 345-373.

Bris, A., Goetzmann, W.N, & Zhu, N. (2007). Efficiency and the bear: Short sales and markets around the world. *The Journal of Finance, 62,* 1029-1079.

Bruner, R.F., Li, W., Kritzman, M., Myrgren, S., & Page, S. (2008). Market integration in developed and emerging markets: Evidence from the CAPM. *Emerging Market Review, 9,* 89-103.

Campbell, J. (2000). Asset pricing at the Millennium. *The Journal of Finance, 55,* 1515-1567.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance, 52*, 57-82.

Chan, K.C., & Chen. N. (1991). Structural and return characteristics of small and large firms. *The Journal of Finance, 46,* 1467-1484.

Chan, L. K. C., Hamao, Y., & Lakoniskok, J. (1991). Fundamentals and stock returns in Japan. *The Journal of Finance, 46,* 1739-1746.

Chang, E. C., Cheng, J. W., & Yu, Y. (2007). Short-sales constraints and price discovery: Evidence from the Hong Kong market. *The Journal of Finance, 62*, 2097-2121.

Charoenrook, A., & Daouk, H. (2008). A study of market-wide short-selling restrictions. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=687562

Chen, C. X., & Rhee, G. (2010). Short sales and speed of price adjustment: Evidence from the Hong Kong stock market. *Journal of Banking and Finance, 34,* 471-483.

Chen, J., Hong, H., & Stein, J. C. (2002). Breadth of ownership and stock returns. *Journal of Financial Economics, 66,* 171-205.

Chen, Z. (1995). Financial innovation and arbitrage pricing in frictional economies. *Journal of Economic Theory, 65,* 117-135.

Chen, Z. (2001). Viable costs and equilibrium prices in frictional securities markets. *Annals of Economics and Finance, 2,* 297-323.

Cho, S. (1987). An alternative model to resolve the underpricing puzzle of initial public offerings. *Unpublished working paper*, University of Michigan.

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market liquidity and trading activity. *The Journal of Finance, 56,* 501-530.

Chordia,T., & Shivkumar. L. (2002). Momentum, business cycle and time-varying expected returns. *The Journal of Finance 57,* 985-1019.

Chui, A. C. W., & Wei, K. C. J. (1998). Book-to-market, firm size, and the turn-of-the-year effect: Evidence from Pacific-Basin emerging markets. *Pacific-Basin Finance Journal, 6*, 275-293.

Cohen, R., Gompers, P., & Vuolteenaho, T. (2002). Who undereacts to cash-flow news? Evidence from trading between individuals and institutions. *Journal of Financial Economics, 66*, 409-462.

Cooper, M.J., Gulen, H., & Schill. M.J. (2008). Asset growth and the cross-section of stock returns. *The Journal of Finance, 63,* 1609-1651.

Cremers, M., Petajisto, A., & Zitzewitz, E. (2008). Should benchmark indices have alpha? Revisiting performance evaluation. *Working Paper*, Binghamton University.

Crombez, J. (2010). Momentum, rational agents and efficient markets. *The Journal of Psychology and Financial Markets, 2,* 190-200.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance, 53,* 1839-1885.

Daniel, K., & Titman, S. (1997). Evidence on the characteristics of cross sectional and stock market seasonality. *The Journal of Finance, 52,* 1-33.

Daniel, K., Titman, S., & Wei, K.C. J. (2001). Explaining the cross-section of stock returns in Japan: Factors or characteristics? *The Journal of Finance, 56,* 743-766.

Danielsen, B. R., & Sorescu, S. M. (2001). Why do option introductions depress stock prices? A study of diminishing short sale constraints. *Journal of Financial and Quantitative Analysis, 36,* 451-484.

DeBondt, W., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance, 40,* 793-805.

DeBondt, W., & Thaler, R. (1987). Further evidence on investor overreaction and stock market seasonality, *The Journal of Finance 42,* 557-580.

DeLong, J., Shleifer, B., Summers, L., & Waldmann, R. (1990). Noise trader risk in financial markets. *Journal of Political Economy, 98,* 703-738.

Desai, H., Ramesh, K., Thiagarajan, S. R., & Balachandran, B.V. (2002). An investigation of the informational role of short interest in the NASDAQ market. *The Journal of Finance, 57,* 2263-2287.

Diamond, D. W., & Verrecchia, R. E. (1987). Constraints on short selling and asset price adjustment to private information. *Journal of Financial Economics, 18,* 277-311.

Diether, K. B., Lee, K-H., & Werner, I. M. (2009). It's SHO time! Short-sale price tests and market quality. *The Journal of Finance, 64*, 37-73.

Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance, 57*, 2113-2141.

Duffie, D., Garleanu, N., & Pedersen, L. H. (2002). Securities lending, shorting, and pricing. *Journal of Financial Economics, 66*, 307-339.

Eun, C., & Huang, W. (2007). Asset pricing in China's domestic stock markets: Is there a logic? *Pacific-Basin Finance Journal, 15,* 452-480.

Faccio, M., Lang, L. H. P., & Young, L. (2001). Dividends and expropriation. *American Economic Review, 91*, 54-78.

Fama, E. F. (1968). Risk, return and equilibrium: Some clarifying comments. *The Journal of Finance, 23,* 29-40.

Fama, E.F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25,* 383-417.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, *47,* 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33,* 3-56.

Fama, E. F., & French, K .R. (1995). Size and Book-to-Market factors in earnings and returns. *The Journal of Finance*, *50*, 131-155.

Fama, E. F., & French, K. R. (1996). Multifactor explanation of asset pricing anomalies. *The Journal of Finance*, *51*, 55-84.

Fama, E. F., & French, K. R. (1997). Industry costs of equity. *Journal of Financial Economics*, *43*,153-193.

Fama, E. F., & French, K. R. (1998). Value versus growth: The international evidence. *The Journal of Finance*, *53*, 1975-1999.

Fama, E. F., & French, K. R. (2002). Testing trade-off and pecking order predictions about dividends and debt. *The Review of Financial Studies*, *15,* 1-33.

Fama, E. F., & French, K. R. (2004). The capital asset pricing model: Theory and evidence. *Journal of Economic Perspectives*, *18,* 25-46.

Fama, E. F., & French, K. R. (2006). The value premium and the CAPM. *The Journal of Finance*, *61,* 2163-2185.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, *105,* 467-472.

Fama, E. F., & MacBeth, J. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, *81,* 607-636.

Figlewski, S. (1981). The informational effects of restrictions on short sales: Some empirical evidence. *Journal of Financial and Quantitative Analysis*, *16,* 463-476.

Gaunt, C. (2004). Size and book to market effects and the Fama French three factor asset pricing model: Evidence from the Australian stock market. *Accounting and Finance, 44,* 27-44.

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica, 57*, 1121-1152.

Glosten, L. R., & Miilgrom, P. R. (1985). Bid, ask and transactions prices in a specialist model with heterogeneously informed traders. *Journal of Financial Economics, 14,* 71-100.

Graham, J. R., Harvey, C. R. (2001). How do CFOs make capital budgeting and capital structure decisions? *Journal of Applied Corporate Finance, 15,* 8-23.

Graves, A. J., & McDonald, B. (1989). Nonnormalities and tests of asset pricing theories. *The Journal of Finance, 44,* 889-908.

Griffin, J. M. (2002). Are the Fama and French factors global or country specific? *The Review of Financial Studies, 15,* 783-803.

Hansen, L. P., Heaton, J., & Luttmer, E. (1995). Econometric evaluation of asset pricing models. *The Review of Financial Studies 8*, 237-274.

Hansen, L. P., & Jagannathan, R. (1997). Assessing specification errors in stochastic discount factor models. *The Journal of Finance, 52*(2), 557-590.

Hansen, L. P., & John, H. (1995). Econometric evaluation of asset pricing models. *The Review of Financial Studies, 8,* 237-274.

Harris, L., Namvar, E., & Phillips. B. (2009). Price inflation and wealth transfer during the 2008 SEC short-sale ban. *Working paper.*

Harris, R. S., & Marston, F.C. (1994). Value versus growth stocks: Book-to-market, growth, and beta. *Financial Analysts Journal, 50,* 18-24.

Harrison, J. M., & Kreps, D. M. (1978). Speculative investor behaviour in a stock market with heterogeneous expectations. *Quarterly Journal of Economics, 92,* 323-336.

Harrison, J. M., & Raviv, A. (1993). Differences of opinion make a horse race. *The Review of Financial Studies, 6,* 473-506.

Hasbrouck, J., & Seppi, D. J. (2001). Common factors in prices, order flows, and liquidity. *Journal of Financial Economics, 59,* 383-411.

Haugan, R.A. (1995). The new finance – The case against efficient market. *Working paper.*

Hausman, J.A. (1978). Specification tests in Econometrics. *Econometrica, 46,* 1251-1271.

He, H., & Modest, D. (1995). Market frictions and consumption-based asset pricing. *Journal of Political Economy, 103,* 94-117.

Herrera, M., & Lockwood, L. J. (1994). The size effect in the Mexican stock market. *Journal of Banking and Finance, 18,* 621-32.

Ho, C., & Hung, C. (2009). Investor sentiment as conditioning information in asset pricing. *Journal of Banking and Finance, 33,* 892-903.

Ho, C., & Hung, C. (2012). Investor sentiment risk factor and asset pricing anomalies. *Working paper.*

Hong,H., & Stein.J.C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance, 54,* 2143-2184.

Hong, H., & Stein, J. C. (2003). Difference of opinion, short-sale constraints and market crashes. *The Review of Financial Studies, 16,* 487-525.

Hong Kong Stock Exchange. http://www.hkex.com.hk/

Huberman, G., & Halka. D.(2001). Systematic liquidity. *Journal of Financial Research, 24,* 161-178.

Huberman, G., & Kandel, S. (1987). Mean variance spanning. *The Journal of Finance, 42,* 873-888.

Jagannathan, R., & Wang, Z. (1992). The cross-section of expected stock returns: Do size and book to market equity measure systematic risk better than beta? *Notes for The Berkeley Program in Finance on "Are Betas Irrelevant? Evidence and Implications for Asset Management", September 13-15, Santa Barbara, California*.

Jagannathan, R., & Wang, Z. (1993). The CAPM is alive and well. *Staff report 165, Federal Reserve Bank of Minneapolis*.

Jarrow, R. (1980). Heterogeneous expectations, restrictions on short sales, and equilibrium asset prices. *The Journal of Finance, 35,* 1105-1113.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of Finance, 45,* 881-898.

Jegadeesh, N. (1992). Does market risk really explain the size effect? *Journal of Financial and Quantitative Analysis, 10,* 337-351.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance, 48,* 65-91.

Jones, C. (2002). A century of stock market liquidity and trading costs. *Working Paper,* Columbia University, New York.

Jones, C., & Lamont, O. A. (2002). Short-sale constraints and stock returns, *Journal of Financial Economics, 66,* 207-239.

Jouini, E., & Kallal, H. (2001). Efficient trading strategies in the presence of market frictions. *The Review of Financial Studies, 14,* 343-369.

Kaldor, N. (1939). Speculation and Economic Stability. *Review of Economic Studies, 7,* 1-27.

Karolyi, G. A., & Wu, Y. (2012). The role of inevitability restrictions on size, value, and momentum in international stock returns. *Working paper.*

Kolasinski, A. C., Reed, A. V., & Thornock, J. R. (2010). Can short restrictions result in more informed short selling? Evidence from the 2008 regulations. *Working Paper.*

Korajczyk, R. A., & Sadka, R. (2008). Pricing the commonality across alternative measures of liquidity. *Journal of Financial Economics, 87,* 45-72.

Kraus, A., & Sick, G. A. (1979). Communication of aggregate preference through market prices. *Journal of Financial and Quantitative Analysis, 4*, 695-703.

Lakonishok, J.A., Shleifer, A., & Vishny, R. (1994). Contrarian investment, extrapolation, and risk. *The Journal of Finance, 49,* 1541-1578.

Lam, K. S. K., & Tam, L. H. K. (2011). Liquidity and asset pricing: Evidence from the Hong Kong stock market. *Journal of Banking and Finance, 35,* 2217-2230.

Lamoureux, C. G., & Sanger, G. (1989). Firm size and turn-of-the-year effects in the OTC/NASDAQ market. *The Journal of Finance, 44,* 1219-1245.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. (2000). Agency problems and dividend policies around the world. *The Journal of Finance, 55*, 1-33.

Lettau, M., & Ludvigson, S. (2001). Consumption, aggregate wealth, and expected stock returns. *The Journal of Finance, 56,* 815-849.

Lewellen, J., Nagel, S., & Shanken, J. (2010). A sceptical appraisal of asset pricing tests. *Journal of Financial Economics, 96,* 175-194.

Lo, A. W., & MacKinlay, A. C. (1990). Data-snooping biases in tests of financial asset pricing models. *The Review of Financial Studies, 3,* 431-468

Li, X., & Bai, M. (2012). Short-selling regimes and stock-valuation pattern. *Working paper.*

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics, 47*, 13-37.

Lintner, J. (1969). The aggregation of investors' diverse judgments and preferences in perfectly competitive security markets. *Journal of Financial and Quantitative Analysis, 4*, 347-400.

Liu, W., (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics, 82*, 631-671.

Luttmer, E. G. J. (1996). Asset pricing with frictions. *Econometrica, 64*, 1439-1467.

Markowitz, H. M. (1952). *Portfolio Selection: Efficient Diversification of Investments.* New York: John Wiley & Sons.

Marsh, I. W., & Payne, R. (2012). Banning short sales and market quality: The UK's experience. *Journal of Banking and Finance, 36,* 1975-1986.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *The Journal of Finance, 32*, 1151-1168.

Mobarek, A., & Mollah, A. (2005). The general determinants of share returns: An empirical investigation on the Dhaka Stock Exchange. *Review of Pacific Basin Financial Markets and Policies, 8,* 593-612.

Morris, S. (1996). Speculative investor behaviour and learning. *Quarterly Journal of Economics, 111,* 1113-1133.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica, 34*(4), 768-783.

Nagel, S. (2005). Short sales, institutional investors and the cross-section of stock returns. *Journal of Financial Economics, 78,* 277-309.

Novy-Marx, R. (2011). Is momentum really momentum. *Journal of Financial Economics.* Forthcoming.

Ofek, E., & Richardson, M. (2003). DotCom mania: The rise and fall of internet stock prices. *The Journal of Finance, 58,* 1113-1137.

Orme, C.D., & Yamagata, T. (2006). The asymptotical distribution of the F-test statistic for individual effects. *Econometrics Journal, 9,* 404-422.

Pastor, L., & Stambaugh, R. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111,* 642-685.

Perez-Quiroz, G., & Timmermann, A., (2000). Firm size and cyclical variations in stock returns. *The Journal of Finance, 55,* 1229-1262.

Petersen, M. A. (2005). Estimating standard errors in finance panel data sets: Comparing approaches. Retrieved from http://www.haas.berkeley.edu/groups/finance/standarderror.pdf

Phalippou, L. (2007). Can risk-based theories explain the value premium? *Review of Finance, 11*, 143-166.

Reinganum, M. R. (1981). Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values. *Journal of Financial Economics, 9,* 19-46.

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. *Journal of Portfolio Management, 11,* 9-17.

Ross, S. A. (1976a). The arbitrage theory of capital asset pricing. *Journal of Economic Theory, 13,* 341-360.

Ross, S. A. (1976b). Risk, return and arbitrage. *Risk Return in Finance ed. I. Friend and J. Bicksler, Cambridge, Mass.: Ballinger.*

Ross, S. A. (1977). The Capital Asset Pricing Model (CAPM), short-sale restrictions and related issues. *The Journal of Finance, 32,* 177-183.

Saffi, P., & Sigurdsson, K. (2011). Price efficiency and short selling. *The Review of Financial Studies, 24*, 821-852.

Scheinkman, J., & Xiong, W. (2003). Overconfidence and speculative bubbles. *Journal of Political Economy, 111*, 1183-1219.

Schwert, G. W. (2003). Anomalies and market efficiency. *Handbook of the Economics of Finance, in: G.M. Constantinides & M. Harris & R.M. Stulz (ed.), Handbook of the Economics of Finance, edition 1, volume 1*, chapter 15, 939-974.

Sehgal, S., & Tripathi, V. (2005). Size effect in Indian stock market. *Vision, 9*(4), 27-42.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance, 19*, 425-442.

Sharpe, W. F. (1991). Capital asset prices with and without negative holdings. *The Journal of Finance, 64*, 489-509.

Shanken. J. (1985). Multivariate tests of the zero-beta CAPM. *Journal of Financial Economics, 14*, 327-348.

Shanken, J., & Zhou, G. (2007). Estimating and testing beta pricing models: Alternative methods and their performance in simulations. *Journal of Financial Economics, 87*, 40-86.

Stattman, D. (1980). Book values and stock returns. *The Chicago MBA: A Journal of Selected Papers, 4*, 25-45.

Stone, B. K. (Ed.). (1970). *Risk, Return, and Equilibrium: A General Single-Period Theory of Asset Selection and Capital-Market Equilibrium*. Cambridge: MIT Press.

Treynor, J. L. (1961). Market value, time, and risk. *Unpublished manuscript*.

Treynor, J. L. (1962). Toward a theory of market value of risky assets. *Unpublished manuscript*.

Wang, Z. (1998). Efficiency loss and constraints on portfolio holdings. *Journal of Financial Economics*, *48,* 359-375.

Welch, I. (2008). The consensus estimate of the equity premium by academic financial economists in December 2007. *Working paper.*

Woolridge, J.R., & Dickinson, A. (1994). Short selling and common stock prices. *Financial Analyst Journal*, *50,* 20-28.

Zhang, C. (2008). Decomposed Fama-French factors for the Size and Book-to-market effects. *Working paper.*

Zhou, G. (1993). Asset-pricing tests under alternative distributions. *The Journal of Finance, 48,* 1927-1942.