Disposition Effect and Momentum based on Prospect Theory/Mental Accounting in the Chinese Stock Markets

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a sustained extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Abstract

The disposition effect, which is first introduced by Shefrin and Statman (1985), refers to the tendency of individuals to profit their gaining transactions (winners) too early and the reluctance to realize their losing transactions (losers). The main purpose of this dissertation is to analyze the relation between the disposition effect and momentum in the Chinese stock markets under the framework of the prospect theory and mental accounting (PT/MA). The sample contains a cross-sectional weekly data for 1,022 stocks with the sample period from January 1991 to November 2008. To measure the relation between the disposition effect and momentum, this dissertation follows the Grinblatt and Han (2002, 2005) model to use unrealized capital gains overhang which is based on past prices and stock volume to estimate the disposition effect. By using double sorting method and cross-sectional Fama-MacBeth (1973) regressions, the findings of this dissertation do not suggest that the unrealized capital overhang is positively related to the future returns. More interestingly, this dissertation finds that there is no significant intermediate horizon momentum effect and there is no evidence to support that the disposition effect drives momentum in the Chinese stock markets.

1. Introduction

The disposition effect, which is first introduced by Shefrin and Statman (1985), is one of the most widely attractive and well-documented behavioral heuristic among investors. This behaviour bias refers to the tendency of individuals to profit their gaining transactions (winners) too early and the reluctance to realize their losing transactions (losers). It is based directly on the prospect theory (Kahneman and Tversky 1979) and mental accounting (Thaler 1985). Under the prospect theory, investors employ an S-shaped value function to evaluate their potential gains and losses to maximize their utility. Under the mental accounting, investors are more likely to assign their assets into different accounts for different stock positions, and then employ the prospect theory to keep track of financial activities. In Shefrin and Statman's (1985) model, investors maintain a separate mental account for each stock position, and are keen to maximize an S-shaped value function that is convex for losses and concave for gains. That is, people are risk-averse in the domain of gains, whereas risk-seeking in the domain of losses.

The prospect theory and mental accounting have also been used to explain the cross-sectional expected return patterns. For instance, Barberis and Huang (2001) find that the prospect theory combined with the concept of individual mental accounting works the best in explaining the cross-sectional expected return patterns, such as the profitability of momentum strategy. Frazzini (2006) finds that the prospect theory and mental accounting framework plays a leading role in explaining the cross-section of stock returns. Grinblatt and Han (2002) also show that the prospect theory and mental accounting can explain the profitability momentum strategy, or the persistence in the returns of stocks over horizons between three months and one year.

In recent papers of Grinblatt and Han (2002, 2005), the authors develop a theoretical model of equilibrium prices where a group of investors have preferences that combine the prospect theory with mental accounting. They suggest that investors with the disposition effect cause momentum in stock prices. That is, the demand for a stock by a prospect theory/mental accounting agent deviates from that of a fully rational investor, with the distortions being inversely related to the unrealized profit experienced on the stock. A stock that has been privy to prior good news has excess selling pressure relative to a stock that has been privy to adverse information. Such demand perturbation tends to generate a price which under-reacts to public information. This distorts equilibrium prices relative to those predicted by standard utility theory. In equilibrium, past winners tend to be undervalued and past losers tend to be overvalued. As the above mispricing gets corrected, return predictability arises. That is, past winners will continue going up and past losers will continue going down. This leads to momentum which is also well documented by Jegadeesh and Titman (1993). In Grinblatt and Han's theoretical model (2002, 2005), the disposition effect is estimated by using unrealized capital gains (losses) on past prices and stock turnover. Their papers suggest that the unrealized capital gains variable is positively related to past returns. The unrealized capital gain is the main cause behind the profitability of a momentum strategy (investing in past winners and shorting past losers, expecting that winners will outperform losers). Moreover, the momentum effect disappears when the PT/MA disposition effect is controlled for with a regressor which proxies for the aggregate capital gain.

As discussed above, these studies pave the way to a line of empirical research exploring the relation between dispositon effect and the cross-sectional stock returns. In China, Shumway and Wu (2006) find that a large majority of Chinese investors exhibit the disposition effect and they also suggest that disposition does indeed drive momentum. However, their study is based on a relatively small sample (from the beginning of 2001 to March 2004) with a short time frame. It seems that they have not enough statistical power to estimate the relation between the disposition effect and momentum very precisely. Moreover, most of the studies follow Odean's (1998) methodology based on individual trading data from the Chinese stock markets (Feng and Seasholes 2003; Chen et al. 2004; Ng and Wu 2007). No researcher uses aggregate market-wide trading data to examine the relation between the disposition effect and momentum. Moreover, Odean (1998)'s methodology suffer from a range of limitations. As argued by Brown et al., (2006), Odean (1998)'s methodology sets reference price as the average of the purchase prices. This equally weighted reference price for all investors and stocks imply homoscedasticity. Also, this approach does not test findings by using capital gains or losses; neither does it consider the mental accounting theory. To overcome homoscedasticity, Grinblatt and Han (2005) and Frazzini (2006) recommend a framework which combines the prospect theory and mental accounting (PT/MA). The advantage of this PT/MA framework is that it employs the unrealized capital gains and provides a unique formation of reference price which assigns more weight to the more recent trading prices.

Therefore, it is of interest for this dissertation to fully uncover the relation between the disposition effect and momentum in the Chinese stock markets using a relatively large aggregate market-wide dataset with a long timeframe based on the combination framework of prospect theory and mental accounting (PT/MA). This dissertation is conducted to find answers to the following questions:

1. Do past returns positively relate to the unrealized capital gains overhang?
2. Do the unrealized gains or losses variables positively relate to the expected returns?
3. Does momentum strategy generate profit in the Chinese stock markets?
4. Does the momentum effect disappear when the capital gains overhang is controlled for?

To answer the above four questions, I use a large sample of aggregate market-wide data from the Shanghai Stock Exchange (SHSE), the Shenzhen Stock Exchange (SZSE), the Hong Kong Stock Exchange and other overseas markets such as U.S., UK., and Singapore, etc. The sample period is from January 1991 to November 2008. In this dissertation, the disposition effect is estimated using the Grinblatt and Han (2002, 2005) measure for unrealized capital gains overhang, which is based on past prices and stock volume. To conduct the empirical analysis, two methods are used in this dissertation. One is double sorting method, and the other is cross-sectional regression approach, as described in Fama and MacBeth (1973). The findings provide some empirical evidence to support that past returns positively relate to the unrealized capital gains overhang. Regarding momentum results, this dissertation finds no significant continuation in returns over intermediate horizon. Results also do not suggest that the unrealized capital gain overhang is positively related to the future returns. More specifically, when capital gains overhang is higher than zero, it is positively related with the future returns; when capital gains overhang is lower than zero, it is negatively related to the future returns. Lastly, when both the positive capital gains and negative capital losses are included in the regression, there is no momentum effect. Therefore, the overall results do not provide statistical evidence to support that the disposition effect drives momentum in the Chinese stock markets. In a word, this paper would make important contributions to the Literature to assess the relation between the disposition effect and momentum in the Chinese stock markets, based on the combination framework of the prospect theory and mental accounting (PT/MA), using aggregate market-wide data for a relatively long period from 1991 to 2008.

The remainder of this dissertation is structured as follows: Section 2 gives a brief literature review on the disposition effect and momentum. Section 3 presents the hypotheses development. In Section 4, the main model and data applied for the empirical analysis are described and explained in detail. In Section 5, the disposition and momentum are investigated and the empirical evidence is presented. The final section gives a brief conclusion.

2. Literature Review

2.1 Disposition Effect

Over the past 30 years, many researchers have looked into the potential influence of the disposition effect by employing a range of theories, different methodologies and various databases (Shefrin and Statman, 1985; Ferris et al., 1988; Odean, 1998; Weber and Camerer, 1998; Shapira and Venezia, 2001; Grinblatt and Han, 2005; Frazzini, 2006). These studies clearly demonstrate the existence of the disposition effect in many countries, such as the U.S., Canada, Japan, etc. Interestingly, the disposition effect has been observed not only in capital markets (e.g., stock, futures, options), but also in real estate markets.

2.1.1 Four Theories

According to the rational decision-making theory, investors tend to make their rational decisions based on the trade-off between the risk and return (Chui, 2001). However, this theory cannot explain the substantial impact of investors' behaviour, such as the disposition effect. There have been four major theories employed to elucidate the disposition effect in conjunction with theories borrowed from psychology (Shefrin and Statman, 1985). These theories are clarified as follows：

2.1.1.1 Prospect Theory

First and foremost, the most widely accepted one is the prospect theory (Kahneman and Tversky, 1979). It is a descriptive model trying to describe how investors evaluate potential gains and losses with uncertain outcomes. It states that there are two stages in the decision-making process for investors. One is called the "editing stage". That is, investors distinguish losses from gains based on the notion of a reference point, which commonly refers to the purchase price. The second phase is labelled the "evaluation stage". Investors employ an S-shaped value function to calculate and maximize their utility. The S-shaped value function is concave in the gains region, but convex in the losses region, implying risk aversion for winning stocks and risk seeking for losing stocks, relative to a reference point which is usually the price at which the stocks have been bought. Risk aversion causes the trader to realize any profits quickly to avoid them turning into losses while risk seeking causes the trader to have a greater appetite for large losers than for small losers and to let losses run in hope of a recovery, thus inducing the observed disposition effect (Shefrin and Statman 1985; Weber and Camerer 1998; Odean 1998; Grinblatt and Han 2005). Particularly, comparing with the purchase price, investors with gaining stocks are assigned in the domain of gains. They are tending to profit their winners because they prefer to lock in their gains. In contrast, investors with losing stocks are assigned in the domain of losses. They are inclined to hold on to their paper losses and reluctant to realize their losers because of the hope that the prices will head back.

2.1.1.2 Mental Accounting

The second theory trying to clarify the disposition effect is mental accounting. Thaler (1980) states that mental accounting is the process that investors set reference points for their accounts to determine gains and losses. Then, they keep track of gains and losses in their mind on (each) individual stock they invested rather than at the portfolio level. According to Thaler (1985), the main idea of mental accounting is that when an investor invests in a stock, she/he opens a mental account. After that, she/he applies the prospect theory to this mental account, firstly by determining paper gains or paper losses based on a reference point (e.g. purchase price), and secondly by maximizing her/his utility according to an S-shaped value function. As discussed in the above subsection, this S-shaped value function differs from a standard utility function. It implies that winners are less desirable than losers and there is a greater appetite for large losers than for small losers. In particular, Thaler (1999) illustrates that a realized loss is more painful than a paper loss. Thus, it is very painful for an investor to close a mental account at a loss. Since she/he is risk seeking for losing stocks, rather than putting up losers for sale, she/he will take an even greater position in the losers in hope that prices will recover and she/he can still break even or even profit from those losing stocks in the near future. On the other hand, as she/he is risk averse for winning stocks, she/he will try to realize profits quickly. In a word, investors under the mental accounting framework tend to sell the winners too soon but hold the losers for too long (Shefrin and Statman, 1985).

2.1.1.3 Seeking Pride and Avoiding Regret

Seeking pride and avoiding regret is the third theory attempting to explicate the disposition effect, which has been demonstrated by Thaler (1985), Kahneman and Tversky (1979), Shefrin and Statman (1985) and further discussed by Shiller (1999). These works clearly verify that investors who are seeking pride and trying to avoid regret will generate a disposition to liquidate their successful investments quickly and hold on to their losers to delay the feeling of regret.

2.1.1.4 Mean Reversion

The fourth explanation theory of the disposition effect is mean reversion. Mean reversion states that investors believe poorer-performing stocks will rebound, and better-performing stocks will decline in price. Andreassen (1988) states that investors are inclined to accelerate winners too soon because they are afraid of expected lower future returns. On the other hand, investors tend to hold on to the losers too long because they believe the prices will increase up to the average level or even above that level. As discussed by Odean (1998), and Weber and Camerer (1998), an irrational belief in mean reversion leads to the disposition effect.

2.1.1.5 The PT/MA Framework

As indicated by Grinblatt and Han (2002, 2005) in their reports, combining the prospect theory with mental accounting (PT/MA) framework works the best in explaining and clarifying the disposition effect and the profitability momentum strategy. Similarly, Frazzini (2006) also confirms that the prospect theory and mental accounting framework can act as a most effective way in explaining the disposition effect and the cross-section of stock returns. There are three reasons to support the PT/MA framework.

One is that prospect theory alone is insufficient to explain the disposition effect and a full explanation of the disposition effect should include mental accounting (Zuchel, 2001; Kaustia, 2004). Shefrin and Statman (1985) state that the discussion of prospect theory emphasizes the importance attached to the editing phase (framing) as well as to the location of the reference point. It only explains the reluctance to sell a stock and realize a loss. However, it does not explain which gains and losses investors pay attention to changes in their total wealth or changes in their individual stocks (Barberis and Huang, 2001). To solve these questions, mental accounting provides a process for investors to think about and evaluate their financial transitions. In particular, it shows investors how to set reference points for the accounts, how to determine gains and losses and how often to group and evaluate their stocks.

The second reason is that the PT/MA framework represents seeking pride and avoiding regret. As indicated by Thaler (1999), the mental accounting of paper gains and losses is tricky. That is, a realized loss is more painful than a paper loss. The author illustrates that one prediction of mental accounting is that it is very painful for investors to close a mental account at a loss as it is painful for them to accept their wrong judgments. They wish to avoid regret. Moreover, Hirshleifer (2001) illustrates that investors want their good decisions to be recognized immediately in their mental accounts so that they can feel good about themselves. On the other hand, they postpone acknowledging their unsuccessful decisions because they are not ready to acknowledge that they have made a mistake. It suggests that mental accounting represent seeking pride and avoiding regret.

The third reason is that the PT/MA framework reflects mean reversion. The PT/MA framework suggests that an S-shaped value function differs from a standard utility function. It implies that winners are less desirable than losers and there is a greater appetite for large losers than for small losers. In particular, as investors are risk averse for winners, they will try to realize profits quickly to avoid decline in value. On the other hand, as investors are risk seeking for losers, they will take additional buying of losers in hope that prices will recover so they can break even in the future. As discussed earlier, mean reversion states that investors believe poorer-performing stocks will rebound, and that better-performing stocks will decline in price. Thus, the PT/MA framework reflects mean reversion in explaining the disposition effect. This is also pointed out by Grinblatt and Han (2002), their findings show that disposition investors will sell their shares as prices rise when good news is revealed, while they will buy their shares as prices drop when bad news is exposed.

2.1.2 Methods and Data Types

This subsection discusses three methods and two types of datasets which are employed to address the disposition effect. The three methods are Odean's (1998) Model, Weber and Camerer's (1998) Experimental Model, and Lakonishok and Smidt's (1986) Regression Model. Two widely used datasets are employed: one is from individual investors' accounts; the other is on the aggregate level of stock exchanges.

2.1.2.1 Odean's (1998) Model with Individual Investors' Data

There are a number of papers analyzing the disposition effect using individual investors' data. These papers employ the purchase prices of stocks as the reference points. Odean (1998) conducts a comprehensive study by accessing 10,000 individual trading accounts at a major discount brokerage house. The reference price in this study is the average purchase price for each account and each stock. As a second step, these studies calculate the disposition spread to measure which investors are affected by the disposition effect. The disposition spread is calculated as the difference between the proportion of realized gains (PRG) and the proportion of realized losses (PRL). An investor is subject to the disposition effect and is more likely to realize gains than losses if there is a positive disposition spread. The findings in this study confirm a significant existence of the disposition effect.

Numerous studies report similar results by employing Odean's methodology. For instance, Shapira and Venezia (2001) demonstrate a stronger preference for Israeli individual investors to sell winners than losers. Dhar and Zhu (2006) find that the tendency towards the disposition effect differs among individual investors depending upon personal characteristics. In terms of the Chinese stock markets, Shumway and Wu (2005) find that individual disposition effect diminishes with trading experience. Feng and Seasholes (2002, 2003) provide evidence that investor sophistication and trading experience alleviates the disposition effect. The findings of Chen et al. (2004,2007) is however at odds with those of Feng and Seasholes (2003), where they show that professional managers are also prone to disposition effect. Ng and Wu (2007) report that Chinese investors tend to decrease their purchases of winner stocks and also decrease their sales of loser stocks. They also state that individual investors show stronger disposition effects in the trades than professionals because individual investors might tend to hold on to losing investments too long, and this inference is in line with the findings of Shapira and Venezia (2001). Although the above studies generate mixed results to some extent, in general, they suggest that in the Chinese stock markets, with the increase of professionalism of investors, the disposition effect tends to be alleviated.

2.1.2.2 Weber and Camerer (1998) Experimental Model

Weber and Camerer (1998) employ an experimental approach to conduct a multi-stage experiment by assessing a range of distinctiveness and various determinants of the disposition effect. According to the experiment design in their paper, there are six different risky stocks and the experiment is divided into fourteen periods. During each of the first thirteen periods, participants can freely make portfolio decisions to buy/sell or hold these six stocks. In the last period (Period 14), participants must liquidate all of their holding stocks. Stock prices for each period are predetermined rather than being set by the trading actions of participants. There are two stages in the process of stock price formation. In the first stage, the probability of increase in stock prices remains fixed for each stock over the entire fourteen trading periods. In the second stage, the magnitude of price changes for each stock is unrelated to the probability of a stock price increases. Based on this experiment design, if participants tend to sell winners earlier and hold losers until Period 14, the number of stocks sold at profit should be larger than those sold at a loss during the first thirteen periods. The disposition effect should be relatively weaker in the last period (Period 14). The authors also compare the average profit from stocks sold in the first thirteen periods with that from Period 14 to examine existence of the disposition effect. That is, if participants sell winners earlier and hold losers until Period 14, the average profit from stocks sold in the first thirteen periods should be higher than those sold in Period 14. Results from their paper suggest that participants tend to sell fewer shares when the price falls than when it rises and sell less when the price is below the purchase price than when it is above.

Similar to the Weber and Camerer's experimental approach (1998), Oehler et al. (2002) analyze a series of 36 stock markets by adopting the purchase price and the last period price as alternative reference points. They find that the disposition effect becomes stronger when they use the purchase price as the reference point rather than using the last period price. Moreover, Chui (2001) employs (the similar technique) a modified version of the experiment designed by Weber and Camerer (1998) to conduct an experimental study of the disposition effect in Macau. Results show that the disposition effect is strong in Macau, and it is stronger for internal traders than for external traders.

2.1.2.3 Lakonishok and Smidt (1986) Regression Model with Market-wide Data

Lakonishok and Smidt (1986) is the first paper to employ aggregate market-wide data to study the disposition effect. According to their regression model, the authors seek to identify the relationship between abnormal volume and past prices using historical stock prices as the reference points. The main data using in their study are monthly prices and share volumes for both NYSE and AMEX stocks during the period from 1968 to 1982. Each month, stocks are classified as winners or losers, depending on whether their prices rise or fall over the previous 5, 11, 23, and 35 months. And then, the authors analyze the relationship between abnormal volume and the direction and magnitude of the past price changes. If the disposition effect exists, the abnormal volume for winners should be greater than that for losers. Their findings point out that winners tend to have higher abnormal volume than losers for both exchanges and for every month of the year.

Employing the similar methodology, Ferris et al. (1988) also find that volume for winners exceeds that for losers using price and volume data for thirty smallest stocks mostly list on the AMEX from December 1981 to January 1985. Similar results have been observed by Bremer and Kato (1996) for Japanese stocks. Kaustia (2004) analyze the US IPOs market by comparing the price performance and their turnover volume setting the offer prices as the reference points. The findings show that the turnover is significantly lower for a negative initial return of IPOs when the stock is traded below the offering price and increases on the day the price surpasses the offering price for the first time. Trading volume increases for positive initial return IPOs on the day the stock price first falls below the offer price. The overall results for winner IPOs do not provide support for the disposition effect.

2.2 Momentum

Over time, a good number of studies have documented that cross-sectional stock returns are related to past stock performance in short (1 week or 1 month), intermediate (over 3 to 12 months), and long horizons (3 to 5 years). Momentum in stock prices refers to the anomaly that past winners continue to outperform past losers.

In the US and European stock markets, quite a few researchers argue that the intermediate-horizon momentum effect is likely to be the strongest one. For example, as reported by Jegadeesh and Titman (1993, 2001), they find significantly positive return continuations in intermediate horizons (over 3 to 12 months). The testing methods employed in their reports are quite simple to implement. In particular, the authors construct their portfolios by following strategies which are popularly known as momentum strategy to buy winner stocks and short-sell loser stocks. Firstly, stocks are ranked in an ascending order based on the past K-week lagged returns. Based on the ranking, an equally weighted portfolio of stocks in the lowest past return quintile is the loser portfolio and an equally weighted portfolio of the stocks in the highest return quintile is the winner portfolio. Then, they calculate the average return for each quintile portfolio and the difference between returns of the loser and the winner portfolios (L-W) over the next H-week holding period. If the difference is statistically significantly negative, then there exists a momentum profit. If it is positive, there exists contrarian profit, which refers to contrarian strategy by buying past losers and short selling past winners.

Similarly, Rouwenhorst (1998) confirms the robustness of this momentum strategy using a data sample of monthly total returns for 2190 stocks from 12 European countries in the period 1980 to 1995. The author states that past medium-term Winners outperform a portfolio of medium-term Losers and lasts on average for about one year in these 12 European equity markets. For the Germany stock market, as Schiereck et al. (1999) point out, intermediate-horizon momentum strategies are profitable, as well as short- and long-horizon contrarian strategies. Moreover, DeBondt and Thaler (1985, 1987) suggest that long horizon (3 to 5 years) price reversals and contrarian strategies (buying past losers and selling past winners) are profitable because past losers outperform past winners.

In contrast, numerous studies suggest that the factors which contribute to the momentum phenomenon in the U.S. are not pervasive in the emerging markets. As per Rouwenhorst (1999), there is no evidence of intermediate-horizon momentum returns in 14 of 20 emerging markets using return data of 1750 individual stocks. Hameed and Yuanto (2003) state no momentum effect by examining the profitability of relative strength strategies over intermediate horizons in six Asian stock markets (Hong Kong, Singapore, Malaysia, South Korea, Taiwan, and Thailand).

For the Chinese stock markets, Kang et al. (2002) examine whether past returns predict future price movements over a horizon of 1 to 26 weeks and report some evidence of return continuations over the holding period of 20 to 26 weeks. Surprisingly, their evidence on intermediate-horizon return momentum is different from that of other Chinese market studies. In the study by Shumway and Wu (2006), the authors examine the nature of momentum effect in Shanghai Stock Exchange stocks during the period from the beginning of 2001 to Mar, 2004. They state that there is no apparent momentum in their Chinese data as past returns do not forecast future returns. Moreover, Wu (2002) finds that the pure momentum strategy in general does not yield excess returns in the Chinese stock markets. Lastly, Wang (2004) documents no intermediate-horizon momentum return but contrarian profits in the Chinese stock markets by examining the role of past stock performance in the prediction of intermediate- and long-horizon returns for individual stocks over a period from July 1994 to December 2000.

2.3 Disposition and Momentum

There are a variety of detailed investigations on the relationship between the disposition effect and momentum which is documented by Jegadeesh and Titman (1993). Recent studies incorporate psychological evidence into models of equilibrium prices. Barberis, Huang and Santos (2001) and Barberis and Xiong (2009) examine prospect theory in asset prices. They find the opposite of the disposition effect by keeping winning and selling losing stocks implies momentum in stock returns. As proposed by Frazzini (2006) and Grinblatt and Han(2005), a combination of prospect theory and mental accounting (PT/MA) framework can play a significant role in explaining asset pricing dynamics and the cross-section stock returns. More specifically, Grinblatt and Han (2002) state that the disposition effect creates a spread between a stock's fundamental value and its equilibrium price, and allows return predictability and momentum in stock prices. Their study derives a theoretical model and several testable implications to explain the relationship between the disposition effect and momentum. Grinblatt and Han (2005) provide evidence to support that the PT/MA disposition effect is the major drive of momentum. They find that a stock's expected return monotonically increases with the marginal investor's (percentage) unrealized capital gain. Also, the return predictability of the intermediate horizon momentum effect is likely to be the strongest one. Frazzini (2006) follows a similar approach but employ various variables to proxy for aggregate unrealized capital gains of disposition (PT/MA) investors, and indicates that stocks which have high capital gains (losses) overhang tend to underreact to positive (negative) news and generate significant positive (negative) excess returns in the following periods. As supported by Grinblatt and Han (2002, 2005) and Frazzini (2006), the unrealized capital gains overhang is a good and significant predictor for future return.

3. Hypothesis Development

This section discusses the hypotheses for this dissertation in more detail. It also describes the methods of the statistical tests.

As previously discussed in the Literature Review section, this dissertation would broadly follow the methodology adopted by Grinblatt and Han (2002, 2005) to analyze the relation between the disposition effect and momentum in the Chinese stock markets based on Prospect Theory/Mental Accounting (PT/MA) framework. In this dissertation, the disposition effect is estimated using unrealized capital gains or losses. As per Grinblatt and Han (2002, 2005), past returns are correlated with capital gains overhang. However, past returns are a noisy proxy for unrealized gains overhang and should be weak predictors of future returns. Thus, Grinblatt and Han suggest that the unrealized gains or losses for PT/MA (disposition-prone) investors should be a sufficient statistic for future returns. They also state that both the past returns and past transaction volume patterns determine whether the stock has experienced an aggregate unrealized capital gain or loss. Thus, in their theoretical model, aggregate capital gains or losses should be the better predictors of future returns, compared to past returns. To examine the relation between the disposition effect and momentum, this dissertation starts to analyze the relation between past returns and unrealized capital gains overhang by testing hypothesis 1:

Hypothesis 1: Stocks with high past returns have a tendency to generate unrealized capital gains, while stocks with low past returns are more likely to generate unrealized capital losses.

As per Grinblatt & Han (2002, 2005), the risk attitude of PT/MA investors differs from that of rational investors. More specifically, PT/MA investors have a greater tendency to sell stocks with unrealized capital gains and keep stocks with unrealized capital losses. That is, the prospect theory and mental accounting (PT/MA) framework generates the disposition effect. As disposition effect trading arises, a stock that has had positive momentum for a while (i.e., is a winner) must have a positive spread between fundamental value and market price that is related to the existence and the position size of disposition investors. The authors states that a stock's expected return monotonically increases in the marginal investors' (percentage) unrealized capital gain. It implies that the model has implications for momentum in stock returns. Therefore, the most significant testable implication of their model is to use the capital gains or losses variables to predict future returns, even after controlling for the effect of past returns. To achieve a more precise analysis, I follow Grinblatt & Han (2002, 2005) to construct unrealized gains or losses and directly test hypothesis 2,

Hypothesis 2: The unrealized gains or losses variables should be positively related to the expected returns

The model of Grinblatt and Han (2002, 2005) does not generate reversals in short or long horizons, but does suggest that the return predictability of the intermediate-horizon momentum effect is likely to be the strongest one, which is documented by Jagadeesh and Titman (1993). Their results support that the disposition effect does appear to drive momentum. However, the momentum effect becomes insignificant when the capital gains overhang is controlled for.

Employing a relatively large sample with a long timeframe, the model in my study would have relatively strong statistical power to estimate the relation between the disposition effect and momentum precisely in the Chinese stock markets. To achieve this goal, Hypothesis 3 and 4 are directly tested,

Hypothesis 3: Stocks should exhibit intermediate horizon (12 months) momentum effect - *past winners should continue to be winners while past loser should be continue to be loser.*

Hypothesis 4: The intermediate horizon momentum effect disappears when the capital gains overhang is controlled for.

4. Methodology and Data Description

In this section, I discuss the methodology and data selection for the empirical analysis. This section is organized as follows: (1) discuss the theoretical model and methods used in the empirical analysis; (2) describe the data sample and control variables.

4.1 Methodology

4.1.1 The Theoretical Model

In this dissertation, the empirical analysis will broadly follow Grinblatt & Han (2002, 2005) approach which has made some significant improvements by employing the prospect theory together with the mental accounting (PT/MA) to assess the relation between the disposition effect and momentum in the Chinese stock markets.

Grinblatt and Han (2002, 2005) describe two types of investors. One type has no disposition effect and is subject to the rational demand function; the other is subject to the prospect theory and mental accounting (PT/MA) demand distortion. More specifically, the authors indicate that PT/MA (disposition-prone) investors are risk averse over gambles for some stocks and risk loving over gambles for others. Because of this risk attitude, investors subject to PT/MA have a greater tendency to sell stocks with unrealized capital gains and keep stocks with unrealized capital losses. That is, the prospect theory and mental accounting (PT/MA) framework generates the disposition effect, which creates a spread between a stock’s fundamental value and its equilibrium price, as well as price underreaction to information and momentum in stock returns.

As per their theoretical model, a stock's expected return monotonically increases with investors' (percentage) marginal unrealized capital gain overhang. That is,

$$E_{t-1}\left[\frac{P_t - P_{t-1}}{P_{t-1}}\right] = (1 - w)v_{t-1}\frac{P_{t-1} - R_{t-1}}{P_{t-1}} \qquad (1)$$

where P_t is the price of the stock on date t. V_{t-1} is turnover ratio on date t-1. R_{t-1} is date t-1's reference price (this is demonstrated more formally below). $\frac{P_{t-1}-R_{t-1}}{P_{t-1}}$ is the aggregate unrealized capital overhang. The variable w is the weight that accounts for the representation of the PT-MA investors in the economy. In particular, $w = \frac{1}{1+\mu\lambda}$, $0<w<1$, where μ is the proportion of disposition (PT-MA) investors and λ is the relative intensity of the demand perturbation induced by the disposition effect.

This equation has implications for momentum in stock returns. It is used to analyze the relation between the aggregate unrealized capital gains/losses and the cross-section of expected returns. Particularly, a winner with a positive momentum should have a positive spread which is the difference between fundamental value and market price. This is related to the existence and the position size of disposition investors. Therefore, the aggregate amount of unrealized capital gains provides a way to test the impact of the disposition effect.

4.1.1.1 The Reference Price

To analyze the disposition effect and momentum, the first and the most important step is to determine whether the share is making a profit or suffering a loss. This is essential in a disposition setting as investors compare current market prices with the reference price to decide whether a stock investment makes a gain or a loss.

Since we cannot identify who the PT-MA investors are this dissertation simply estimates a proxy for the market's cost basis in a stock and assume it is the relevant reference price for the mental account.

The estimate of reference price is shown as follows:

$$R_t = \sum_{n=1}^{\infty}\left(V_{t-n} \prod_{\tau=1}^{n-1}[1-V_{t-n+\tau}]\right)P_{t-n}$$

where V_t is date t's turnover ratio in the stock. The term in parentheses multiplying

P_{t-n} is a weight and all weights sum to one. The weight on P_{t-n} reflects the probability of the shares purchased on date t-n which have not been traded since then.

If we truncate the reference price estimation process at the price five years prior to week t, the data t reference price is:

$$R_t = \frac{1}{k}\sum_{n=1}^{260}\left(V_{t-n} \prod_{\tau=1}^{n-1}[1-V_{t-n+\tau}]\right)P_{t-n} \qquad (2)$$

where *k* is a constant that makes the weights on past prices sum to one.

$$k = \sum_{n=1}^{260} V_{t-n}\left(\prod_{\tau=1}^{n-1}[1-V_{t-n+\tau}]\right)$$

As noted by Grinblatt and Han (2002), the logic behind the expression for the reference price in equation (2) is straightforward if we assume k=1, as is the case when the sum is infinite rather than over 260 weeks. Each of the bracketed factors inside the product symbol represents the probability that a stock is not traded on date t-n + τ; the term in front of the product symbol, V_{t-n}, represents the probability that the stock traded on date t-n; the term in large parentheses is the probability that the stock's basis is the price on date t-n; and the sum is the expected cost basis.

Moreover, since the survival probability for a historical price declines geometrically with the passage of time, more recent trading prices have more weight on the reference price, other things being equal. In fact, as reported by Brown et al., (2006), assigning more weight to the more recent prices could capture the homoscedasticity induced by Odean (1998)'s approach. Indeed, distant market prices have little influence on the reference price. Consequently, this dissertation truncates the estimation over five years and effectively rescale the weights to sum to one by having a k<1. This allows us to estimate the reference price in a consistent manner across the sample period.

4.1.1.2 The Unrealized Capital Gains

To proxy for the aggregate unrealized capital gains or losses, the capital gains overhang is defined as the percentage deviation of the aggregate cost basis from the current price.

$$g_{t-1} = \frac{P_{t-2} - R_{t-1}}{P_{t-2}} \qquad (3)$$

In order to avoid confounding market microstructure effect, such as bid-ask bounce, I use lag one week market price P_{t-2} rather than P_{t-1}. As supported by Frazzini (2006), this proxy is expected to provide a more efficient estimator of aggregate unrealized capital gain or losses

4.1.2 Methods for Empirical Analysis

As suggested in the report of Grinblatt & Han (2002, 2005), the authors use two methods to conduct the empirical analysis. One is double sorting method, and the other is cross-sectional regression approach, as in Fama and MacBeth (1973). Similarly, to test the four hypotheses, the empirical analysis in this dissertation firstly uses a double sorting method. That is, all stocks are first ranked based on their past one-year returns and then further sorted by their unrealized gains or losses. Furthermore, a second way of double sorting is adapted to reverse the sort order. The returns of momentum strategies (long winners and short losers) are assessed to see whether they are generally significantly higher than zero.

However, double sorting method is not practical for more than two variables. Consequently, in order to control for variables other than past one-year returns and the capital gains overhang, I employ Fama and MacBeth (1973) approach to conduct the regression analysis. The average weekly return of each stock is regressed on past returns, firm size, volume and capital gains and losses variables over the whole sample period and a set of subsamples, such as January only, February through November only, and December only. The time series of the corresponding cross-sectional regression coefficients are examined, which the specific focus on the coefficients of the intermediate horizon past returns, capital gains and losses.

4.2 Data Description and Control Variables

4.2.1 Data Description

This dissertation analyzes a sample consisting of all A-shares, B-shares, and H-shares which are listed on the Shanghai Stock Exchange (SHSE), the Shenzhen Stock Exchange (SZSE), the Hong Kong Stock Exchange and other overseas markets such as U.S., UK., and Singapore, etc. This is a cross-sectional weekly dataset and mainly comes from DataStream. It spans the period from January 1991 to November 2008, and consists of 931 weeks.

I start by extracting weekly data include date, stock ticker code, adjusted share price, total assets[1], trading volume in shares, total number of shares outstanding, and the percentage of total number of tradable shares outstanding (free float), to calculate weekly returns, past cumulative short, intermediate, and long-horizon returns, average weekly turnover ratio, logarithm of firm total assets, reference price, and capital gain overhang. As noted earlier in the previous subsection, distant market prices have little influence on the reference price. Therefore, in this dissertation more recent trading prices are assigned more weight on the reference price. By doing this, this dissertation excludes stocks which have less than five years of historical return, turnover, and accounting data. Furthermore, to make sure that there are enough observations for every cross-sectional regression each week, firms with fewer than 100 observations are not included in the dataset. As a result, the final dataset has 1,022 stocks, and the sample period is from October 1998 to December 2008, consisting of 528 weeks.

For the test purpose of this dissertation, which is to directly assess the relation between the disposition effect and momentum in the Chinese stock markets, higher frequency data are required. This dissertation uses weekly data rather than monthly

[1] For Industrials, total assets represent the sum of total current assets, long term receivables, investment in unconsolidated subsidiaries, other investments, net property plant and equipment and other assets; For Banks, total assets represent the sum of cash & due from banks, total investments, net loans, customer liability on acceptances (if included in total assets), investment in unconsolidated subsidiaries, real estate assets, net property, plant and equipment and other assets; For Insurance Companies, total assets represent the sum of cash, total investments, premium balance receivables, investments in unconsolidated subsidiaries, net property, plant and equipment and other assets; For Other Financial Companies, total assets represent the sum of cash & equivalents, receivables, securities inventory, custody securities, total investments, net loans, net property, plant and equipment, investments in unconsolidated subsidiaries and other assets.

data because it provides more reasonable proxy for the capital gains overhang in the market but is less influenced by market microstructure which is induced by daily data.

4.2.2 Control Variables

This dissertation employs Fama and MacBeth (1973) approach to conduct the regression analysis, and to analyze the average slope coefficients of weekly cross-sectional regressions and their time series t-statistics. The week-t return of stock j ($r_t^j = \frac{p_t^j - p_{t-1}^j}{p_{t-1}^j}$) is used as the dependent variable. This dissertation use the prior cumulative returns ($r_{t-t_2:t-t_1}^j$) over short, intermediate, long horizons returns as control variables to control for return effects, as noted in De Bondt and Thaler (1985), and Jegadeesh and Titman (1993). To control for the return premium effect of firm size, the logarithm of firm total assets at the end of week t-1 (s_{t-1}^j) is used as a proxy for firm size of stock j. This dissertation includes the average weekly turnover over the 52 weeks ($\overline{V}_{t-52:t-1}^j$) to control for volume effect, as described in the report of Lee and Swaminathan (2000). The focus is on the coefficient of a capital gains/losses proxy (g_{t-1}^j) to examine the impact of disposition effect.

5. Empirical Analysis

This section firstly presents the time series average of summary statistics of the key regressors. Next, as mentioned in the methodology section, the results for using double sorting method to assess the disposition effect and momentum are presented. Finally, regression results using Fama and MacBeth (1973) approach are presented.

5.1 Summary Statistics

Summary statistics on each of the variables used in this dissertation are presented in Table 1. These include the time-series averages of the cross-sectional means, medians, standard deviations, and 10th, 50th, 90th percentiles of the key variables used in the regressions. As shown in Table 1, the mean (median) of the short, intermediate, long horizon returns are 0.57% (0.00%), 27.69% (-2.74%), and 40.06% (-11.24%) respectively. The mean (median) of the average weekly turnover ratio, size and the capital gain overhang are 10.54% (7.02%), 2.67(2.67), and -27.91% (-16%) respectively. The 10th, 50th, 90th percentiles of capital gain overhang are -96.52%, -16%, and 26.78% respectively[2].

[INSERT TABLE 1 HERE]

Figure 1 presents the weekly time series of the 10th, 50th, and 90th percentile of the cross-section of the capital gains overhang of the sample stocks. As we can see from this figure, there is wide cross-sectional dispersion in this key regressor and time-series variation as well. More specifically, staring from 2001, the difference between the 90th percentile and the 10th percentile of the capital gains overhang continues to increase,

[2] I obtain essentially similar results when I exclude the outliers or exclude the current global financial crisis periods of 2007 to 2008.

and reaches its maximum on June, 2005. This movement of the difference between these two percentiles represents a four-year market slump of the Chinese stock markets from 2001 to 2005. In particular, after reaching its record-high of 2,245.44 points on June 14, 2001, the Shanghai Composite Index plunged to 998.23 points on June 6, 2005. This was partly due to a ban on new initial public offerings (IPOs) started in April 2005 to curb the slump and allow more than US$200 billion of mostly state-owned equity to be converted to tradable shares. This marked the bottom of the Chinese bear market.

Starting from the second half of 2005, the difference between the 90th percentile and the 10th percentile of the capital gains overhang decreases and reach its minimum at the end of 2006. However, starting from early 2007, this difference increases again and becomes much larger in the second half of 2008. This difference shows that the Chinese stock markets shrank dramatically from 2007 to 2008. After reaching an all-time high of 6,124.044 points in October 2007, the benchmark Shanghai Composite Index dropped by 65% to 1.820.81 points by the end of 2008. This is mainly due to the impact of the global financial crisis.

[INSERT FIGURE 1 HERE]

5.2 Disposition and Momentum: Double Sorting Method

This subsection firstly presents the time series average of gain and past return for cutoff-percentiles of double sorts. Next, the average weekly returns of portfolios on capital gains overhang within each past one-year return quintile are presented. Finally, average weekly returns of portfolios on past returns within each capital gains overhang quintile are discussed.

5.2.1 *Time Series Average of Gain/Past return for Cutoff-percentiles of Double Sorts*

As discussed previously in the methodology section, the theoretical model suggests that the expected return of a stock is determined only by its capital gains overhang. Past returns, which are correlated with the capital gains variable is a noisy predictor. To examine the relationship between the past returns and capital gains overhang, this dissertation studies the average returns of portfolios which are constructed by double sorting the past one-year returns and the capital gains overhang variable.

The double sorting is conducted in two ways. For the first way, stocks are firstly ranked in a descending order (from higher to lower) based on their past one-year return to form five portfolios. Based on the ranking, an equally weighted portfolio of stocks in the lowest past return quintile is assigned to be losers (R1), and an equally weighted portfolio of stocks in the highest past return quintile is assigned to be winners (R_5). Secondly, within each past return quintile, stocks are further ranked into five portfolios from the lowest to the highest based on their capital gains overhang labelled as G1, . . ., G5. For the second way, it reverses the sort order by first ranking stocks into five groups on capital gains overhang, and then further ranking the stocks based on past one-year return within each capital gains quintile. Table 2 reports the results.

[INSERT TABLE 2 HERE]

Panel A of Table 2 presents the time-series average value of the capital gains portfolios within each past one-year return sort. Panel B of Table 2 presents the values for the past one-year return portfolios within each capital gain sort. As we can see from these two

Panels, capital gains overhang of a stock is positively correlated with its past one-year return. More specifically, as it shows in Panel A, portfolios with lower past one-year returns, such as R1 and R2, have lower capital gains overhang, whereas portfolios with higher past one-year returns, such as R4 and R5, have higher capital gains overhang. Indeed, portfolios with the highest past one-year returns (R5) have the highest positive capital gains overhang comparing with other portfolios in each past one-year return quintile. Moreover, Panel B indicates that portfolios with the largest capital gains overhang are the past winners, as the portfolio returns in the highest capital gains quintile (G5) are all positive and higher than other portfolios. Overall, to conclude from Panels A and B of Table 2, portfolios with lowest past returns have the lowest capital gains overhang, and portfolios with highest past returns have the highest capital gains overhang. Therefore, these results provide evidence to support Hypothesis 1.

5.2.2 Average Weekly Returns of Portfolios on Capital Gains Overhang within Each Past One-year Return Quintile

Panel C of Table 2 presents the average weekly returns of 25 equally weighted portfolios ranked first based on one-year past returns and then further by capital gains overhang within each past return quintile. The average weekly returns of these 25 portfolios for the January months, the period of February through December and the period of January through December are presented separately. The differences of average weekly returns between the highest and lowest capital gain quintiles (G5-G1) within each past return quintile are calculated. The purpose of doing this arrangement by controlling for past one-year returns is to analyze whether the intermediate horizon momentum effect is explained by the capital gains overhang or not. If the disposition effect does drive momentum, one would see that the difference of average weekly returns (G5-G1) between capital gains overhang portfolios within each past return quintile would indicate statistically significantly positive returns. It should imply that a momentum strategy which is buying past winners and selling past losers yields abnormal profits[3]. In contrast, if the difference is statistically significantly negative, there exists contrarian profit. Therefore, by following a contrarian strategy, which is buying past losers and selling past winners, an investor will earn abnormal profits.

As we can see in Panel C of Table 2, results indicate that for the period of February through December, for each given past return quintile, the average returns of portfolios decrease monotonically with their capital gains overhang quintile. That is, stocks with lower capital gains overhang outperform stocks with higher capital gains overhang. As a result, the differences of average weekly returns (G5-G1) between capital gains overhang portfolios within each past return quintile have statistically significantly negative returns in most cases, except quintile R4. The negative returns are ranging from about 0.16% to 0.65% per week (about 8.32%-33.8% per annum) for the period of February through December. The portfolio returns for the January months and the period of January through December show a similar pattern. To conclude the overall results in Panel C of Table 2, there is no momentum profit but contrarian profit in the Chinese stock markets based on the sample of this dissertation. In fact, this finding is inconsistent with the third hypothesis. These results also differ from the findings of Grinblatt and Han (2002, 2005) and Rouwenhorst (1998), which find that the intermediate-horizon momentum return is likely to be strongly significant in the U.S. and European markets. Since double sorting can only control for one variable at a time, this dissertation also conducts regression

[3] Following the Grinblatt and Han's (2002) theoretical model, this dissertation assumes that investors are allowed to do short-selling.

analyses by simultaneously controlling for two or more than two variables, which will be demonstrated in the next section.

5.2.3 Average Weekly Returns of Portfolios on Past Returns within Each Capital Gains Overhang Quintile

As discussed in the previous subsection, after controlling for past one-year returns, the average returns of portfolios decrease monotonically with their capital gains overhang quintile. It shows in Panel C of Table 2 that for the differences of average weekly returns (G5-G1) between capital gains overhang portfolios, during the January months, 4 out of 5 past return quintiles have statistically significantly negative returns; during non-January months, 4 out of 5 past return quintiles have significantly negative returns. However, one past return quintile (R4) has significantly positive returns. This indicates there may be a seasonal effect in the sample. To achieve a more precise analysis, I conduct a double sorting by first ranking stocks into five groups based on capital gains overhang, and further ranking these groups into five based on past returns. The average weekly returns of these 25 portfolios for the January months, the period of February through December and the period of January through December are presented separately. The differences of average weekly returns between the highest and lowest past returns (R5-R1) within each capital gains overhang quintile are calculated.

Results from Panel D of Table 2 show that the average portfolio weekly returns in the lowest and highest capital gain overhang quintiles are generally significantly higher than the rest quintiles in most cases. During the period from February to December, for almost every row, the returns follow a U-shape curve from the lowest capital gain quintile to the highest capital gain quintile. This finding suggests that stocks have a tendency to generate higher future returns when capital gains overhang is either higher or lower than zero, but generate the lowest returns when capital gains overhang is equal to zero. The portfolio returns for the January months and the period of January through December show a similar pattern. To conclude the overall results in Panel D of Table 2, the results do not suggest that the unrealized gains or losses variables are positively related to the expected returns, which do not support the second hypothesis. Again, since double sorting only can control for one variable at a time, this dissertation conducts more detailed analyses by simultaneously controlling for two or more than two variables.

5.3 Disposition and Momentum: Fama and MacBeth (1973) Approach

As discussed earlier in the Methodology section, the disadvantage of double sorting is that it is only possible to control for one variable at a time. However, many variables, other than past returns and capital gains overhang, which cannot be controlled by using double sorting, can influence the expected returns. Therefore, in order to control for more than two variables simultaneously, this dissertation adopts a regression approach based on Fama and MacBeth (1973) to further test the hypotheses.

5.3.1 Capital Gains Overhang, Past Returns

As discussed previously, Grinblatt & Han (2002, 2005) employ both the past returns and past transaction volume patterns to determine whether the stock has experienced an aggregate unrealized capital gain or loss. Thus, to examine the relation between past returns and unrealized capital gains overhang, this dissertation adopts two models to regress the capital gains variable on a set of firm explanatory variables cross-sectionally. In Model 1, the explanatory variables are stock *j*'s cumulative returns for three past periods: short horizon (defined as the last 4 weeks), intermediate horizon (between 5 weeks and 52 weeks), long horizon (between 53 weeks and 156 weeks) and the natural logarithm of total assets at the end of the previous week. In Model 2, in addition to the explanatory variables already described, the average weekly turnover over the same three past periods are included.

Model1: $g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 s$

Model 2:

$$g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{-4:-1} + a_5 V_{-52:-5} + a_6 V_{-156:53} + a_7 s$$

Since there are more than one independent variable in these two multiples regression equations, one of the most frequent problems is that two or more of the independent variables are highly correlated to one another. This is called multicollinearity. To ensure that multicollinearity is not a concern, an analysis is conducted to examine the correlation among variables used in Model 1 and Model 2. Panel A of Table 3 reports the results. As observed, variable $r_{-4:-1}$ and $r_{-156:-53}$ have the lowest correlation with a value of -0.152, while variable $v_{-4:-1}$ and $v_{-52:-5}$ have the highest correlation with a value of 0.594. Since all correlation coefficients are lower than 0.75, there is no evidence to support that there is a problem of multicollinearity in these two models.

Table 3 Panel B reports results of Model 1. As observed, on average, about 37.94% of the cross-sectional variation in the capital gains variable can be explained by differences in past returns and firm size. The coefficients of cumulative returns for the three past periods are all positive. The t-statistics for these three past cumulative returns are 20.64, 26.62, and 20.36, respectively, which are highly significant. The results of Model 2 are shown in Panel C of Table 3. Results show that, on average, about 42.77% of the cross-sectional variation in the capital gains variable can be explained by differences in past returns, past turnover, and firm size. The coefficients of average weekly turnovers for the three past periods are all positive and significant. It indicates that stocks with high transaction volume tend to generate larger capital gains, whereas stocks with low transaction volume tend to have smaller capital losses. Moreover, the t-statistics for these three past cumulative returns are 18.91, 27.09, and 20.97, respectively, which are still highly significant. It illustrates that past returns are positively related to the unrealized capital gains overhang. That is, winning (losing) stocks display large unrealized capital gains (losses). This finding provides some empirical evidence to support Hypothesis 1 that stocks with higher past returns tend to generate unrealized capital gains, while lower past return stocks are more likely to generate unrealized capital losses.

The coefficients of size variable in both Model 1 and 2 are positive. It might reflect that large stocks have a diverse ownership structure, and investors are more likely to ride gains rather than realize them, or it might reflect liquidity issues.

[INSERT TABLE 3 HERE]

5.3.2 Expected Returns, Past Returns, and the Capital Gains Overhang

This subsection continues to investigate the relation between the disposition effect and momentum in the Chinese stock markets. To achieve a more precise analysis, I perform the Fama and MacBeth (1973) approach to regress the average weekly returns on other control variables discussed earlier in the Data Description section. There are five different regression models used in this subsection.

Model 3 includes only past return regressors.

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53}$$

Model 4 includes past return regressors plus volume regressor.

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V}$$

Model 5 adds size as a regressor to the four regressors from Model 4.

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V} + a_5 s$$

Model 6 adds capital gain overhang to the regressors from Model 5.

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V} + a_5 s + a_6 g$$

Model 7 replaces the capital gain overhang in Model 6 with positive capital gains and negative capital losses.

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V} + a_5 s + a_6 g^{+} + a_7 g^{-}$$

where g^+ is the positive capital gains regressor, and g^- the negative capital losses regressor , computed as one less the ratio of the beginning of week t-1 reference price to the end of week t-2 price.

There might be a problem of multicollinearity in the above multiples regression models. Thus, a correlation analysis among variables used in the above models is conducted beforehand. Panel A of Table 4 reports the results. Results show that almost all of the correlation coefficients are lower than 0.75. The only exception is that capital gain overhang (g) and negative capital losses (g^-) are highly correlated with a correlation coefficient of 0.977. If adding these two variables into a regression equation, there may be a problem of multicollinearity. However, in Model 7, since the capital gain overhang is replaced by the positive capital gains and negative capital losses, the multicollinearity problem is not a concern.

The rest panels of Table 4 reports the average coefficients and time-series t-statistics for the regressions described above. Each panel reports average coefficients and test statistics for all months (January through December) in the sample, for January only, for February through November only, and for December only.

[INSERT TABLE 4 HERE]

Panels B, C, and D of Table 4 report the results when the capital gains overhang, the positive capital gains and negative capital losses variables are excluded from the regressions. These three panels show that there is no continuation in returns over the short ($r_{-4:-1}$) and intermediate horizons ($r_{-52:-5}$), as the coefficients, a_1 and a_2 are insignificant for all months, January months, and the period of February through November. Interestingly, the intermediate horizon momentum effect appears to be effective in December, as the coefficient (a_2) is positive and significant for December only. This indicates a seasonal effect in December in the Chinese stock markets. This seasonality is consistent with the findings of Jegadeesh and Titman (1993), Grundy and Martin (2001), and Grinblatt and Moskowitz (2004) that momentum strategies which form portfolios from past returns over intermediate horizons appear to be most effective in December. However, even though there is a continuation in returns over the intermediate horizon for December, it does not change the overall conclusions for the whole sample period.

As a result, there is no statistical evidence to support the third hypothesis: stock returns exhibit intermediate horizon momentum effect. Although this is not in conformity with

Rouwenhorst (1998), and Grinblatt and Han (2002, 2005), as discussed earlier in the Literature section, numerous studies suggest that the factors which contribute to the momentum phenomenon in the U.S. are not pervasive in the emerging markets (Rouwenhorst 1999; Hameed and Yuanto 2003). In fact, the finding in this dissertation is consistent with Shumway and Wu (2006), Wang (2004), and Wu (2002). They state that there is no apparent momentum in their Chinese data as past returns do not forecast future returns and pure momentum strategy in general does not yield excess returns in the Chinese stock markets.

Moreover, results from these three panels indicate that there is no volume effect or size effect. There is a weak reversal of returns in the short ($r_{-4:-1}$) horizon for February through November. However, there is a strong reversal of returns in long horizons ($r_{-156:-53}$) for all months, and for February through November. This result is consistent with the finding of De Bondt and Thaler (1985), which indicates price trend reversals over the past three to five years. The result is also in line with earlier work on momentum and mean reversion in the Chinese stock market by Wu (2002), which finds strong mean reversion in the Chinese stock markets.

Panel E reports results when the capital gain overhang is incorporated into the regression. Results show that the coefficient of the capital gain overhang is -0.0073 with a t-statistic of -3.32 which is significantly negative for all months. More interestingly, the coefficient (a_2=0.0018, t-statistic=1.88) of the intermediate horizon momentum effect appears to be positive and significant. These findings are not in line with the evidence of Grinblatt and Han (2002, 2005). These two studies indicate that expected future return is positively related to the capital gains overhang, and intermediate horizon momentum effect will disappear when the capital gain overhang is controlled for. Since the findings in Panel E differ from the evidence of Panels B, C, and D of Table 4, I conduct a more precise analysis using Model 7, replacing the original capital gain overhang variable with the positive capital gains and negative capital losses. As shown in Panel F of Table 4, the intermediate horizon momentum effect still appears to be effective in December. There is also a strong reversal of returns in long horizons for all months, and the period of February through November. More importantly, there is statistically significant evidence to support the strong cross-sectional relation between the capital gains overhang variable and expected returns for all months. More specifically, the coefficient of the positive capital gains regressor is 0.006 with a t-statistic of 2.027 which is significantly positive for all months, 0.0043 (t-statistic=1.93) for the period of February through November, and 0.0142 (t-statistic=1.81) for December months. For the negative capital losses regressor, the coefficient is -0.012 with a t-statistic of -2.43 which is significantly negative for all months, and -0.0148 (t-statistic=-2,46) for February through November. These results indicate that capital gains overhang is positively related to the future returns when it is higher than zero; it is negatively related to the future returns when it is lower than zero; there is no abnormal return when it is equal to zero. In a word, after controlling for past returns, firm size, and volume regressors, the results do not suggest that capital gains overhang is positively related to the future returns. This is inconsistent with the second hypothesis. Moreover, when both the positive capital gains and negative capital losses are included in the regression, there is no intermediate momentum effect as the coefficient (a_2) of momentum effect is insignificant for all months. This indicates that the momentum does not associate with the disposition effect, which is inconsistent with the fourth hypothesis.

To conclude Table 4, the results suggest that when capital gains overhang is higher than zero, it is positively related to the future returns. This is consistent with the PT/MA framework demonstrated by Grinblatt and Han (2002, 2005). However, when capital gains overhang is lower than zero, it is negatively related to the future returns. This result cannot be explained by PT/MA framework, which states that stock with capital losses will have lower average future returns in the succeeding periods. Moreover, results also show that there is no intermediate momentum effect in the Chinese stock markets. These findings are inconsistent with the evidence of Grinblatt and Han (2002, 2005), and Shumway and Wu (2006). There are two possible explanations for the result. One possible explanation is argued by Grinblatt and Han (2002, 2005) which demonstrate that investors would only buy stocks with capital losses on sufficiently bad news. The more negative the unrealized capital losses (g^-) is, the worse the news must be to induce additional purchase. The other explanation is the short-sale constraints applied to the Chinese stock markets. As indicated by Miller (1977) short-sale constraints can prevent negative information or opinions from being expressed in stock prices. That is, rational investor fails to short the overpriced stocks. As a result, stock price will not go down further and experiences higher return than it should be. This is also consistent with Ali and Trombley (2006), which states that the future return of stocks is positively related to short sales constraints, and loser stocks rather than winner stocks drive this result.

5.3.3 Robustness checks

In order to provide robustness checks on the results of Fama-MacBeth (1973) cross-sectional regressions reported in Tables 3 and 4, this subsection continues to investigate the relation between the disposition effect and momentum using the seven different regression models discussed earlier in the previous section. Since the financial crisis starting in around 2007 and 2008 may affect the empirical results in the Chinese Stock Markets, the subsample for robustness checks is from October 1998 to December 2006, excluding periods of 2007 to 2008.

Table 5 Panel A reports results of Model 1. As observed, on average, about 39.95% of the cross-sectional variation in the capital gains variable can be explained by differences in past returns and firm size. The coefficients of these three past cumulative returns are all positive. The t-statistics for these three past cumulative returns are 18.83, 27.66, and 20.18, respectively, which are highly significant. The results of Model 2 are shown in Panel B of Table 3. Results show that when the past three average weekly turnovers are incorporated into the regression, on average, about 43.96% of the cross-sectional variation in the capital gains variable can be explained by differences in past returns, past turnover, and firm size. The coefficients of the three cumulative returns still remain positive and significant with t-statistics of 16.93, 28.22, and 21.13 respectively. Results of Table 5 demonstrate that stocks with higher past returns tend to generate unrealized capital gains, while lower past return stocks are more likely to generate unrealized capital losses. This finding is in line with Hypothesis 1.

[INSERT TABLE 5 HERE]

Table 6 reports the average coefficients and t-statistics for Model 3 to Model 7. Each panel reports average coefficients and t statistics for all months (January through December) in the sample, for January only, for February through November only, and for December only.

[INSERT TABLE 6 HERE]

Panels A, B, and C of Table 6 report the results when the capital gains overhang, the positive capital gains and negative capital losses variables are excluded from the regressions.

Panels A and B of Table 6 report results of Models 3 and 4 respectively. These two panels indicate that there is no momentum effect over the intermediate horizons as the coefficients (a_2) are insignificant with a t-statistic of 0.59 in Model 3 and 0.49 in Model 4 for all months in the dataset. Similar results are shown for January months, and the period of February through November. Results of these two panels also illustrate that there is a weak reversal of returns in the long horizon. However, results of Model 5 in Panel C show that when the average weekly turnover ratio and size are included in the regression, there is a reversal of returns in long horizons for all months (t-statistic=-1.82), and the period of February through November (t-statistic=-2.20). Similar to the results in Table 4, the intermediate horizon momentum effect appears to be effective in December, as the coefficient (a_2) is positive and significant for December in Panels A, B, and C.

Panel D reports results of Model 6 when the capital gain overhang is incorporated into the regression. Results show that the coefficient of the capital gain overhang is negatively related to the expected return with a t-statistic of -3.20 which is significantly negative for all months. Similar to the results in Table 4, the coefficient (a_2=0.0024, t-statistic=2.10) of the intermediate horizon momentum effect appears to be positive and significant. Panel E reports results of Model 7 when the original capital gain overhang variable is replaced by both the positive capital gains and negative capital losses. Results show that the coefficient (a_2) of momentum effect is always insignificant for all months, January months, and the period of February through November, expect for December. Results also illustrate that there is a weak reversal of returns in the long horizon for all months. More importantly, the coefficient of the positive capital gains is 0.0076 for all months with a t-statistic of 2.47 which is significantly positive, 0.0061 (t-statistic=1.88) for the period of February through November, and 0.0181 (t-statistic=2.17) for December months. For the negative capital losses regressor, the coefficient is -0.0049 with a t-statistic of -3.20 which is significantly negative for all months, and -0.0058 (t-statistic=-3.27) for February through November. Again, similar to the results in Table 4, capital gains overhang is positively related to the future returns when it is higher than zero; it is negatively related to the future returns when it is lower than zero; there is no abnormal return when it is equal to zero. These results do not suggest that capital gain overhang is positively related to the future return. Thus, the finding does not support Hypothesis 2. Moreover, as the coefficient (a_2) of momentum effect is insignificant for all months in most cases using different models, there is no statistical evidence to support that the Chinese Stock Markets exist intermediate horizon momentum effect which is driven by the disposition effect. These results do not provide evidence to support Hypotheses 3 and 4.

6. Conclusions

This dissertation analyzes the relation between the disposition effect and momentum in the Chinese stock markets over the period from January 1991 to November 2008. It follows the model introduced by Grinblatt and Han (2002, 2005) to test whether the unrealized capital gains variable of a stock is positively related to the future return, and whether the disposition effect appears to drive momentum.

The study of double sorting, both on past one-year returns and the capital gains overhang variable, indicates that stocks with higher past returns tend to generate higher unrealized capital gains, while lower past return stocks are more likely to generate unrealized capital losses. Moreover, it also finds that controlling for past one-year returns, the average returns of portfolios decrease monotonically with their capital gains overhang quintile. The findings provide some empirical evidence to support that there is no intermediate horizon momentum profit but contrarian profit for the Chinese stock markets.

The study of the relation between unrealized gains or losses and expected future returns in weekly cross-sectional Fama and MacBeth (1973) regressions suggests when capital gains overhang is higher than zero, expected future returns are positively related to the capital gains overhang; when capital gains overhang is lower than zero, expected future returns are negatively related to the capital gains overhang. Therefore, we cannot conclude that the unrealized capital gain overhang is positively related to the future returns. Furthermore, the overall results of different regression models show that there is no significant intermediate horizon momentum effect in the Chinese stock markets. Therefore, the overall results do not provide statistical evidence to support that the disposition effect drives momentum in the Chinese stock markets.

There are two limitations in this dissertation which should be taken into account for future research.

Firstly, this dissertation mostly focuses on the relation between the disposition effect and momentum in the setting of the Chinese stock markets by using an initial sample period from January 1991 to November 2008 and a final sample period from October 1998 to November 2008. No specific study has been conducted in this dissertation with a focus on the relation between the disposition effect and momentum during, for example, the 1997 Asian financial crisis, the September 11 attacks, and the current global financial crisis. Detailed studies over these periods can be conducted in the future.

Secondly, the theoretical model in this dissertation suggests that aggregate capital gains variable is the critical variable in forecasting the cross-sectional returns. This model also implies a relation between volume and future returns, as the capital gain variable is a volume weighting of past returns. However, this dissertation has not explored the volume implications empirically. Therefore, further investigations can be conducted on the volume implications of this theoretical model.

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Table 1: Summary Statistics

Table 1 presents summary statistics of weekly data on SHSE, SZSE, HKSE and other overseas markets from October 1998 to November 2008, obtained from DataStream. Panel A provides time series averages of the cross-sectional mean, median, standard deviation, and 10th, 50th, and 90th percentiles of each of the variables used in the regression

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V} + a_5 s + a_6 g$$

where r is the week t return, $r_{-t1:-t2}$ is the cumulative return from week $t - t_1$ through $t - t_2$; $\overline{V}$ is the average weekly turnover ratio over the prior 52 weeks, the ratio of the week's share volume to the number of outstanding shares; s is log(assets) measured at the beginning of week t; g is the capital gains regressor, computed as one less the ratio of the end of week $t - 1$ reference price to the end of week $t - 2$ price, where the week $t - 1$ reference price is the average cost basis calculated from the formula

$$R_{t-1} = \frac{1}{k}\sum_{n=1}^{260}\left(V_{t-1-n}\prod_{\tau=1}^{n-1}[1-V_{t-1-n+\tau}]\right)P_{t-1-n}$$

with k a constant that makes the weights on past prices sum to one.

Time series average of summary statistics of the regressors

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V} + a_5 s + a_6 g$$

	$r_{-4:-1}$	$r_{-52:-5}$	$r_{-156:-53}$	$\bar{V}$	s	g
Mean	0.0057	0.2769	0.4006	0.1054	2.6663	-0.2791
Median	0.0000	-0.0274	-0.1124	0.0702	2.6659	-0.1600
Std.dev.	0.1444	0.9239	1.5641	0.1202	0.0779	0.5532
10th percentile	-0.1371	-0.4013	-0.5251	0.0177	2.5747	-0.9652
50th percentile	0.0000	-0.0274	-0.1124	0.0702	2.6659	-0.1600
90th percentile	0.1521	1.3656	1.8681	0.2341	2.7613	0.2678

Figure 1: Time Series of Cross-Sectional Percentiles of the Capital Gains Regressor

This figure plots the time series of the empirical 10th, 50th and 90th percentiles of the cross-sectional distribution of the capital gains regressor. The sample period is from October 1998 to November 2008, for a total of 528 weeks. Each week, I include all stocks which have at least five years of historical trading data and accounting data from DataStream. The previous five years of return and turnover data are used to calculate the capital gains variable as one less the ratio of the end of week $t-1$ reference price to the end of week $t-2$ price, where the week $t-1$ reference price is the average cost basis obtained from the formula

$$R_{t-1} = \frac{1}{k}\sum_{n=1}^{260}\left(V_{t-1-n}\prod_{\tau=1}^{n-1}[1-V_{t-1-n+\tau}]\right)P_{t-1-n}$$

with k a constant that makes the weights on past prices sum to one.

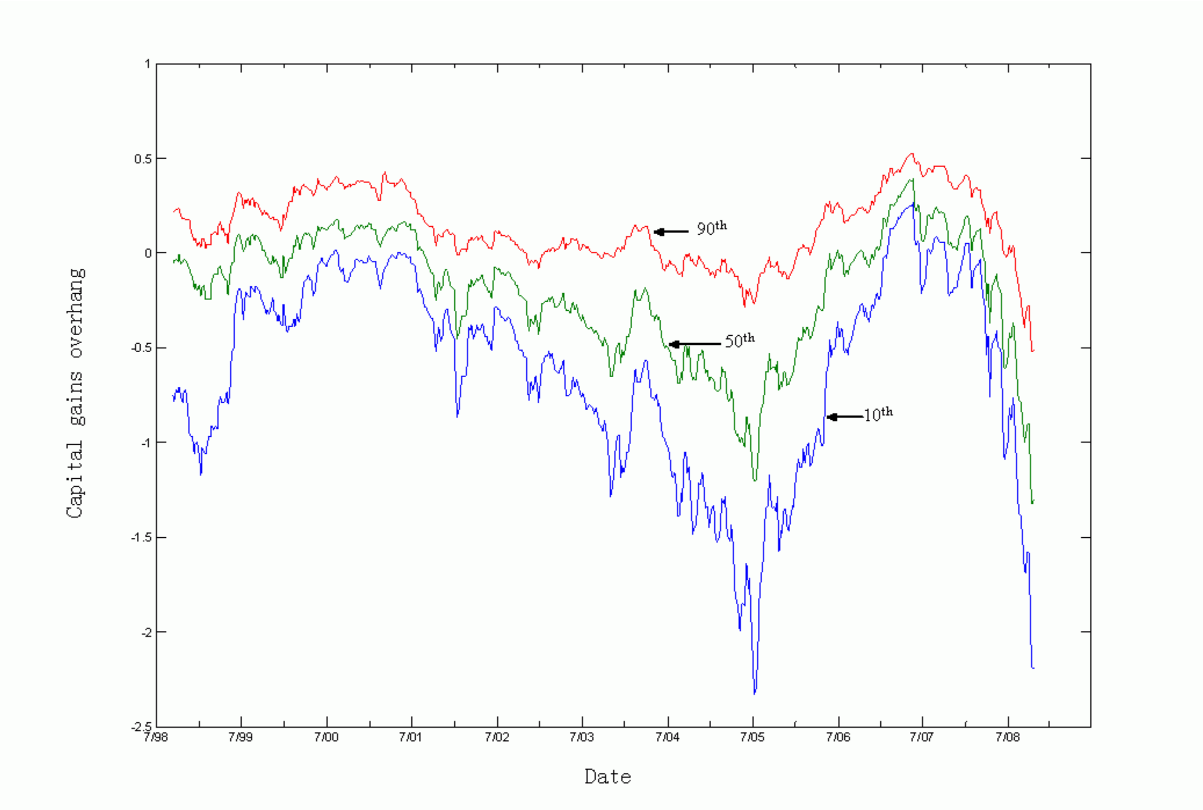

Table 2: Portfolios Double Sorted on Past Returns and Capital Gains

At the beginning of each week t, all stocks with five years of prior data are double sorted in two ways. In one double sort, stocks are first sorted into quintiles (R1=losers, R5=winners) based on the cumulative return from week t - 52 through t - 1. Then within each past return quintile, stocks are further sorted into five equally weighted portfolios by their capital gains g (G1=lowest, G5=highest), where g is computed as one less the ratio of the beginning of week t – 1 reference price to the end of week t - 2 price. The week t -1 reference price is the average cost basis calculated from the formula

$$R_{t-1} = \frac{1}{k}\sum_{n=1}^{260}\left(V_{t-1-n}\prod_{\tau=1}^{n-1}[1-V_{t-1-n+\tau}]\right)P_{t-1-n,}$$

with k a constant that makes the weights on past prices sum to one.

Panel A reports the average weekly return for the 25 portfolios arranged first on past returns and then within each past return portfolio, additionally arranged on the basis of capital gains overhang. Panel B reports the second double sort which reverses the sort order. Results are reported separately during the January and February through December, and t-statistics are reported in parentheses. The sample period is from October 1998 to November 2008.

Time series average of gain/past return for cutoff-percentiles of double sorts											
Panel A: Gain Overhang for Cutoff Percentile						*Panel B: Past One-Year Return for Cutoff Percentile*					
Percentile	R1	R2	R3	R4	R5	Percentile	G1	G2	G3	G4	G5
G_20	-1.297	-1.040	-0.874	-0.747	0.073	R_20	-0.537	-0.452	-0.395	-0.350	0.478
G_40	-0.925	-0.699	-0.540	-0.398	0.182	R_40	-0.412	-0.333	-0.273	-0.211	0.933
G_60	-0.662	-0.466	-0.315	-0.177	0.272	R_60	-0.319	-0.242	-0.167	-0.057	1.471
G_80	-0.416	-0.261	-0.132	0.007	0.373	R_80	-0.216	-0.129	-0.008	0.241	2.283

Table 2 (continued): Portfolios double sorted on past returns and capital gains
Panel C: Mean portfolio return: first sort on past 1-year return

	January					February Through December					All Months				
	R1	R2	R3	R4	R5	R1	R2	R3	R4	R5	R1	R2	R3	R4	R5
G1	0.0128	0.0124	0.0129	0.0132	0.0264	-0.0031	-0.0032	-0.0028	-0.0030	0.0113	-0.0023	-0.0022	-0.0016	-0.0017	0.0125
	(6.36)	(9.78)	(13.16)	(16.20)	(11.41)	(-4.74)	(-7.46)	(-5.49)	(-6.46)	(16.27)	(-3.63)	(-5.35)	(-3.42)	(-4.01)	(18.69)
G2	0.0107	0.0120	0.0127	0.0113	0.0156	-0.0075	-0.0057	-0.0047	-0.0048	0.0070	-0.0063	-0.0043	-0.0033	-0.0034	0.0078
	(7.48)	(13.07)	(15.84)	(14.44)	(6.24)	(-12.73)	(-14.66)	(-11.26)	(-17.32)	(9.34)	(-11.25)	(-11.77)	(-8.32)	(-13.16)	(11.02)
G3	0.0104	0.0092	0.0081	0.0071	0.0101	-0.0088	-0.0066	-0.0056	-0.0036	0.0121	-0.0078	-0.0056	-0.0045	-0.0028	0.0116
	(6.87)	(8.87)	(8.36)	(7.28)	(4.15)	(-15.05)	(-17.35)	(-18.16)	(-13.18)	(11.77)	(-14.05)	(-15.54)	(-15.36)	(-10.47)	(12.03)
G4	-0.0021	0.0009	0.0059	0.0171	0.0082	-0.0100	-0.0067	-0.0055	-0.0020	0.0153	-0.0094	-0.0063	-0.0047	-0.0005	0.0149
	(-1.15)	(0.70)	(5.07)	(16.00)	(3.26)	(-15.90)	(-17.25)	(-18.51)	(-7.02)	(18.07)	(-15.72)	(-17.02)	(-16.50)	(-1.91)	(18.60)
G5	-0.0225	-0.0120	0.0085	0.0201	0.0131	-0.0096	-0.0067	-0.0044	0.0019	0.0107	-0.0103	-0.0072	-0.0038	0.0031	0.0110
	(-10.29)	(-8.24)	(7.56)	(18.02)	(5.07)	(-15.17)	(-18.16)	(-14.59)	(6.10)	(11.29)	(-16.90)	(-20.23)	(-12.93)	(10.73)	(12.23)
G5-G1	-0.0353	-0.0244	-0.0043	0.0069	-0.0133	-0.0065	-0.0034	-0.0016	0.0048	-0.0006	-0.0080	-0.0050	-0.0022	0.0049	-0.0015
	(-11.88)	(-10.56)	(-2.63)	(4.75)	(-4.71)	(-7.12)	(-4.77)	(-2.35)	(7.89)	(-0.60)	(-9.12)	(-7.27)	(-3.30)	(8.47)	(-1.56)

Table 2 (continued)
Panel D: Mean portfolio return: first sort on capital gains

	January					February Through December					All Months				
	G1	G2	G3	G4	*G5*	G1	G2	G3	*G4*	G5	G1	G2	G3	*G4*	G5
R1	0.0118	0.0053	0.0023	0.0013	0.0111	-0.0178	-0.0141	-0.0111	-0.0091	-0.0004	-0.0169	-0.0129	-0.0101	-0.0083	0.0000
	(5.73)	(3.80)	(2.04)	(1.37)	(5.72)	(-25.73)	(-29.23)	(-29.19)	(-28.46)	(-0.67)	(-25.36)	(-28.00)	(-27.76)	(-27.20)	(0.02)
R2	0.0101	0.0057	0.0028	0.0047	0.0158	-0.0033	-0.0024	-0.0026	-0.0031	0.0115	-0.0015	-0.0021	-0.0024	-0.0027	0.0120
	(6.98)	(4.99)	(2.93)	(5.87)	(6.53)	(-5.59)	(-5.86)	(-8.33)	(-12.48)	(13.62)	(-2.66)	(-5.38)	(-8.23)	(-11.39)	(15.01)
R3	0.0129	0.0102	0.0086	0.0134	0.0114	0.0004	-0.0024	-0.0036	-0.0044	0.0146	0.0010	-0.0015	-0.0028	-0.0032	0.0145
	(9.58)	(10.43)	(9.64)	(16.52)	(4.46)	(0.69)	(-7.02)	(-13.03)	(-18.16)	(14.52)	(2.05)	(-4.54)	(-10.75)	(-13.82)	(15.28)
R4	0.0117	0.0148	0.0169	0.0259	0.0104	0.0005	-0.0033	-0.0042	0.0007	0.0135	0.0019	-0.0017	-0.0023	0.0028	0.0132
	(8.84)	(14.59)	(18.02)	(26.81)	(4.17)	(1.04)	(-9.94)	(-14.63)	(1.52)	(16.21)	(4.23)	(-5.46)	(-8.38)	(6.62)	(16.66)
R5	0.0174	0.0193	0.0265	0.0273	0.0082	0.0053	0.0034	0.0062	0.0068	0.0077	0.0066	0.0052	0.0080	0.0087	0.0078
	(10.55)	(15.87)	(21.25)	(22.35)	(3.32)	(3.51)	(4.15)	(10.48)	(20.36)	(8.80)	(4.73)	(6.81)	(14.44)	(26.86)	(9.32)
R5-R1	0.0056	0.0139	0.0242	0.0260	-0.0030	0.0231	0.0174	0.0173	0.0159	0.0082	0.0235	0.0180	0.0181	0.0170	0.0078
	(2.12)	(5.98)	(13.01)	(16.02)	(-1.12)	(13.91)	(16.43)	(22.97)	(31.93)	(8.73)	(15.16)	(18.05)	(25.45)	(35.52)	(8.74)

Table 3: Capital Gains Overhang and Past Returns

This table presents more detailed data on the association between the capital gains regressor and other variables. It contains the time-series average of the coefficients and their associated time series t-statistics for 528 weekly Fama-MacBeth type cross-sectional regressions and t-statistics are reported in parentheses. Panel A reports the results of Model1 which includes short/intermediate/long horizon returns, and firm size.

$$g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 s$$

Panel B reports the results of Model 2 which adds the average weekly turnover to Model 1.

$$g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{-4:-1} + a_5 V_{-52:-5} + a_6 V_{-156:53} + a_7 s$$

where g is the proxy for the capital gains overhang, $r_{-t1:-t2}$ is the cumulative return from week $t - t_1$ through $t - t_2$; s is log(assets) measured at the beginning of week t; $V_{-t1:-t2}$ is the average weekly turnover from $t - t_1$ through $t - t_2$. R^2/Adjusted R^2 is the average of the weekly cross-sectional regression R^2s/Adjusted R^2s adjusted for degrees of freedom.

Panel A: correlation analysis among variables

	$r_{-4:-1}$	$r_{-52:-5}$	$r_{-156:-53}$	$V_{-4:-1}$	$V_{-52:-5}$	$V_{-156:-53}$	g	s
$r_{-4:-1}$	1	0.082	-0.152	0.188	0.036	-0.034	0.211	0.007
$r_{-52:-5}$	0.082	1	-0.117	0.265	0.364	0.010	0.518	0.103
$r_{-156:-53}$	-0.152	-0.117	1	-0.037	0.083	0.254	-0.011	0.099
$V_{-4:-1}$	0.188	0.265	-0.037	1	0.594	0.300	0.262	-0.005
$V_{-52:-5}$	0.036	0.364	0.083	0.594	1	0.564	0.271	0.000
$V_{-156:-53}$	-0.034	0.010	0.254	0.300	0.564	1	0.089	-0.068
g	0.211	0.518	-0.011	0.262	0.271	0.089	1	0.140
s	0.007	0.103	0.099	-0.005	0.000	-0.068	0.140	1

Average coefficients and t-statistics (in parentheses) for the regression

Panel B: $g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 s$

a_0	a_1	a_2	a_3	a_4	R^2	$Adj.R^2$
-0.5649	0.6274	0.6001	0.1847	0.1570	0.3848	0.3794
(-11.93)	(20.64)	(26.62)	(20.36)	(9.37)		

Panel C: $g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{-4:-1} + a_5 V_{-52:-5} + a_6 V_{-156:53} + a_7 s$

a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	R^2	$Adj.R^2$
-0.8844	0.5852	0.6024	0.1743	0.3274	0.2075	0.1403	0.2670	0.4367	0.4277
(-12.91)	(18.91)	(27.09)	(20.97)	(11.41)	(3.83)	(10.02)	(11.30)		

Table 4: Cross-sectional Regression Estimates

This table presents the results of Fama-MacBeth (1973) cross-sectional regressions run each week on SHSE, SZSE, HKSE and other overseas markets from October 1998 to November 2008. The weekly cross-sectional regressions include all stocks that have at least five years of historical trading data on DataStream. The cross section of stock returns in week t, denoted r, are regressed on a constant and some or all of the following variables: $r_{-t1:-t2}$ = the cumulative return from week $t-t_1$ through $t-t_2$, computed over three past return horizons; $\overline{V}$= the average weekly turnover ratio over the prior 52 weeks, with turnover being the ratio of the week's share volume to the number of outstanding shares; s = log(total assets) measured at the beginning of week t; and g= the capital gains overhang regressor, g^+ is the positive capital gains, g^- is the negative capital losses, computed as one less the ratio of the beginning of week t − 1 reference price to the end of week t − 2 price, where the week t − 1 reference price is the average cost basis calculated from the formula

$$R_{t-1} = \frac{1}{k}\sum_{n=1}^{260}\left(V_{t-1-n}\prod_{\tau=1}^{n-1}[1-V_{t-1-n+\tau}]\right)P_{t-1-n}$$

with k a constant that makes the weights on past prices sum to one. There are a total of 528 weekly regressions. The parameter estimates and t-statistics (in parentheses) are obtained from the time series of the corresponding cross-sectional regression coefficients. R^2/Adjusted R^2 is the average of the weekly cross-sectional regression R^2s/Adjusted R^2s adjusted for degrees of freedom. I report the results of regressions over all months, for January only, February through November only, and December only.

Panel A: correlation analysis among variables

	$r_{-4:-1}$	$r_{-52:-5}$	$r_{-156:-53}$	$\overline{V}$	g	s	g^+	g^-
$r_{-4:-1}$	1	0.082	-0.152	0.053	0.211	0.007	0.261	0.169
$r_{-52:-5}$	0.082	1	-0.117	0.368	0.518	0.103	0.624	0.421
$r_{-156:-53}$	-0.152	-0.117	1	0.074	-0.011	0.099	-0.009	-0.010
$\overline{V}$	0.053	0.368	0.074	1	0.280	0.000	0.151	0.276
g	0.211	0.518	-0.011	0.280	1	0.140	0.568	0.977
s	0.007	0.103	0.099	0.000	0.140	1	0.134	0.122
g^+	0.261	0.624	-0.009	0.151	0.568	0.134	1	0.381
g^-	0.169	0.421	-0.010	0.276	0.977	0.122	0.381	1

Cross-sectional regression estimates

Panel B: $r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53}$

Period	a_0	a_1	a_2	a_3	R^2	$Adj.R^2$
All months	0.0026	-0.0022	0.0000	-0.0013	0.0637	0.0578
	(1.63)	(-0.54)	(0.02)	(-2.37)		
Jan	0.0083	0.0114	-0.0011	-0.0003	0.0699	0.0634
	(1.30)	(0.76)	(-0.30)	(-0.15)		
Feb-Nov	0.0026	-0.0048	-0.0005	-0.0016	0.0636	0.0577
	(1.46)	(-1.09)	(-0.46)	(-2.64)		
Dec	-0.0003	0.0096	0.0070	0.0018	0.0579	0.0513
	(-0.07)	(0.71)	(2.29)	(0.96)		

Panel C: $r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V}$

Period	a_0	a_1	a_2	a_3	a_4	R^2	$Adj.R^2$
All months	0.0025	-0.0026	-0.0001	-0.0013	0.0018	0.0693	0.0614
	(1.71)	(-0.66)	(-0.09)	(-2.38)	(0.76)		
Jan	0.0070	0.0110	-0.0021	-0.0003	0.0087	0.0763	0.0678
	(1.11)	(0.72)	(-0.58)	(-0.20)	(1.33)		
Feb-Nov	0.0027	-0.0052	-0.0006	-0.0016	0.0010	0.0693	0.0613
	(1.66)	(-1.22)	(-0.52)	(-2.64)	(0.37)		
Dec	-0.0013	0.0093	0.0073	0.0019	0.0051	0.0637	0.0549
	(-0.36)	(0.70)	(2.35)	(1.03)	(0.89)		

Panel D: $r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V} + a_5 s$

Period	a_0	a_1	a_2	a_3	a_4	a_5	R^2	$Adj.R^2$
All months	-0.0050	-0.0060	-0.0006	-0.0015	0.0023	0.0027	0.0815	0.0717
	(-0.47)	(-1.55)	(-0.57)	(-3.08)	(0.97)	(0.72)		
Jan	-0.0406	0.0074	-0.0025	-0.0009	0.0091	0.0177	0.0906	0.0801
	(-1.04)	(0.49)	(-0.72)	(-0.52)	(1.51)	(1.25)		
Feb-Nov	0.0025	-0.0088	-0.0011	-0.0017	0.0015	0.0000	0.0814	0.0717
	(0.21)	(-2.11)	(-0.96)	(-3.22)	(0.55)	(0.00)		
Dec	-0.0740	0.0057	0.0066	0.0009	0.0079	0.0271	0.0771	0.0663
	(-2.36)	(0.43)	(2.37)	(0.56)	(1.35)	(2.37)		

Panel E : $r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V} + a_5 s + a_6 g$

Period	a_0	a_1	a_2	a_3	a_4	a_5	a_6	R^2	$Adj.R^2$
All months	-0.0099	-0.0036	0.0018	-0.0008	0.0016	0.0046	-0.0073	0.0961	0.0846
	(-0.97)	(-0.94)	(1.88)	(-1.62)	(0.61)	(1.22)	(-3.32)		
Jan	-0.0510	0.0034	-0.0004	0.0002	0.0204	0.0214	0.0018	0.1056	0.0933
	(-1.31)	(0.24)	(-0.13)	(0.11)	(3.95)	(1.53)	(0.52)		
Feb-Nov	-0.0026	-0.0057	0.0015	-0.0010	-0.0001	0.0019	-0.0085	0.0964	0.0849
	(-0.23)	(-1.35)	(1.42)	(-1.88)	(-0.05)	(0.46)	(-3.29)		
Dec	-0.0696	0.0059	0.0064	0.0006	0.0054	0.0255	-0.0008	0.0886	0.0757
	(-2.33)	(0.48)	(2.98)	(0.37)	(0.91)	(2.33)	(-0.27)		

Panel F: $r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V} + a_5 s + a_6 g^+ + a_7 g^-$

Period	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	R^2	$Adj.R^2$
All months	-0.0106	-0.0054	0.0004	-0.0012	0.0034	0.0044	0.0060	-0.0124	0.1022	0.0888
	(-1.04)	(-1.43)	(0.45)	(-2.47)	(1.52)	(1.18)	(2.03)	(-2.43)		
Jan	-0.0507	0.0044	0.0003	0.0010	0.0196	0.0214	0.0043	0.0020	0.1143	0.1000
	(-1.32)	(0.32)	(0.08)	(0.46)	(3.39)	(1.55)	(0.31)	(0.60)		
Feb-Nov	-0.0036	-0.0079	0.0000	-0.0015	0.0021	0.0017	0.0062	-0.0148	0.1025	0.0891
	(-0.32)	(-1.89)	(-0.03)	(-2.84)	(0.79)	(0.42)	(1.93)	(-2.46)		
Dec	-0.0684	0.0033	0.0047	-0.0006	0.0082	0.0246	0.0142	-0.0018	0.0925	0.0775
	(-2.33)	(0.27)	(1.90)	(-0.36)	(1.37)	(2.31)	(1.81)	(-0.59)		

Table 5: Robustness Check – Capital Gains Overhang and Past Returns

This table provides robustness checks on the results of Fama-MacBeth (1973) cross-sectional regressions reported in Panels B and C of Table 3. Panel A reports the results of Model1 which includes short/intermediate/long horizon returns, and firm size.

$$g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 s$$

Panel B reports the results of Model 2 which adds the average weekly turnover to Model 1.

$$g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{-4:-1} + a_5 V_{-52:-5} + a_6 V_{-156:53} + a_7 s$$

where g is the proxy for the capital gains overhang, $r_{-t1:-t2}$ is the cumulative return from week t − t1 through t − t2; s is log(assets) measured at the beginning of week t; $V_{-t1:-t2}$ is the average weekly turnover from t − t1 through t − t2. R^2/Adjusted R^2 is the average of the weekly cross-sectional regression R^2s/Adjusted R^2s adjusted for degrees of freedom.

Average coefficients and t-statistics (in parentheses) for the regression

Panel A: $g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 s$

a_0	a_1	a_2	a_3	a_4	R^2	$Adj.R^2$
-0.5135	0.6691	0.6866	0.2132	0.1284	0.4056	0.3995
(-9.15)	(18.83)	(27.66)	(20.18)	(6.46)		

Panel B: $g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{-4:-1} + a_5 V_{-52:-5} + a_6 V_{-156:53} + a_7 s$

a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	R^2	$Adj.R^2$
-0.9148	0.6182	0.6894	0.2026	0.3455	0.3788	0.1510	0.2600	0.4497	0.4396
(-11.09)	(16.93)	(28.22)	(21.13)	(10.38)	(6.00)	(9.46)	(9.09)		

Table 6: Robustness Check - Cross-sectional Regression Estimates

This table provides robustness checks on the results of Fama-MacBeth (1973) cross-sectional regressions reported in Table 4. The weekly cross-sectional regressions include all stocks that have at least five years of historical trading data on DataStream. The cross section of stock returns in week t, denoted r, are regressed on a constant and some or all of the following variables: $r_{-t1:-t2}$ = the cumulative return from week $t-t_1$ through $t-t_2$, computed over three past return horizons; $\overline{V}$= the average weekly turnover ratio over the prior 52 weeks, with turnover being the ratio of the week's share volume to the number of outstanding shares; s = log(total assets) measured at the beginning of week t; and g= the capital gains overhang regressor, g^+ is the positive capital gains, g^- is the negative capital losses, computed as one less the ratio of the beginning of week t − 1 reference price to the end of week t − 2 price, where the week t − 1 reference price is the average cost basis calculated from the formula

$$R_{t-1} = \frac{1}{k}\sum_{n=1}^{260}\left(V_{t-1-n}\prod_{\tau=1}^{n-1}[1-V_{t-1-n+\tau}]\right)P_{t-1-n}$$

with k a constant that makes the weights on past prices sum to one. The sample period is from October 1998 to December 2006. The parameter estimates and t-statistics (in parentheses) are obtained from the time series of the corresponding cross-sectional regression coefficients. R^2/Adjusted R^2 is the average of the weekly cross-sectional regression R^2s/Adjusted R^2s adjusted for degrees of freedom. I report the results of regressions over all months, for January only, February through November only, and December only.

Panel A: $r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53}$

Period	a_0	a_1	a_2	a_3	R^2	$Adj.R^2$
All months	0.0020	0.0000	0.0007	-0.0005	0.0703	0.0636
	(1.39)	(0.00)	(0.59)	(-1.01)		
Jan	0.0016	0.0168	-0.0007	0.0003	0.0800	0.0727
	(0.26)	(0.94)	(-0.16)	(0.14)		
Feb-Nov	0.0028	-0.0027	0.0001	-0.0009	0.0703	0.0636
	(1.74)	(-0.55)	(0.05)	(-1.59)		
Dec	-0.0043	0.0091	0.0079	0.0020	0.0620	0.0549
	(-1.12)	(0.63)	(2.36)	(0.95)		

Panel B: $r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V}$

Period	*a₀*	*a₁*	*a₂*	*a₃*	*a₄*	R^2	$Adj.R^2$
All months	0.0019	-0.0003	0.0006	-0.0005	0.0023	0.0742	0.0653
	(1.29)	(-0.06)	(0.49)	(-1.01)	(1.35)		
Jan	0.0012	0.0167	-0.0019	0.0001	0.0041	0.0861	0.0765
	(0.20)	(0.94)	(-0.43)	(0.03)	(0.61)		
Feb-Nov	0.0027	-0.0030	0.0000	-0.0009	0.0022	0.0739	0.0650
	(1.68)	(-0.62)	(0.00)	(-1.54)	(1.17)		
Dec	-0.0046	0.0090	0.0082	0.0020	0.0020	0.0670	0.0576
	(-1.29)	(0.63)	(2.43)	(0.95)	(0.34)		

Panel C: $r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V} + a_5 s$

Period	a_0	a_1	a_2	a_3	a_4	a_5	R^2	$Adj.R^2$
All months	-0.0074	-0.0043	0.0000	-0.0009	0.0026	0.0034	0.0867	0.0757
	(-0.65)	(-0.98)	(0.02)	(-1.82)	(1.57)	(0.81)		
Jan	-0.0484	0.0128	-0.0023	-0.0003	0.0048	0.0184	0.1004	0.0885
	(-1.08)	(0.73)	(-0.56)	(-0.17)	(0.79)	(1.13)		
Feb-Nov	0.0050	-0.0071	-0.0006	-0.0011	0.0021	-0.0010	0.0861	0.0752
	(0.40)	(-1.50)	(-0.44)	(-2.20)	(1.18)	(-0.21)		
Dec	-0.0799	0.0052	0.0075	0.0009	0.0048	0.0281	0.0805	0.0689
	(-2.44)	(0.35)	(2.46)	(0.50)	(0.80)	(2.34)		

Panel D : $r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V} + a_5 s + a_6 g$

Period	a_0	a_1	a_2	a_3	a_4	a_5	a_6	R^2	$Adj.R^2$
All months	-0.0110	-0.0035	0.0024	-0.0003	0.0042	0.0045	-0.0042	0.1024	0.0894
	(-0.99)	(-0.82)	(2.10)	(-0.59)	(2.51)	(1.10)	(-3.20)		
Jan	-0.0614	0.0083	0.0002	0.0010	0.0182	0.0231	0.0012	0.1181	0.1042
	(-1.38)	(0.50)	(0.06)	(0.52)	(3.68)	(1.44)	(0.35)		
Feb-Nov	0.0013	-0.0057	0.0020	-0.0005	0.0030	0.0002	-0.0052	0.1020	0.0891
	(0.11)	(-1.21)	(1.57)	(-1.01)	(1.62)	(0.04)	(-3.49)		
Dec	-0.0748	0.0051	0.0072	0.0005	0.0032	0.0262	0.0002	0.0928	0.0791
	(-2.39)	(0.38)	(3.06)	(0.30)	(0.51)	(2.28)	(0.07)		

Panel E: $r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \overline{V} + a_5 s + a_6 g^+ + a_7 g^-$

Period	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	R^2	$Adj.R^2$
All months	-0.0111	-0.0048	0.0008	-0.0008	0.0047	0.0043	0.0076	-0.0049	0.1084	0.0933
	(-1.00)	(-1.12)	(0.71)	(-1.55)	(2.80)	(1.05)	(2.47)	(-3.20)		
Jan	-0.0599	0.0080	0.0003	0.0011	0.0187	0.0226	0.0104	0.0017	0.1275	0.1113
	(-1.36)	(0.49)	(0.07)	(0.49)	(3.46)	(1.42)	(0.64)	(0.47)		
Feb-Nov	0.0010	-0.0069	0.0004	-0.0009	0.0031	0.0001	0.0061	-0.0058	0.1078	0.0929
	(0.08)	(-1.46)	(0.28)	(-1.80)	(1.73)	(0.01)	(1.88)	(-3.27)		
Dec	-0.0739	0.0021	0.0052	-0.0009	0.0064	0.0253	0.0181	-0.0024	0.0969	0.0809
	(-2.41)	(0.15)	(1.93)	(-0.47)	(0.99)	(2.27)	(2.17)	(-0.71)		