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**Stocks as Lotteries: Can Extreme Positive Returns Predict Future  
Returns? – Evidence From Hong Kong Stock Market**

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A thesis  
submitted in partial fulfilment  
of the requirements for the Degree of  
Master of Commerce and Management

at  
Lincoln University

By  
Yi Zeng (Leo)

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Lincoln University

2011

Abstract of a thesis submitted in partial fulfilment of the  
requirements for the Degree of M. C. M.

**Stock as Lotteries: Can Extreme Positive Returns Predict Future  
Returns? – Evidence from Hong Kong Stock Market**

**By Yi Zeng (Leo)**

This study examines the significance of extreme positive returns measured by maximum daily returns in the previous month (MAX) in the Hong Kong stock market from 1990 to 2009. We follow the original study of Bali et al. (2011), who adopted both a portfolio sorting approach and the Fama-Macbeth regressions to test the MAX effect. Of special interest, we also determine if the puzzling negative relationship between the one-month lagged idiosyncratic volatility and future returns documented in Ang et al. (2006, 2009) can be explained by the MAX effect.

The results of this study contribute two major findings. First, we found that there was a strong negative relationship between MAX and future stock returns in the subsequent month based on the Fama-Macbeth regressions, but this MAX effect appeared more likely to occur among small stocks. In contrast, we found no MAX effect for large stocks based on portfolio analysis as the idiosyncratic volatility effect explains the MAX effect. Second, we found a significantly negative idiosyncratic volatility effect for large stocks

and none for small stocks. In addition, we documented that the MAX effect could potentially reverse the negative relationship between the one-month lagged idiosyncratic volatility and expected returns based on both the equal-weighted portfolio analysis and the Fama-Macbeth regressions, which confirm the findings of Bali et al. (2011) for the U.S. stock market.

Keywords: MAX, Portfolio Sorting Approach, Fama-Macbeth Regressions and Idiosyncratic Volatility

## **Acknowledgment**

I would like to acknowledge the people who have contributed to my thesis and have supported me in conducting my research over the past year.

My first and foremost thanks and gratitude go to my supervisor - Dr. Gilbert Nartea. His consistent encouragement and instructions helped me to solve many difficulties throughout my research. I also would like to thank my associate supervisor - Dr. Zhaohua Li. Dr Li has given me valuable advice on how to use SAS software and assisted me in running the Fama and Macbeth regressions.

I also would like to express my gratitude to my good friend - Cheema. He made an incredible contribution to my data analysis and also made my research enjoyable. I cannot imagine completing the data analysis alone without his huge help.

Finally, I would like to deeply and sincerely appreciate my parents for everything they have done for me. My special thanks to Helen who accompanied me and looked after me over the years. In addition, I would show my appreciation to the postgraduate fellows and staff of the Commerce Division at Lincoln University for their help and support.

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# Chapter 1 Introduction

## 1.1 Introduction

Since Sharpe (1964), Lintner (1965) and Black (1972) developed the single factor Capital Asset Pricing Model (CAPM), which posits a positive linear relationship between market betas and expected stock returns, many empirical researchers have followed this theory to study asset pricing. Other authors also stated that other variables could also predict future asset returns, i.e., firm size (Banz, 1981; Lam, 2002; Chui & Wei, 1998); book-to-market equity ratio (Rosenberg, Reid & Lanstein, 1985; Stattman, 1980; Fama & French, 1992, 1993); and idiosyncratic volatility (Bali & Cakici, 2009; Fu, 2009; Malkiel & Xu, 2002). Following these fundamental variable effects, many investment decisions of investors could be influenced by certain firm-specific characteristics such as small-capital stocks and high book-to-market ratio stocks. Recently, there is evidence that a certain number of investment choices of investors are also affected by their decisions about lottery participation and gambling (Kumar, 2009), namely, a preference for lottery-type assets. Lottery-type assets are defined as assets that have a relatively small probability of a large payoff. Two classic examples are racetrack betting and lotto games (Thaler & Ziemba, 1988). In the context of the stock market, certain groups of individual investors are also willing to pay more for lottery-type stocks (Kumar, 2009). Some characteristics of lottery-type stocks are that they are low-priced stocks with high idiosyncratic volatility, offer high extreme returns and low expected returns (Kumar, 2009). This study focuses

on lottery-type stocks to see if the payoffs from these stocks – extreme positive returns - can predict the cross-section of expected returns.

Bali, Cakici and Whitelaw (2011) conducted empirical tests on the significance of extreme positive returns in a cross-section of expected returns. Their findings revealed that extreme positive returns measured by maximum daily returns in the previous month (MAX) had a significantly negative relationship with expected stock returns in the U.S. stock market. The interpretation given was that less-diversified investors who exhibit a preference for purchasing lottery-type stocks expect to capture extreme positive returns and get a large future payoff, even if only with a small probability. Consequently, this behavioural bias by investors drove these stocks to have low expected returns.

According to the cumulative prospective theory (Tversky & Kahneman, 1992), investors who transform objective probabilities through a weighting function overestimate the tails of the probability distribution. Barberis and Huang (2008) suggested that investors whose preferences conform to the cumulative prospective theory caused the over-priced stocks to have low expected returns. These investors love lottery-type wealth distributions and are willing to pay more for stocks that have lottery-like characteristics. Barberis and Huang (2008) argued that this would explain why stocks with high MAX have low future returns in the subsequent month. In addition, the evidence of the MAX effect is consistent with Brunnermeier, Gollier and Parker's (2007) optimal belief framework, which showed that investors overestimated expected payoffs of their investment in order to maximise

their present utility based on their optimistic beliefs. Such optimism leads to low average stock returns.

Ang, Hodrick, Xing and Zhang (2006, 2009) documented a significantly negative relationship between one-month lagged idiosyncratic volatility and expected returns. This means high idiosyncratic volatility stocks produce low subsequent returns. Bali et al. (2011) stated that it is not surprise for stocks with extreme positive returns to have high idiosyncratic volatility. This raises the question of whether the MAX effect is explained by the idiosyncratic volatility effect. In investigating this relationship, Bali et al. (2011) found that the MAX effect is not only robust to control for idiosyncratic volatility but also influences the volatility-returns relationship by reversing the negative relationship between the lagged idiosyncratic volatility and the expected returns. This evidence could provide a new explanation for the puzzling negative idiosyncratic volatility effect as documented in Ang et al. (2006, 2009), which has attracted much attention recently. This study also examines the relationship between extreme positive returns and idiosyncratic volatility in the Hong Kong stock market.

The main focus of this study is to investigate whether maximum daily returns in the past month (MAX) can determine the returns in the subsequent month in the Hong Kong stock market.

## **1.2 Problem Statement and Research Importance**

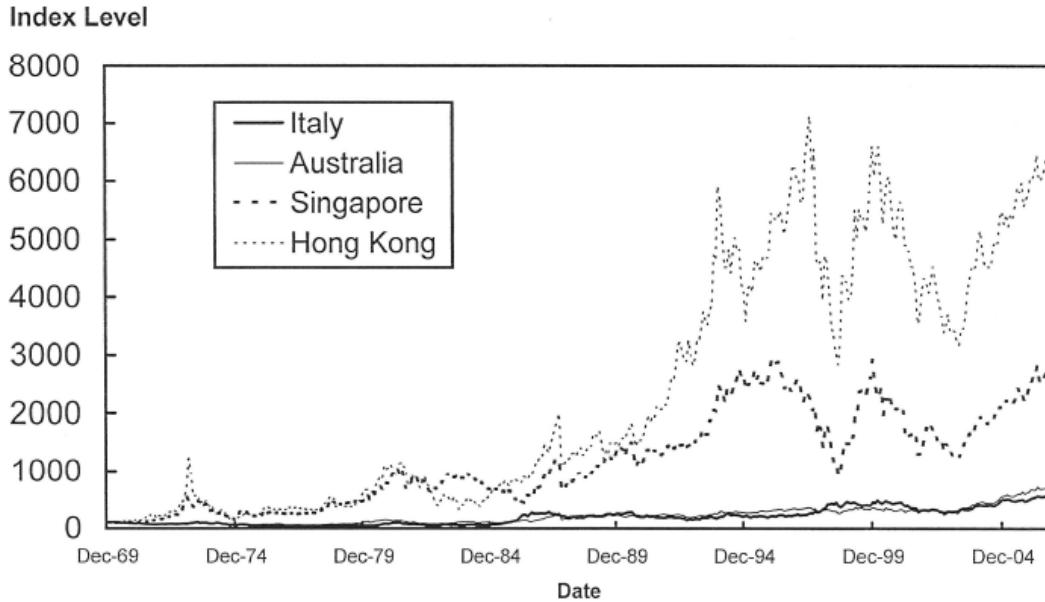
Bali et al. (2011) were the pioneers who documented a significantly negative relationship between maximum daily returns over the previous month (MAX) and the cross-section of expected stock returns in the U.S. stock market. So far, this is the only investigation of the significance of extreme positive returns in the cross-section of stock pricing. Evidence supporting Bali et al.'s (2011) findings from outside the U.S. is nonexistent. Hence, it would be interesting to verify if these results also hold in other stock markets.

This study will apply similar testing methods as Bali et al.'s (2011) to examine the importance of maximum daily returns in the past month (MAX) to explain the cross-section of expected stock returns in the Hong Kong stock market. If there is a MAX effect on the Hong Kong stock market, we will also investigate whether the result is robust to control for size, book-to-market ratio, illiquidity, momentum, short-term reversals, idiosyncratic volatility, skewness and market beta.

As the Hong Kong stock market became an internationally recognised leading financial centre, an increasing number of finance researchers have been studying the behaviour of stock returns in that stock market. However, there is a lack of empirical evidence in the Hong Kong stock market to support the existence of a MAX effect.

Bali et al. (2011) documented that, on average, stocks with high MAX are small, illiquid, low priced and with high idiosyncratic volatility (or total volatility) in the same month. The Hong Kong stock market is very volatile and very sensitive to market news. Figure 1.1 shows the extreme fluctuations in the Hang Seng Index (the stock index of Hong Kong stock market) compared with other stock indices in the world (Huang, 2009). Thus, in order to prove that the relationship between MAX and expected return is not explained by some known effects such as size, illiquidity and idiosyncratic volatility, it is necessary to investigate the robustness of the MAX effect in the Hong Kong stock market using a double-sort procedure as in Bali et al. (2011) and cross-sectional Fama-Macbeth regressions.

In addition, stocks with high maximum daily returns within the month that generate low subsequent returns in this study are considered to be lottery-type stocks. Hong Kong has a developed lottery market (ReportLinker, 2010) and Hong Kong residents enjoy lottery games such as Mark Six lotto game (World Casino Directory, 2010). Kumar (2009) posited that people's security about investment choices may be affected by their attitudes toward lottery-playing and gambling. This may imply that local Hong Kong investors may prefer to select lottery-type stocks when they choose to invest in the stock market. Hong Kong is, therefore, a suitable place to examine the effect of lottery-type payoff – extreme positive returns on stock returns.



(Source: Huang, 2009)

**Figure 1.1 A Comparison of the Hong Kong Exchange Hang Seng Index and some other Stock Exchange Indices**

**December 1969- December 2004**

There is also evidence that individual investors are more willing to purchase lottery-type stocks than institutional investors because of socio-economic and psychological factors (Kumar, 2009). In the survey of distribution of trading by type of trade in the Hong Kong Stock Exchange (HKEx) (see Table 1.1a and Table 1.1b), local investors (mainly local retail investors) had been major contributors to the largest proportion of trading value in the HKEx securities market for the past 20 years, compared with overseas investors. In conclusion, it is necessary to examine extreme positive returns in the Hong Kong stock market to see if the MAX effect is true only for the U.S. stock market.

**Table 1.1a Distribution of trading on the Hong Kong Stock Exchange by type of trade (1991-1999)**

Type of trade	1991 %	1992 %	1993 %	1994 %	1995 %	1996 %	1997 %	1998 %	1999 %	% of 1991- 1999 market turnover
Overseas agency trading	25.04	22.84	29.43	25.15	30.02	31.84	21.85	32.11	31.53	28.42
Retail trading	2.36	2.05	1.96	1.85	2.08	2.35	2.49	1.54	1.3	2.01
Institutional trading	22.68	20.79	27.47	23.3	27.94	29.49	19.36	30.58	30.23	26.41
Local agency trading	72.36	74.83	69.14	72.15	65.54	59.73	73.38	62.83	63.09	66.43
Retail trading	47.24	52.8	42.4	45.75	32.73	33.76	52.94	41.16	44.87	43.12
Institutional trading	25.12	22.03	26.74	26.4	32.81	25.97	20.44	21.67	18.22	23.3
Principal trading	2.6	2.33	1.43	2.7	4.43	8.43	4.77	5.06	5.38	5.15

(Source: Hong Kong Stock Exchange)

**Table 1.1b Distribution of trading on the Hong Kong Stock Exchange by type of trade (2000-2009)**

Type of trade	2000 %	2001 %	2002 %	2003 %	2004 %	2005 %	2006 %	2007 %	2008 %	2009 %	% of 2000-2009 market turnover
Overseas agency trading	30.19	40.23	37.08	38.84	36.34	36.14	41.47	43.1	41.49	41.84	40.65
Retail trading	2.13	2.58	2.39	4.1	3.36	2.34	2.96	3.81	3.24	4.32	3.43
Institutional trading	28.06	37.65	34.69	34.73	32.99	33.8	38.51	39.3	38.25	37.52	37.23
Local agency trading	66.91	55.77	56.27	57.67	56.77	56.3	53.12	52.75	52.39	49.66	53.38
Retail trading	49.38	36.27	32.46	29.69	34.29	29.78	27.34	27.5	25.88	25.2	28.36
Institutional trading	17.53	19.5	23.81	27.98	22.48	26.51	25.78	25.24	26.51	24.46	25.02
Principal trading	2.9	4	6.65	3.49	6.89	7.57	5.41	4.15	6.12	8.49	5.97

(Source: Hong Kong Stock Exchange)

The findings of this research will also contribute to asset pricing theory as well as having practical implications for investors. First, if the effect of extreme positive returns holds in the Hong Kong stock market, this means that Bali et al.'s (2011) findings of a negative MAX effect are not due to data snooping and could well be a pervasive anomaly. Second, our findings could also be used to generate profitable trading strategies. For example, if our evidence supports a negative MAX effect, investors can systematically increase returns by buying stocks with low MAX and short-selling stocks with high MAX. Finally, the findings of this research could also shed light on whether or not the puzzling negative relationship between the one-month lagged idiosyncratic volatility and future returns in

the stock market, as documented by Ang et al. (2006, 2009), can be explained by the MAX effect.

### **1.3 Research Objectives**

Given the growing interest in investigating the role of extreme daily returns in the previous month (MAX) in predicting future stock returns and a lack of empirical evidence to support Bali et al.'s (2011) findings, this study addresses the following two research objectives:

The first research objective is to examine whether maximum daily returns in the previous month (MAX) can predict the cross-sectional future stock returns in the subsequent month in the Hong Kong stock market using both portfolio analysis and Fama-Macbeth (1973) regressions.

The second research objective is to determine whether the puzzling negative cross-sectional relationship between one-month lagged idiosyncratic volatility and expected returns can be explained by the MAX effect in the Hong Kong stock market.

### **1.4 Research outline**

This study is reported in five chapters. Chapter 1 introduces the background and motivation for this research, the importance of the research and the research objectives. Chapter 2 presents a review of the previous literature with respect to this topic. Chapter 3 describes the source of the sample data, the derivation of the variables and methods used in this study. Chapter 4 discusses the findings of this study. Chapter 5 offers conclusions, implications of the results and limitations of this study.

## **Chapter 2 Literature**

### **2.1 Introduction**

According to the small amount of empirical literature studying the MAX effect on the stock market, this chapter will not only review the relevant studies of the MAX, but will also review the literature about the relevant interpretations behind that effect. For example, the reasons investors prefer for stocks with extreme positive returns and previous empirical studies on the relevant determinants of the cross-sectional expected returns. We will first review the study by Bali et al. (2011) because it is the only recent study on the MAX effect. We will then review the previous theoretical and empirical studies regarding the characteristics of lottery-type assets, the reasons people prefer for lottery-type assets, i.e., lotto, racetrack betting and lottery-type stocks, and the impact of investors' preferences for lottery and lottery-type assets on expected returns. Finally, we will review previous empirical evidence on certain known effects on asset pricing worldwide, i.e., firm size, book-to-market ratio, illiquidity, momentum, short-term reversals and idiosyncratic volatility.

### **2.2 The MAX effect**

Recently, Bali et al. (2011) investigated the significance of extreme daily returns over the previous month (MAX) in predicting future stock returns by considering the characteristics of investors' preferences for assets with lottery-type payoffs and poor diversification. By testing the common stocks of all NYSE, AMEX and NASDAQ

sample firms during the period from July 1962 to December 2005, the findings indicated a significant negative relationship between MAX and expected stock returns in the U.S. stock market.

During their investigation, Bali et al. (2011) initially employed single-sorting on MAX to test the variability in the subsequent stock returns. For the value-weighted decile portfolios, the raw return difference between the highest MAX and lowest MAX portfolios was -1.03% and the corresponding four-factor alpha difference was -1.18%. Both return differences were statistically significant at all standard significance levels. This means that stocks with the highest extreme returns have lower future returns than stocks with the lowest extreme returns. For the equal-weighted decile portfolios, the difference in raw returns between the highest MAX and lowest MAX portfolios was -0.65% per month with a t-statistic of -1.83. The highest-lowest difference in alphas was -0.66% with a t-statistic of -2.31. Although the results from the equal-weighted portfolios were less significant than the value-weighted portfolios, deciles 9 and 10 in the equal-weighted portfolios exhibited low future returns and negative alphas, similar to the pattern in the value-weighted portfolios.

Bali et al. (2011) then used alternative ways to obtain MAX by the average of the N (N=1, 2... 5) highest daily returns within a month instead of the single high extreme daily returns. The results showed the variability patterns of average returns and risk adjusted returns for both the value-weighted and equal-weighted portfolios sorted on multiple days

were similar to those on the single maximum daily return, except that the raw return and risk-adjusted return differences became more significant as more numbers of days of extreme daily returns were averaged.

In order to see if the result from the single-sorting portfolio-level analysis was robust, Bali et al. (2011) conducted double-sorting analyses to test the relationship between the average returns and the MAX after controlling for size, book-to-market ratio, momentum, short-term reversals and illiquidity. Both returns and alpha differences between the highest MAX and lowest MAX portfolios were negative and statistically significant after controlling for these variables. This implied that these well-known cross-sectional effects could not explain the lowest (highest) returns to stocks with the highest (lowest) MAX.

Bali et al. (2011) also employed Fama-Macbeth (1973) cross-sectional monthly regressions to examine the robustness of the MAX effect. The univariate regression results demonstrated a significantly negative relationship between MAX and future stock returns. The average slope coefficient on MAX alone was -0.0434 with a t-statistic of -2.92. The results of the full specification regression with MAX and the six explanatory variables indicated that the average slope coefficient on MAX was -0.0637 with a t-statistic of -6.16. These regression results provided strong evidence that certain known effects could not explain the significantly negative relationship between the extreme positive returns (MAX) and the expected stock returns.

Bali et al. (2011) also investigated the relationship between extreme positive returns and idiosyncratic volatility. They found that idiosyncratic volatility could not explain the negative MAX effect. In contrast, the MAX effect could reverse the negative relationship between the one-month lagged idiosyncratic volatility and future returns documented in Ang et al. (2006, 2009). The reason for the presence of the puzzling negative idiosyncratic volatility effect was that idiosyncratic volatility was a proxy for extreme returns.

In conclusion, the empirical evidence of Bali et al. (2011) documented a significantly negative relationship between maximum daily returns in the past month (MAX) and the expected stock returns. This result was robust to control for a number of known risk factors. This result implied that under-diversified investors were willing to pay more for stocks with lottery-type payoffs – extreme returns - causing these stocks to have low future returns.

### **2.3 Preference for Lottery-Type Assets and Expected Returns**

Previous studies provided evidence that investors have a preference for lottery-type assets, those defined as assets with a relatively small probability of a large return (Bali et al. 2009). Thaler and Ziemba (1988) documented two classic examples: racetrack betting and lotto games. For the favourite-longshots bias at racetracks, the expected payoff per dollar bet tended to increase monotonically with the probability of the horse winning.

Extreme favourites had more chances to win bets than the subjective probability – long shots, i.e., preference odds of more than 70% chance to win actually having positive expected returns. For lotto games, the expected return can be positive, but the chance of winning prizes is extremely small. One of the most attractive features of lotto games is that the grand prizes are carried over to the next draw if no one wins the jackpot in a given draw, which also makes the expected value extremely large. Quandt (1986) suggested that racetrack bettors are risk-seeking with the mean-variance utility function referring to the favourite-longshots bias, because bettors prefer high-variance, low-mean return bets (long shorts). In contrast, from the evidence of Golec and Tamarkin (1998) regarding the long shot anomaly, in which low-probability, high variance bets (long shot) generate low mean returns and high-probability, low variance bets generate relatively high mean returns, their findings documented that racetrack bettors are risk-averse and prefer positive skewness of returns - they are not risk lovers. Garrett and Sobel (1999) extended the study of Golec and Tamarkin (1998) by modelling and testing an expected utility function for lottery players. Their theoretical and empirical evidence indicated that lottery participants, like racetrack bettors, are risk averse and prefer positive skewness of returns.

In the context of security markets, Kumar (2009) provided evidence that people's preference toward gambling affects their decisions about stock investments and stock returns. He further stated that individual investors preferred to invest more in stocks with lottery-type features, which are identified as high variance (or high idiosyncratic volatility or extreme returns) stocks with low prices and positive skewness of returns. He

also said that investors who held riskier lottery-type stocks are not necessarily risk lovers, but rather they like positively skewed returns, even though they are extremely small. This is consistent with previous studies that showed those investors who exhibited a preference for lottery or lottery-type stocks were risk-averse.

According to the cumulative prospect theory of Tversky and Kahneman (1992), investors transformed objective probabilities by applying a weighting function, in which the main effect was to overweight the tails of a probability distribution. This trait helped to explain the reasons for investors' demand for lotteries or gambling, which provided a relatively small chance of a large payoff. Investors preferred stocks with positively skewed returns under the cumulative prospect theory. Barberis and Huang (2008) conducted an analysis about the implications of the cumulative prospect theory for pricing financial securities, where the results indicated that stocks with positively skewed returns can be overpriced and thus, earn extremely low expected returns. The evidence for low future returns to positively skewed assets is also consistent with the optimal beliefs framework (Brunnermeier, Gollier & Parker, 2007). Given their model, they claimed that investors optimally overestimated expected payoffs of their portfolios in order to maximise their present utility. Such optimism led to low average stock returns.

In conclusion, investors who exhibited a preference for lottery or lottery-type securities actually preferred lottery-type payoffs rather than variance (risks), which implies that those investors are risk-averse. Lottery-type stocks can be overpriced, and earn very low

expected returns. In addition, the empirical findings of Bali et al. (2011) provided evidence that investors who were willing to pay more for stocks with extreme positive returns will experience low expected returns and investors actually exhibited a preference for extreme positive returns rather than idiosyncratic volatility when purchasing lottery-type stocks.

## **2.4 Stock Preference and Under-diversification**

Idiosyncratic volatility could be reduced through portfolio diversification. However, in reality individual investors hold under-diversified portfolios. Traditional determinants for portfolio under-diversification have been discussed extensively in previous studies, i.e., small portfolio size, transaction and searching costs and stock preferences. In this study, we will review only the literature regarding under-diversification caused by stock preferences.

Many investors exhibit a preference for certain types of stocks such as those with positively skewed returns (Barberis & Huang, 2008; Golec & Tamarkin, 1998; Kumar, 2009), which could cause under-diversification. Investors choose to hold under-diversified portfolios because of their preferences for skewed returns, not variance (or idiosyncratic volatility). Goetzmann and Kumar (2004) conducted an investigation regarding the issue of whether preferences for certain types of stocks led to under-diversification by studying low and high diversification investor groups (quintiles) using

the Fama-MacBeth cross-sectional regressions. The regression results showed that the less diversified investors had a preference for stocks with higher skewness of returns and stocks with greater volatility and market beta. Mitton and Vorkink (2004) showed, theoretically, that investors' heterogeneous preference for skewness led to under-diversification in equilibrium based on their model. They also showed empirical evidence to corroborate their theoretical results using a dataset of investment accounts from over 60,000 households in the sample period January 1991 to November 1996. They documented that under-diversified investors held substantially more positively skewed returns in their portfolios than diversified investors. Moreover, they also showed that under-diversified investors intentionally traded lower mean-variance efficiency to obtain higher skewness of returns. Under-diversified investors selected highly skewed stocks to increase their portfolios' skewed returns more than diversified- investors.

## **2.5 Cross-sectional Effects on Expected Stock Returns**

Since the single factor (beta) was explored by the framework of Capital Asset Pricing Model (CAPM), many empirical studies have suggested the importance of additional variables in asset pricing, such as firm size, book-to-market ratio and idiosyncratic volatility. The following sub-sections will present evidence for additional variables in predicting the cross-sectional asset returns.

### **2.5.1 The Size Effect**

The exploration of the relationship between the total market value of the common stock of a firm and its expected returns traces back to the early 1980s. Banz (1981) examined the relationship between firm size and stock returns on the common stock of NYSE firms for the period 1926-1975 using a generalised asset pricing model. He concluded that small firms generated greater risk-adjusted returns than large firms, which implied a negative relationship between firm size and expected stock returns. Due to there being no theoretical foundation to support his findings at that time, Banz (1981) suggested that insufficient information about small firms caused limited diversification, and thus led to undesirable stocks of small firms having higher returns. The study of Reinganum (1981) indicated that small firms yielded significantly larger average returns than large firms after controlling the earnings-to-price ratio (E/P ratio) in terms of a sample of AMEX-NYSE firms, but the P/E ratio effect on stock returns disappeared after controlling for firm size. This implied that the E/P ratio is a proxy for firm size but not vice-versa.

Roll (1981) gave an opposite interpretation with regard to the firm size effect. He asserted that the abnormal returns caused by small firms might be attributed to improper estimation of the portfolios' betas. Trading infrequency for small firms led to underestimating risk measures and produced upward biased measures of rate of risk-adjusted returns. As a result, the size effect is suspected to be a proxy for risk. Following Roll (1981)'s conjecture, Reinganum (1982) conducted a study to verify whether mis-assessment of risk was sensitive to infrequent trading of securities by using the data on market capitalisation of securities for the NYSE and AMEX sample of firms instead of using Roll's (1981) time series data of returns for value-weighted and equally-weighted

indexes. Reinganum's (1982) tests demonstrated that small firms yielded greater rates of average risk-adjusted returns than large firms by more than 30% on an annual basis, and the difference in the estimation of betas between the small firms and the large firms was only 0.7. Consequently, Reinganum (1982) concluded that the downward biased measures of portfolio betas for small firms did not influence the large returns produced by small firms, so firm size still significantly and negatively affected portfolio excess returns.

Keim's (1982) findings confirmed Reinganum's (1982) results that the bias in risk measurement corroborated Roll's (1981) conjecture that portfolio risk-adjusted returns still showed an obviously negative relationship with firm size. Keim (1982) employed samples of the NYSE and AMEX firms from 1963 to 1979 to investigate the monthly relationship between stock returns and firm size (market value of securities). His empirical findings showed that there was a significant negative relationship between returns and firm size, particularly in January. He further indicated that nearly 50% of the firm size effect was attributable to abnormal returns in January, in which more than 50% was due to great abnormal returns in the first week of the year, especially the first trading day.

A study by Fama and French (1992), based on non-financial stocks of NYSE, AMEX and NASDAQ firms over the period 1963-1990, revealed that firm size displayed a strong effect in determining the variations of cross-sectional stock returns and the size effect

was independent and robust when adding other explanatory variables such as book-to-market ratio and E/P ratio. This implied that firm size is a proxy for risk.

With the firm size effect in the U.S. stock market, many scholars also examined whether this effect could predict future stock returns in stock markets outside the U.S.A. The first empirical evidence on the robustness of the multifactor model in the Pacific-Basin region, Korea, Taiwan, Malaysia, Thailand and Hong Kong, was produced by Chui and Wei (1998). Using Fama and Macbeth (1973) regressions during the period July 1977 - June 1993, they concluded that firm size had a pronounced impact on explaining the average stock returns. There were especially strong small firm effects in the Korean stock market in January. Fama and French (1998) conducted a similar study on the firm size effect on 16 global emerging market returns during 1987-1995. They corroborated the existence of a size effect that small firms tended to yield higher average stock returns than large firms.

Drew, Naughton and Veeraraghavan (2003) also employed the multifactor asset-pricing model to examine the size effect on the average stock returns in the Shanghai Stock Exchange in China over 1993-2000. They found that small and growth firms tended to earn greater returns than large and valued firms. This was consistent with the findings of Drew and Veeraraghavan (2003) who suggested that small firms generated higher returns than big firms in four emerging markets in Asia (Hong Kong, Korea, Malaysia and the Philippines), using the multifactor model approach.

In contrast to the existence of empirical evidence on the firm size effect, Lam (2002) documented that there was a positive relationship between firm size and future stock returns in the Hong Kong stock market during the period July 1984- June 1997. Lam (2002) used the Fama and Macbeth (1973) approach to run monthly cross-sectional regressions that indicated that firm size tended to capture the variation in future stock returns. However, there was an obvious limitation in Lam's (2002) tests in that he only chose 100 stocks out of nearly 1000 stocks traded on the Hong Kong stock market at the time of the tests. Consequently, any bias in selecting the sample data might lead his findings to be criticised by other researchers.

In summary, firm size generally had a significantly negative influence in cross-sectional pricing of stocks.

### **2.5.2 The Book-to-Market Ratio Effect**

Much empirical research has revealed that the book-to-market ratio and firm size were the two most important factors in the cross-sectional pricing of stocks. Fama and French (1992) indicated that firm size and book-to-market ratio effects contributed to the variation in the cross-section of average stock returns. They also documented that the firm size effect had a significantly negative effect, but the book-to-market ratio had a strong positive relationship with average returns. Following Fama and French (1992), Fama and French (1993) extended the tests of asset pricing by using time series

regressions. They found that size and book-to-market ratio captured most variation in average stock returns, which implied that size and the book-to-market ratio were proxy for risk factors in stock returns. Fama and French (1992, 1993) showed supporting evidence for the earlier study by Stattman (1980), who first posited the book-to-market ratio effect on asset pricing. He reported that the book-to-market ratio positively related to future stock returns in the U.S. stock market.

Like the firm size factor, the book-to-market ratio as a proxy for common risk factors has been examined widely in global stock markets. For example, Chan, Hamao and Lakonishok (1991) conducted a study on the predictability of the cross-section of expected returns in the Japanese stock market covering the period from 1971 to 1988. Their findings demonstrated that the book-to-market ratio generated a strong positive effect on future stock returns. Chui and Wei (1998) also showed evidence from Asian emerging markets that the book-to-market ratio played a significant role in determining the variation in expected stock returns in Hong Kong, Korea and Malaysia.

Fama and French (1998) provided international evidence of the book-to-market ratio effect. Their main findings revealed that, in 12 of 13 major stock markets during 1975-1995, value stocks that had a high book-to-market ratio tended to generate greater average stock returns than growth stocks that had a low book-to-market ratio. This was consistent with the results of the study by Drew and Veeraraghavan (2003). Employing the three-factor model, their analysis suggested that small and high book-to-market ratios

earned higher returns than big and low book-to-market ratios in four Asian emerging stock markets.

Lam (2002) also investigated the relationship between the book-to-market ratio and future stock returns on the Hong Kong stock market. His analysis confirmed the effect of the book-to-market ratios in capturing the cross-sectional variation of expected returns using the Fama and French (1992) approach.

In conclusion, numerous tests on asset pricing around the world's stock markets showed that the significance of the book-to-market ratio in explaining expected stock returns was as important as the firm size effect.

### **2.5.3 The Idiosyncratic Volatility Effect**

Recently, there has been a popular issue about idiosyncratic volatility effect for predicting cross-sectional expected returns. Much previous theoretical and empirical evidence indicated that idiosyncratic volatility played a significant role in explaining the variability of expected returns. However, there has been debate about whether idiosyncratic volatility had a positive or negative relationship with the expected returns. For example, Ang, Hodrick, Xing and Zhang (2006, 2009) documented a significant negative relationship between idiosyncratic volatility and the expected returns, whereas

other groups of researchers demonstrated a positive relationship, i.e., Bali and Cakici (2009), Fu (2009), Malkiel and Xu (2002) and Nartea, Ward and Yao (forthcoming).

Malkiel and Xu (2002) showed that the idiosyncratic volatility variable had an important role in explaining the cross-section of expected returns in both the U.S. and Japanese stock markets when investors were unable to hold the market portfolio. In particular, the effect of idiosyncratic volatility persisted after controlling for firm characteristics such as size, book-to-market ratio and liquidity. Malkiel and Xu (2002) found that idiosyncratic volatility was more pronounced in predicting the cross-section of expected stock returns than market beta and size. Drew, Naughton and Veeraraghavan (2004) presented supporting evidence that idiosyncratic volatility had a significant effect on asset pricing in the Shanghai Stock Exchange, China. However, they suggested that small and low idiosyncratic volatility yielded greater returns than large and high idiosyncratic volatility.

Similarly, Ang et al. (2006) documented that stocks with high idiosyncratic volatility tended to earn low expected returns when the idiosyncratic volatility was measured relative to the Fama and French (1993) three-factor model. To check the robustness of their findings, Ang et al. (2006) employed a double-sorted portfolio analysis to test the significance of the idiosyncratic volatility. The results revealed that low average returns were still pronounced for stocks with high volatility after controlling for various cross-sectional risk variables including size, book-to-market ratio, leverage, liquidity risk, volume, turnover, bid-ask spreads, skewness risk and dispersion in analysts' forecasts

based on NYSE stocks. Ang et al. (2006) also posited that their findings could not be explained by exposure to aggregate volatility risk and that the negative relationship between idiosyncratic volatility and expected returns were a substantive puzzle for relevant financial theories.

Following Ang et al.'s (2006) study, a more recent study by Ang, Hodrick, Xing and Zhang (2009) provided international evidence to corroborate the negative relationship between idiosyncratic volatility and expected returns. They argued that it was hard to be convinced of the robustness of Ang et al.'s (2006) results because of a small sample size. Consequently, Ang et al. (2009) investigated the relationship between idiosyncratic volatility and future average returns across 23 countries, where idiosyncratic volatility was defined relative to local, regional and world versions of Fama and French's (1993,1998) approach. Ang et al.'s (2009) findings showed that there was a statistically significant negative relationship between idiosyncratic volatility and future average returns in the seven large security markets - Canada, France, Germany, Italy, the U.K., the U.S. and Japan. However, compared with Ang et al.'s (2006) study, Ang et al. (2009) focused on the cross-sectional relationship between idiosyncratic volatility and expected returns using Fama and Macbeth (1973) regressions. Furthermore, Ang et al. (2009) confirmed that the robustness of the idiosyncratic volatility effect world-wide was not just a sample-specific or country-specific effect.

Motivated by the existing studies regarding conflicting empirical evidence on the cross-sectional relationship between idiosyncratic volatility and expected returns, Bali and Cakici (2009) conducted a study on the idiosyncratic volatility effect based on: 1) data frequency (daily and monthly data) used to measure idiosyncratic volatility, 2) weighting schemes (value-weighted, equal-weighted and inverse volatility-weighted used to estimate portfolio average returns, 3) breakpoints (CRSP, NYSE and 20% market capitalisation) used to construct portfolios by sorting stock returns, and 4) two types of sample data (NYSE/AMEX/NASDAQ and NYSE) for the period July 1958-December 2004. The findings of Bali and Cakici (2009) illustrated that when idiosyncratic volatility was measured by monthly data, there was no evidence showing that idiosyncratic volatility explained the cross-sectional expected returns for all three breakpoints and three weighted schemes. When idiosyncratic volatility was estimated by daily data, the empirical evidence showed a negative relationship between idiosyncratic volatility and expected returns only when the value-weighted portfolios were formed in terms of the CRSP breakpoint. However, they found monthly idiosyncratic volatility was a better estimator of future volatility than daily idiosyncratic volatility. They concluded, therefore, that there was no robustly significant relationship between idiosyncratic volatility and the expected returns.

Fu (2009) argued that Ang et al.'s (2006) findings cannot represent the relationship between idiosyncratic volatility and expected stock returns, which is attributed to idiosyncratic volatility varying across time, and that lagged idiosyncratic volatility is not able to predict expected returns well. He further reported that the expected idiosyncratic

volatility had a significant positive relationship with the expected returns using the EGARCH model. Fu's (2009) findings are consistent with under-diversification theories that stocks generate high expected return compensation for having high expected idiosyncratic volatility.

While these results identified an interesting puzzle, Huang, Liu, Rhee and Zhang (2010) demonstrated that there was no negative relationship between idiosyncratic volatility and value-weighted portfolio returns in the following month and no relationship between idiosyncratic volatility and equal-weighted portfolio returns. These two findings were - both explained by short-term monthly return reversals. They defined the reason that stocks in the value-weighted portfolio with the highest idiosyncratic volatility tended to be either winner stocks or loser stocks. The winner stocks were more likely to be large cap stocks than the loser stocks in the portfolio formation month, which led to low returns of the value-weighted portfolio in the following month. In the equal-weighted portfolio, return reversals of winner and loser stocks offset each other, which led to no relationship between idiosyncratic volatility and expected returns. Furthermore, their cross-sectional regression supported that there was no significant relationship between idiosyncratic volatility and expected returns after controlling for short-term reversals. Thus, they concluded that return reversals was the underlying reason of why there was a negative relationship between idiosyncratic volatility and stock returns in the following month.

In addition, the most recent study by Wong (2011) found that the negative idiosyncratic volatility effect was explained by earning momentum effect and post-formation earnings shocks. After controlling for these two effects, idiosyncratic volatility had little impact on predicting stock returns. He also found that the earnings momentum effect alone accounted for approximately 42% of the idiosyncratic volatility effect. Boquist (2010) also found that the negative idiosyncratic volatility effect can be driven by illiquidity. If only liquid firms were included, there was a flat relationship between idiosyncratic volatility and subsequent returns. Moreover, he documented that a portion of the puzzling negative relationship between idiosyncratic volatility and stock returns can be explained by extreme returns (either positive or negative).

#### **2.5.4 The Short-Term Reversal Effect**

Jegadeesh (1990) investigated the role of individual stocks' monthly returns in predicting average returns during the period 1934-1987. The evidence documented in his study indicated that there was a significant negative first-order serial correlation in individual securities' monthly returns, which implied that the individual stock returns predictability in a given month tended to exhibit a negative effect on the predictability of stock returns in the next month. Following Jegadeesh's (1990) findings, Lehmann (1990) examined the significance of the weekly returns of individual securities on NYSE and AMEX stocks for the period 1962-1986. He found that stocks with positive (negative) returns in a given week generated negative (positive) returns in the following week. Combining the empirical results documented by Jegadeesh (1990) and Lehmann (1990), showed that

individual securities that have positive (negative) returns in a month or week tended to show negative (positive) returns in a subsequent month or week. That phenomenon is called the short-term reversal phenomenon.

In addition, Jegadeesh and Titman (1995) revealed supporting evidence from NYSE stocks during the period 1963-1979 that short-term return reversals can be explained by the way the bid and ask prices were set by dealers with respect to their inventory imbalance. They further pointed out that reversal trading profits were compensated for bearing inventory risk and traders could not realise these trading profits at bid-ask prices during the transactions. In a related study, Huang et al. (2010) provided supportive evidence that there is a significantly negative relationship between returns in the past one-month and returns in the current month, thereby indicating a strong return reversal effect. They also demonstrated that return reversals were the driving force of the puzzling negative relationship between idiosyncratic volatility and stock returns in the subsequent month.

### **2.5.5 The Momentum Effect**

The short-term reversal effect in the previous section documented by Jegadeesh (1990) and Lehmann (1990) generated significantly abnormal returns based on contrarian strategies that concentrated on trading strategies in terms of very short time horizons return reversals, i.e., one week or one month. However, Jegadeesh and Titman (1993) conducted a study on the relative strength of trading rules based on stock price

movements from the past three to 12 months. By analysing stocks listed in the NYSE and AMEX during the period 1965-1989, their findings suggested that trading strategies that buy past winners and sell past losers over the previous three to 12 months tended to earn significantly abnormal returns. For example, losers in the past six months usually lost money in the next six months and winners in the past six months continued to gain money in the next six months. In other words, previous stock returns tended to predict expected stock returns. Their findings also suggested that the profitability of the relative strength strategies was caused by delayed price reactions to firm-specific information. Furthermore, an earlier study referred to the relative strength strategies by Levy (1967) who documented supportive evidence that a trading strategy that buys previous winners (stocks with current prices that are much greater than average prices) over the last 27 weeks generated abnormal returns for the stocks listed on NYSE during the periods October 1960 to October 1965.

### **2.5.6 The Illiquidity Effect**

Amihud and Mendelson (1986) explored the relationship between stock illiquidity and expected returns of stocks listed on the NYSE for the period 1961-1980. In their study, illiquidity was measured by the spread between the bidding and asking prices. Their results suggested that expected stock returns were an increasing function of the bid-ask spread, which meant that stocks with wider-spreads generated greater expected returns. That implied that expected returns were positively correlated with illiquidity. They also presented a clientele effect, which meant that investors with longer holding periods held

stocks with higher spreads. Hence, investors willing to accept longer holding periods could earn higher returns by holding illiquid (higher bid-ask spread) assets.

In addition, Brennan and Subrahmanyam (1996) conducted a study of the relationship between stock returns and illiquidity. They focused on intraday transaction data for estimating illiquidity and used the Fama and French (1992) approach to adjust for risk. Their findings indicated that measures of illiquidity significantly affected average stock excess returns.

However, Amihud (2002) argued that previous studies on measures of illiquidity such as the bid-ask spread, transaction-by-transaction market impact or the probability of information in terms of trading might not be available in many stock markets and could not cover very long time periods. Consequently, he employed the average ratio of absolute stock returns to their dollar volume as a measure of illiquidity. Using stocks listed on the NYSE over the periods from 1964 to 1997, the findings showed that expected returns were an increasing function of illiquidity and market expected illiquidity positively affected *ex ante* stock excess returns.

## **2.6 Conclusions**

According to the review, the only study of the effect of extreme positive returns on expected returns done by Bali et al. (2011) revealed that there was an economically and

statistically significantly negative relationship between the extreme positive returns measured by the maximum daily returns in the previous month (MAX) and the cross-section of expected returns in the U.S. stock market. The previous theoretical and empirical studies explaining the MAX effect documented in Bali et al. (2011) showed that under-diversified investors (mainly retail investors) prefer stocks with extreme positive returns, which caused these stocks to exhibit low expected stock returns.

In addition, we reviewed previous empirical studies on certain known risk factors in asset pricing based on the variables used in the robustness test in Bali et al. (2011). Table 2.1 summarises the well-known effects of a cross-section of expected stock returns worldwide.

**Table 2.1 Summary of the literature on certain known risk factors on expected stock returns**

<b>Effect</b>	<b>Authors</b>	<b>Period</b>	<b>Sample Data</b>	<b>Results</b>
Size	Banz (1981)	1926-1975	NYSE common stocks in U.S.	Small firms generated higher risk-adjusted returns than large firms
	Roll (1981)	1962-1977	S&P 500 and Equal-weighted indexes in U.S.	Trading infrequency for small firms caused under-estimating risk measures and over-estimating risk-adjusted returns. The size effect was suspected to be proxy to risk.
	Keim (1982)	1963-1979	NYSE and AMEX common stocks in U.S.	A significant negative relation between size and expected returns, especially for January
Size and Book-to-Market Ratio (BTM)	Fama and French (1992)	1963-1990	Non-financial stocks of NYSE, AMEX and NASDAQ in U.S.	Size displayed a strong negative effect on expected returns, but BTM had a significant positive effect. Both effects contributed to explain expected stock returns
	Fama and French (1993)	1963-1991	All NYSE, AMEX and NASDAQ in U.S.	Size and BTM captured the most variation in average stock returns
	Fama and French (1998)	1987-1995 and 1975-1995	16 global emerging market and 15 major stock markets	Small firm effect and BTM effect confirmed in 16 global emerging market for 1987-1995 and Value stocks (high BTM) generated greater average returns than growth stocks (low BTM) in 12 out of 13 major markets for 1975-1995
	Chui and Wei (1998)	July 1977-June 1993	Pacific-Basin emerging markets: Korea, Taiwan, Malaysia and Hong Kong	A significant negative relation between size and expected returns, especially a strong small size effect on Korean stock market in January, and BTM had a significant positive relation with expected returns in those five countries

<b>Effect</b>	<b>Authors</b>	<b>Period</b>	<b>Sample Data</b>	<b>Results</b>
Size and Book-to-Market Ratio (BTM)	Drew, Naughton and Veeraraghavan (2003)	1993-2000	Shanghai Stock Exchange in China	Small (size) and growth firms (low BTM) generate superior risk-adjusted returns than big (size) and value firms (high BTM)
	Drew and Veeraraghavan (2003)	December 1991- December 1999	Four emerging markets: Hong Kong, Korea, Malaysia and Philippines	Small (size) and high BTM firms generated higher returns than big and low BTM firms in 4 emerging markets
	Lam (2002)	June 1984- June 1997	Hong Kong Stock Exchange in Hong Kong	A positive relation between size and expected returns and both firm size and BTM captured the variation in average monthly returns
Idiosyncratic Volatility (IVOL)	Malkiel and Xu (2002)	1975-1999	NYSE, AMEX and NASDAQ stocks in U.S. and Tokyo Stock Exchange (TSE) in Japan	IVOL had an important role in explaining the cross-section of expected returns in both markets, even more pronounced than beta and size
	Drew, Naughton and Veeraraghavan (2004)	1993-2000	Shanghai Stock Exchange in China	Small and low IVOL yielded greater returns than large and high IVOL. IVOL played an important role in explaining expected returns
	Ang, Hodrick, Xing and Zhang (2006)	1963-2000	NYSE, AMEX and NASDAQ stocks in U.S.	A significant negative relationship between IVOL and expected returns
	Ang, Hodrick, Xing and Zhang (2009)	1980-2003, 1963-2000	23 countries including U.S.	High IVOL and low return relation were strongly statistically significant
	Bali and Cakici (2009)	July 1958- December 2004	NYSE, AMEX and NASDAQ stocks in U.S.	There was no robustly significant relation between IVOL and expected returns

<b>Effect</b>	<b>Authors</b>	<b>Period</b>	<b>Sample Data</b>	<b>Results</b>
Idiosyncratic Volatility (IVOL)	Fu (2009)	July 1963-December 2006	NYSE, AMEX and NASDAQ stocks in U.S.	Stocks generated high expected returns compensation for having high expected IVOL
Short-term Reversal	Jegadeesh (1990)	1934-1987	CRSP monthly returns in U.S.	Stock returns predictability in a given month tended to exhibit a negative effect on stock returns predictability in the next month
	Lehmann (1990)	1962-1986	All NYSE and AMEX stocks in U.S.	Stocks with positive (negative) returns in a given week generated negative (positive) returns in the next week
Momentum	Jegadeesh and Titman (1993)	1965-1989	All NYSE and AMEX stocks in U.S.	Trading strategies that buy past winners and sell past losers over the previous 3 to 12 months earned significant abnormal returns
	Levy (1967)	October 1960-October 1965	NYSE stocks in U.S.	A trading strategy that buys past winners in the past 27 weeks generated abnormal returns.
Illiquidity	Amihud and Mendelson (1986)	1961-1980	NYSE stocks in U.S.	Stocks with higher bid-ask spread generated higher future returns, which implies expected returns positively correlated with illiquidity
	Amihud (2002)	1964- 1997	NYSE stocks in U.S.	Expected returns were an increasing function of illiquidity and market expected illiquidity positively affected ex ante stock excess returns

## **Chapter 3 Data and Methods**

### **3.1 Introduction**

This chapter describes the sample data and test methods employed in this study. The layout of this chapter is as follows. First, the research objectives of this study are introduced, followed by a description of the Hong Kong stock market. Then the data collection methods are documented, followed by a presentation of the control variables relevant to this study. The test methods for this study, including portfolio-level analysis and firm- level cross-sectional regressions, are presented in the last section of this chapter.

### **3.2 Research Objectives**

There are two research objectives in this study, as presented briefly in chapter one. In this section, we detail these two research objectives.

The first research objective is to examine whether the maximum daily returns in the previous month (MAX) can predict the cross-sectional future stock returns in the subsequent month in the Hong Kong stock market using both portfolio analysis and Fama-Macbeth (1973) regressions. According to Bali et al. (2011), there is a statistically significantly negative relationship between extreme positive returns measured by MAX and future returns in the subsequent month in the U.S. stock market. This MAX effect is also robust to control for certain known effects, namely size, book-to-market ratio, short-

term reversals, momentum, illiquidity, idiosyncratic volatility and skewness, which they demonstrated by both portfolio analysis and cross-sectional Fama-Macbeth (1973) regressions. However, so far, the effect of MAX had only been observed in the U.S. stock market, so this study conducts similar tests as Bali et al. (2011) in the Hong Kong stock market seeking support for the MAX effect on the cross-sectional pricing of stocks. Following Bali et al. (2011), we use double-sorting to control for the variables of interest including size, book-to-market ratios, short-term reversals, momentum, illiquidity, idiosyncratic volatility, skewness and market beta. We also used Fama-Macbeth (1973) regressions to simultaneously control for all variables of interest.

The second research objective is to determine if the puzzling negative relationship between idiosyncratic volatility and expected returns can be explained by the MAX effect in the Hong Kong stock market. Ang et al. (2006, 2009) identified a puzzling negative and significant relationship between the one-month lagged idiosyncratic volatility and expected returns in the U.S. stock market. This evidence meant stocks with high idiosyncratic volatility generated low subsequent returns. However, Bali et al. (2011) suggested that there was no relationship between idiosyncratic volatility and expected stock returns in the U.S. stock market. Instead, the MAX effect reversed the puzzling negative relationship between lagged idiosyncratic volatility and future returns. Bali et al. (2011) concluded that the reason for the presence of the negative idiosyncratic volatility effect was that idiosyncratic volatility was a proxy for extreme returns. Thus, it was necessary to reinvestigate if the puzzling negative idiosyncratic volatility effect can be explained by the MAX effect in the Hong Kong stock market using both portfolio

analysis and Fama-Macbeth (1973) regressions. Before doing so, this study first examined if there was a negative idiosyncratic volatility effect on the Hong Kong stock market.

### **3.3 Description of Hong Kong Stock Market**

The Stock Exchange of Hong Kong is the main exchange for shares traded in Hong Kong. The history of the Hong Kong Stock Exchange can be traced back to the late 19<sup>th</sup> century. The exchange was first established in 1891 and named the Association of Stockbrokers. It changed its name to the Hong Kong Stock Exchange in 1914. In 1921, the Association of Stockbrokers in Hong Kong was incorporated as a second exchange. After over two decades, in 1947, the Association of Stockbrokers was unified with the Hong Kong Stock Exchange. In 2000, the Stock Exchange of Hong Kong Limited (SEHK), the Hong Kong Futures Exchange Limited (HKFE) and Hong Kong Securities Clearing Company (HKSCC) were incorporated into one holding company named the Hong Kong Exchanges and Clearing Limited (HKEx), a publicly traded company (HKEx, 2009; Investopedia, 2010).

The Hong Kong Stock Exchange (HKSE) securities market consists of two trading platforms- the Main Board and the Growth Enterprise Market (GEM). The Main Board is the market for the capital growth of established companies to meet their profit requirements. The GEM, which opened in 1999, offers a fund raising venue for “high

growth, high risk” companies. It promotes technology industry development and makes access to the capital market easier for riskier businesses (Advfn, 2011).

As of 31 December 2010, the Hong Kong Stock Exchange (main board) had 1,244 listed companies with a total market capitalisation of nearly 21 trillion HKD and total turnover of 5.4 trillion HKD (HKEx, 2010). Today the HKSE ranks eighth in the world and is the third largest stock exchange in Asia, behind the Tokyo Stock Exchange and Shanghai Stock Exchange, based on market capitalisation (Advfn, 2010). The Hong Kong Stock Market’s initiatives should reinforce Hong Kong’s standing as an international financial centre and support China’s further development (Company profile, 2010). Table 3.1 presents the recent general information about the main board of Hong Kong Stock Exchange.

**Table 3.1 Hong Kong Stock Exchange: The Main Board**

(As of 31 December 2010)

<b>General information</b>	<b>2010</b>	<b>2009</b>	<b>2008</b>	<b>2007</b>	<b>2006</b>
<b>No. of listed companies</b>	1,244	1,145	1,087	1,048	975
<b>No. of listed securities</b>	7,730	6,441	5,654	5,896	3,184
<b>Total market capitalization (HK\$Million)</b>	20,942,284	17,769,271	10,253,589	20,536,463	13,248,821
<b>Average P/E ratio (times)</b>	16.67	18.13	7.26	22.47	17.37
<b>Average dividend yield (%)</b>	2.31	2.33	5.38	2.21	2.19

(Source: Hong Kong Stock Exchange)

### **3.4 Data Collection**

#### **3.4.1 Sample Data Selection and Sample Period**

The sample stocks that were traded on the main board of the Hong Kong Stock Exchange were examined during the sample period from January 1990 to December 2009. This research did not include stocks listed on the GEM, which was established in 1999. Also, the history of GEM was not long enough to be used for this research. The sample data for stocks from Hong Kong Stock Exchange (Main Board) were obtained from the DataStream database.

#### **3.4.2 Daily and Monthly Returns for Individual Stocks**

The data of daily and monthly returns of individual stocks were obtained from DataStream for the sample period 1990-2009, where the data for the individual stock

return was named “Total Return Index”. The “Total Return Index” was actually adjusted prices for stocks that have already been modified by capital distribution such as dividend reinvestment (or payment) and share repurchase. Thus, further calculations were needed to obtain daily and monthly stock returns, taking the natural logarithm of the ratio of individual stock prices at time  $t+1$  relative to stock prices at time  $t$ .

The daily stock returns were used to calculate the maximum daily returns for stocks in every month and to compute the monthly idiosyncratic volatility and market beta in the relative models. The monthly stock returns were used to compute the monthly variables, including intermediate-term momentum and short-term reversals.

### **3.4.3 Market Value (Market Capitalisation) for Individual Stocks**

Data on daily and monthly market value (market capitalisation) for each stock were obtained directly from DataStream covering the period from January 1990 to December 2009. Daily data on the market value of each stock were used to calculate the value-weighted daily market returns when we computed monthly idiosyncratic volatility and monthly beta. The monthly market values were used to represent monthly size (SIZE) for individual stocks. Following most previous studies, the firm size was computed by the natural logarithm of the market value at the end of month  $t-1$  for each stock because they were significantly skewed.

#### **3.4.4 Book-to-Market Ratio for Individual Stocks**

Data on monthly market-to-book ratio values for individual stocks were obtained directly from DataStream. Those data were used to calculate the book-to-market ratios for individual firms by taking the inverse of the market-to-book ratio. The book-to-market ratio (BTM) variable was used in both the double-sorting portfolio-level analysis and the cross-sectional regressions.

#### **3.4.5 The Trading Volume and Risk-Free Rate**

The monthly trading volume data for each stock were obtained directly from DataStream and were used to calculate the monthly illiquidity of the monthly returns for individual stocks. The daily risk-free rate for the Hong Kong stock market was obtained from DataStream during the period from 1 January 1990 to 1 December 2009. We chose the Hong Kong prime rate as the suitable risk-free rate in this study. The daily risk-free rate was used to compute daily excess individual returns as well as the daily excess value-weighted market returns.

### **3.5 Measurement of the Variables**

#### **3.5.1 Extreme Positive Returns for Individual Stocks**

The extreme positive return for a stock was measured by the maximum daily return in the previous month (MAX) during the sample period. For example, a stock with the MAX

value at the beginning of May 1990 represented the maximum daily returns in the month of April 1990.

### 3.5.2 Estimating the Market Beta

The market beta (Beta), also called systematic risk, was derived from the Capital Asset Pricing Model (CAPM). Since the CAPM model stated there was a positive relationship between asset returns and market risks denoted by  $\beta$ , many scholars have conducted studies on this fundamental theory and found that the CAPM cannot predict the expected returns. Because of the failure of the CAPM to explain cross-sectional returns and the well-known Fama and French (1993) three-factor approach in the asset-pricing field, monthly market beta in this study was computed using the FF-3 factor model:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + s_iSMB_d + h_iHML_d + \varepsilon_{i,d}$$

where  $R_{i,d}$  is an individual stock  $i$ 's return on day  $d$ ,  $R_{f,d}$  is the risk-free rate on day  $d$ ,  $R_{m,d}$  is the value-weighted market return on day  $d$ ,  $R_{i,d} - R_{f,d}$  is the daily excess returns of an individual stock,  $R_{m,d} - R_{f,d}$  is the daily excess valued-weighted market returns,  $\varepsilon_{i,d}$  is the idiosyncratic return on day  $d$ .  $SMB_d$  is the difference in average returns between the three small-stock portfolios (S/L, S/M and S/H) and the big-stock portfolios (B/L, B/M and B/L) so this difference should have no influence on book-to-market ratios. The SMB should concentrate only on the different return behaviours of small and large stocks.  $HML_d$  is the difference in average returns between the high book-to-market ratio portfolios (S/H and B/H) and the low book-to-market ratio portfolios (S/L and B/L) so this difference should have no influence on size. The HML should concentrate only on

the different return behaviours of the high and low book-to-market ratio firms.  $\beta_i$  is the market beta for stock  $i$  in month  $t$ .

### 3.5.3 Idiosyncratic Volatility

The computation of idiosyncratic volatility (IVOL) in this study adopted the method of Ang et al. (2006) that focused on the FF-3 factor model, which was consistent with most literature regarding the measure of idiosyncratic volatility. Bali et al. (2011) however, reported that they obtained similar results whether idiosyncratic volatility was measured using a single-factor returns model or the FF-3factor model. The model in this study for calculating idiosyncratic volatility was generated as follows:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + s_iSMB_d + h_iHML_d + \varepsilon_{i,d}$$

where  $R_{i,d}$  is the return on stock  $i$  on day  $d$ ,  $R_{f,d}$  is the risk-free rate on day  $d$ ,  $R_{m,d}$  is the value-weighted market return on day  $d$ ,  $\varepsilon_{i,d}$  is the idiosyncratic return on day  $d$ . The stock  $i$  with idiosyncratic volatility in month  $t$  was measured as the standard deviation of daily residuals in month  $t$  i.e.,  $IV_{i,t} = \sqrt{\text{var}(\varepsilon_{i,d})}$ . SMB and HML were as defined previously.

### 3.5.4 Estimating Past Monthly Returns

The intermediate-term momentum (MOM) variable for each stock in month  $t$  in this study was measured using Bali et al.'s (2011) approach; they had used the method of Jegadeesh and Titman (1993). The estimating procedure was that momentum in month  $t$

was defined as the cumulative return from the past 11 months, lagged by one month, i.e.,  $t-12$  to the month  $t-2$ .

The monthly short-term reversal (REV) for individual stocks was estimated in terms of the relative stock returns in the past month, following the evidence from Jegadeesh (1990) and Lehman (1990) that stocks with past one-week or one-month returns would negatively influence the expected returns. In this study, if the expected return as the dependent variable in the cross-sectional regressions was in month  $t$ , the reversal variable, as an independent variable, should be the monthly return in the previous month ( $t-1$ ), i.e., the return in the portfolio formation month.

### **3.5.6 Pricing Illiquidity**

Bali et al. (2011) posited that liquidity (ILLIQ) was generally reflected in stocks with the ability to trade large quantities immediately at low cost and without inducing large bid-ask spreads. Amihud and Mendelson (1986) employed the spread between the bidding and asking prices as the measure of illiquidity. Brennan and Subrahmanyam (1996) used intra-day transaction data to estimate illiquidity. However, Amihud (2002) argued that those previous measures of illiquidity may be not available in every stock market and cannot cover the long sample periods. Thus, this study followed Amihud's (2002) approach to compute monthly illiquidity for each stock by employing the ratio of absolute monthly stock returns to its monthly dollar trading volume. This measure can be explained as the monthly price response based on one dollar of trading volume, thus

serving as a rough measure of price impact (Amihud, 2002). The model was generated as follows:

$$ILLIQ_{i,t} = |R_{i,t}| / VOLD_{i,t}$$

where  $ILLIQ_{i,t}$  is the illiquidity on stock  $i$  in month  $t$ ,  $R_{i,t}$  is the monthly returns on stock  $i$  in month  $t$ ,  $VOLD_{i,t}$  is the trading volume in dollars on stock  $i$  in month  $t$ .

### 3.5.7 Skewness

The skewness of a stock estimated the asymmetry of the return distribution around its mean. Following the Excel function - SKEW, the skewness variable for each stock for month  $t$  was estimated from daily returns:

$$SKEW = \frac{n}{(n-1)(n-2)} \sum \left( \frac{R_{i,d} - \mu_i}{\sigma_i} \right)^3$$

where  $n$  is the number of trading days in month  $t$ ,  $R_{i,d}$  is the daily return on stock  $i$  on day  $d$ ,  $\mu_i$  is the average returns of stock  $i$  in month  $t$ , and  $\sigma_i$  is the standard deviation of returns of stocks  $i$  in month  $t$ .

### 3.6 Test Methods

This study used three main tests in order to investigate two research objectives. The first test was single-sorting portfolio-level analysis, followed by two robustness tests, namely, the alpha of double-sorted portfolio analysis and Fama-Macbeth (1973) regressions.

These techniques examined a comprehensive list of explanatory variables on the cross-section of expected returns. These three tests represented methods that aimed at validating and qualifying the data, and thus the establishment of empirical evidence appropriate for the evaluation of the objectives.

### **3.6.1. Single-Sorting Portfolio-Level Analysis**

We first allocated stocks into three portfolios ranked in terms of extreme returns, which were measured by maximum daily returns over the past month (MAX), for each month in the sample period. For example, Portfolio 1 (high MAX) included stocks with the highest maximum daily returns over the previous month. Portfolio 2 (medium MAX) included stocks with the medium maximum daily returns over the previous month. Portfolio 3 (low MAX) included stocks with the lowest maximum daily returns in the previous month.

For each MAX portfolio, the portfolio formation was both value-weighted and equal-weighted using market value (weights) at the end of month  $t-1$ . Thus, Portfolios 1, 2 and 3 would finally have the corresponding average monthly raw returns under both the equal-weighted and the value-weighted portfolios. The differences in average monthly raw returns between Portfolio 1 (high MAX) and Portfolio 3 (low MAX) under equal-weighted and value-weighted conditions were also calculated in this study as well as the corresponding t-statistics. The difference and the corresponding t-values allowed the results to show whether the maximum daily returns in the previous month (MAX) have a statistically significantly negative relationship with expected stock returns.

In addition to the average raw returns, we also computed the alpha of each portfolio relative to the traditional single-factor (CAPM) model. In order to do so, we ran three regressions of the excess monthly returns of each MAX portfolios on excess market returns using contemporaneous data. For example, for each regression, the independent variable was the same - excess market return. For the first regression, the dependent variable was the excess return of the high MAX portfolio, i.e., high MAX portfolio return minus the risk-free rate. For the second regression, the dependent variable was the excess return of the medium MAX portfolio and for the third regression the dependent variable was the excess return of the low MAX portfolio.

The single-factor (CAPM) regression was used in the following model.

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + \varepsilon_{i,d} \quad (\text{Equation 1})$$

where:  $R_{i,d} - R_{f,d}$  = the excess return of each MAX portfolio at time t;

$R_{m,d} - R_{f,d}$  = the excess market return at time t;

$\alpha_i$  = intercept term;

$\beta_i$  = the slope of excess market return;

$\varepsilon_{i,d}$  = error term;

Although the use of the single day maximum return may be both a simple and intuitive proxy for extreme positive returns, it was also slightly arbitrary (Bali et al, 2009), therefore, following Bali et al. (2011), we also sorted stock portfolios in terms of the

average of the N (N=1, 2, 3, 4, 5) highest daily returns (MAX (N)) over the previous month. For each MAX (N) portfolio, both the equal-weighted and the value-weighted average monthly return patterns over multiple days were similar to those when sorting on the single maximum daily return. The single-factor model CAPM was also employed to compute the risk-adjusted return (alpha) for each MAX (N) portfolio, as previously described.

In the study by Bali et al. (2011), their findings revealed that stocks with high extreme positive daily returns tended to be small, illiquid and low priced, with high systematic risk, high idiosyncratic volatility and high returns, on average, in the same month. These cross-sectional control variables could all affect the expected returns. Hence, the results from single sorting on MAX may actually be driven by these other variables. For example, if the MAX had an impact on the expected returns in the single-sorting method, the effect may be attributed to those risk factors relative to stocks with high MAX such as size, idiosyncratic volatility and illiquidity. This study employed two different robustness tests – the alpha from the double sorting method and Fama-Macbeth (1973) regressions to control for various variables of interest such as size, illiquidity, idiosyncratic volatility and other cross-sectional effects in predicting expected stock returns. The procedures for these two tests are shown in sections 3.6.2 and 3.6.3.

### **3.6.2 Double-Sorting Portfolio-Level Analysis**

We used alphas with double sorting to control for the following variables - size, book-to-market ratio, illiquidity, momentum, short-term reversals, idiosyncratic volatility, market beta and skewness. Alpha not only controlled for systematic risk, but it was also a more valid measure of return in our study. Thus, we concentrated on the analysis of the alphas of the double-sorted portfolios in this study.

In terms of double sorted portfolios on size – market value (MV) and MAX, we first allocated stocks into three portfolios ranked in terms of MV, i.e., high MV, medium MV and low MV. Then within each MV portfolio, stocks were again sorted based on MAX, i.e., high MAX, medium MAX and low MAX portfolios. Thus, there were nine (3X3) portfolios, namely lowMVlowMAX, lowMVmediumMAX, lowMVhighMAX, mediumMVlowMAX, mediumMVmediumMAX, mediumMVhighMAX, highMVlowMAX, highMV mediumMAX and highMVhighMAX. All the portfolios formed on MAX were value-weighted. Finally, in order to obtain the risk-adjusted returns (alphas) for each portfolio, we ran regressions of the excess returns of these nine MAX portfolios against the excess market returns, respectively. We followed the same procedure in controlling for the other variables. One drawback for this procedure was that it can only control for one variable at a time.

### **3.6.3 Cross-Sectional Fama-Macbeth Regression**

The cross-sectional regression remedied the major weakness of portfolio-level analysis. First, it was difficult for the portfolio analysis to control more than two dimensions

without getting portfolios with only a few stocks. This is especially problematic for countries with only relatively few listed stocks compared with markets such as the U.S.. In contrast, the Fama-Macbeth (1973) regressions allowed us to control for multiple characteristics and effects in a setting that retained power (Ang et al., 2009). Second, much useful information in the cross-section was lost through the aggregation employed in portfolio-level analysis (Bali et al., 2011).

As a result, this study examined the firm-level cross-sectional relationship between MAX and expected stock returns by employing Fama-Macbeth regressions. First, we ran the monthly regressions of stock returns on the one-month lagged control variables every month from January 1990 to December 2009. Then, we computed the time-series averages of the slope coefficients from the regressions for all variables.

The independent variables were the one-month lagged values for the maximum daily return (MAX), size (MV), book-to-market ratios (BTM), momentum (MOM) – the cumulative monthly returns over the past 11 months before the portfolio formation month, short-term reversals (REV) – the monthly return in the portfolio formation month, illiquidity (ILLIQ), market beta (BETA), idiosyncratic volatility (IVOL) and Skewness (SKEW). The regressions were run monthly with the following econometric specification:

$$R_{i,t+1} = \alpha_{0,t} + \alpha_{1,t} MAX_{i,t} + \alpha_{2,t} MV_{i,t} + \alpha_{3,t} IVOL_{i,t} + \alpha_{4,t} REV_{i,t} + \alpha_{5,t} BETA_{i,t} + \alpha_{6,t} ILLIQ_{i,t} + \alpha_{7,t} SKEW_{i,t} + \alpha_{8,t} BTM_{i,t} + \alpha_{9,t} MOM_{i,t} + \varepsilon_{i,t+1}$$

where:

$R_{i,t+1}$  is the expected return on stock  $i$  in month  $t+1$ ;

$MAX_{i,t}$  is the maximum daily returns on stock  $i$  in month  $t$ .

$MV_{i,t}$  is the natural logarithm of the market value for stock  $i$  at the end of month  $t$ ;

$BTM_{i,t}$  is the book-to-market ratio for stock  $i$  in month  $t$ .

$REV_{i,t}$  is the monthly stock return in the previous month, i.e., if the expected return is in month  $t+1$ , the REV should represent the monthly return in month  $t$ .

$MOM_{i,t}$  is the cumulative monthly returns from month  $t-12$  to month  $t-1$ , i.e., the cumulative returns over the past 11 month prior to the portfolio formation month.

The other control variables, including ILLIQ, BETA, SKEW and IVOL for stock  $i$  in month  $t$ , were defined in section 3.5. For example, if the dependent variable – stocks returns in the regression was in June 1991, the independent variables should contain maximum daily returns in May 1991 (MAX), the monthly stock returns in May 1991 (REV), the cumulative monthly returns from May 1990 to April 1991 (MOM) and other values (MV, IVOL, BETA, ILLIQ, SKEW and BTM) in May 1991.

### **3.7 Conclusion**

This chapter presented the research methods employed in this study, including the data collection, the derivation of the variables and test methods, which included single-sorting portfolio-level analysis and two robustness tests: alpha of double-sorted portfolio analysis

and Fama-Macbeth regressions. All the daily and monthly sample data were obtained from the DataStream database. The test methods used in this study primarily follows Bali et al.'s (2011) method for better comparability of results.

## **Chapter 4 Results and Discussion**

### **4.1 Introduction**

This chapter first reports the results of the value-weighted and equal-weighted average monthly returns and the single-factor alpha differences between the high MAX and low MAX portfolios in section 4.2. Section 4.3 presents the differences in the value-weighted and equal-weighted average returns and alpha on portfolios of stocks sorted by the average of multiple days (N=1, 2, 3, 4 and 5) maximum returns.

To control for certain known cross-sectional effects that can explain cross-sectional stock returns, we used a double-sorting procedure as well as Fama-Macbeth firm-level regressions and report the results in section 4.4. Section 4.4.1 reveals the results of the MAX effect after controlling for size, short-term reversals, book-to-market ratio, momentum, illiquidity, idiosyncratic volatility, skewness and beta based on the value-weighted portfolios. Finally, section 4.4.2 reports the results of the predictive cross-sectional Fama-Macbeth (1973) regressions on the one-month lagged values of MAX and the control variables.

### **4.2 Analysis of the MAX-Sorted Portfolios**

A single sort on MAX was used first to examine the relationship between MAX and returns. Table 4.1 reports the results of the value-weighted and equal-weighted average monthly returns, risk-adjusted returns (alphas) on low MAX, medium MAX and high

MAX portfolios formed by sorting the stocks listed in the Hong Kong Stock Exchange (main board) in terms of maximum daily returns over the previous month (MAX) during the period January 1990 to December 2009. The low MAX portfolio was the portfolio of stocks with the lowest maximum daily returns in the past month and the high MAX portfolio was the portfolio of stocks with the highest maximum daily returns in the past month.

For the value-weighted portfolios, the difference in average return between the high MAX and low MAX portfolios was -0.86% per month with the t- statistic of -1.94. This indicated that the MAX effect based on the monthly return difference between the high MAX and low MAX portfolios was statistically insignificant at the 5% significance level, but it still provided weak evidence of a negative relationship between MAX and the expected stock returns based on the fact that the return difference was marginally statistically significant at the 10% level. As shown in the first column of Table 4.1, from the low MAX portfolio to high MAX portfolio, the average monthly returns decreased monotonically from 0.38% to -0.48%. The reverse of this pattern indicated low expected returns to high MAX stocks and also confirmed the conjecture of Bali et al. (2011) that investors preferred to pay more for stocks that showed high extreme positive returns that eventually earned lower expected returns.

**Table 4.1 Monthly Returns and Alphas on Stock Portfolios Sorted by MAX**

<b>Portfolio</b>	<b>Value-weighted Average return</b>	<b>Value-weighted Alpha</b>	<b>Equal-weighted Average Return</b>	<b>Equal-weighted Alpha</b>
<b>High MAX</b>	-0.48	-1.22	-0.59	-0.08
<b>Medium MAX</b>	0.26	-0.40	0.33	0.81
<b>Low MAX</b>	0.38	-0.09	0.08	0.48
<b>High-Low Difference</b>	-0.86 (-1.94)	-1.13 (-2.84)	-0.67 (-1.58)	-0.56 (-1.31)

1. The three MAX portfolios were formed every month from January 1990 to December 2009.
2. Low MAX is the portfolio of stocks with the lowest maximum daily returns in the previous month; High MAX is the portfolio of stocks with the highest maximum daily returns in the previous month.
3. The last row presents the differences in average monthly returns and the differences in CAPM Alpha between High MAX and Low MAX portfolios.
4. Value-weighted and equal-weighted average returns, alphas, and high-low difference are reported in percentage terms.
5. The t-statistics are given in brackets.

In addition to the average raw returns, Table 4.1 also showed the risk-adjusted returns measured by the CAPM alpha from the regressions of each return series of the value-weighted MAX portfolios on a constant and the excess market return. As indicated in the last row of Table 4.1, the alpha difference between the high max and low max portfolios was -1.13%, which was highly statistically significant with a t-statistic of -2.84. If we took a closer look at the second column of Table 4.1, it was clear that the risk-adjusted returns declined dramatically from -0.09% to -1.22% per month, as we moved from low MAX to high MAX. Interestingly, all MAX portfolios (low, medium and high) generated

negative average risk-adjusted returns, but the negative alpha difference between the high MAX and low MAX portfolios indicated that the high MAX stocks produced lower alphas than low MAX stocks.

Furthermore, Table 4.1 showed the difference in average return between the high MAX and low MAX for equal-weighted portfolios at -0.67% per month. However, this return spread was not statistically significant at all conventional levels with a t- statistic of -1.58. This insignificant return spread implied that there was no evidence of a negative relationship between MAX and future stock returns in the equal-weighted portfolios. The corresponding difference in alpha is -0.56% per month with an insignificant a t-statistic of -1.31.

According to the results in Table 4.1, it was clearly seen that the MAX effect was evident only for value-weighted portfolios. This finding was broadly consistent with the findings of Bali et al. (2011), in which the value-weighted average return difference between the high MAX and low MAX portfolios was more statistically significant with a t-statistic of -2.83 than that in the equal-weighted portfolios with a t-statistic of -1.83. Thus, this suggested that the negative relationship between extreme positive returns and expected stock returns were more apparent among large stocks, because the value-weighted portfolios were dominated by large stocks. Consequently, this study focused more on the value-weighted portfolios for the further robustness tests.

In conclusion, the value-weighted single-sorting on maximum daily returns over the previous month (MAX) provided evidence of a negative relationship between MAX and expected stock returns, which was all the more significant when we used risk-adjusted returns. In contrast, the equal-weighted single-sorting on MAX provided no evidence of a MAX effect, no matter whether in terms of raw returns or alpha. Thus, this evidence implied that the MAX effect was only observed in large stocks in the Hong Kong stock market.

### **4.3 Analysis of the MAX (N)-Sorted Portfolios**

As an alternative to the single day maximum daily return as a proxy for extreme positive returns, we also sorted stocks by averaging the N (N=1, 2, 3, 4 and 5) highest daily returns in a given month. The results of Table 4.2, Panels A and B, document the average returns on multiple days of maximum daily returns in both value-weighted and equal-weighted portfolios across each MAX portfolio. As shown in the first column (N=1) in both Panels A and B, the average return patterns in both the value-weighted and equal-weighted portfolios were the same as those reported in Table 4.1.

**Table 4.2 Monthly Returns on Stock Portfolios Sorted by Multi-Day MAX**

**Panel A. Value-Weighted Returns and Alphas on MAX (N) Portfolios**

<b>Portfolio</b>	<b>N=1</b>	<b>N=2</b>	<b>N=3</b>	<b>N=4</b>	<b>N=5</b>
<b>High MAX</b>	-0.48	-0.68	-0.54	-0.54	-0.38
<b>Medium MAX</b>	0.26	0.37	0.30	0.53	0.51
<b>Low MAX</b>	0.38	0.34	0.26	0.16	0.13
<b>Return Difference (High-Low)</b>	-0.86 (-1.94)	-1.02 (-2.21)	-0.80 (-1.64)	-0.70 (-1.42)	-0.51 (-1.01)
<b>Alpha Portfolio</b>	<b>N=1</b>	<b>N=2</b>	<b>N=3</b>	<b>N=4</b>	<b>N=5</b>
<b>High MAX</b>	-1.22	-1.48	-1.31	-1.31	-1.17
<b>Medium MAX</b>	-0.40	-0.28	-0.34	-0.12	-0.14
<b>Low MAX</b>	-0.09	-0.14	-0.19	-0.28	-0.87
<b>CAPM Alpha (High-Low)</b>	-1.13 (-2.84)	-1.34 (-3.26)	-1.12 (-2.64)	-1.03 (-2.41)	-0.30 (-0.52)

**Table 4.2 (continued)****Panel B. Equal-Weighted Returns and Alphas on MAX (N) Portfolios**

<b>Portfolio</b>	<b>N=1</b>	<b>N=2</b>	<b>N=3</b>	<b>N=4</b>	<b>N=5</b>
<b>High MAX</b>	-0.59	-0.64	-0.67	-0.65	-0.62
<b>Medium MAX</b>	0.33	0.38	0.41	0.37	0.35
<b>Low MAX</b>	0.08	0.08	0.08	0.11	0.09
<b>Return Difference (High-Low)</b>	-0.67 (-1.58)	-0.72 (-1.61)	-0.75 (-1.67)	-0.76 (-1.70)	-0.71 (-1.58)
<b>Alpha Portfolio</b>	<b>N=1</b>	<b>N=2</b>	<b>N=3</b>	<b>N=4</b>	<b>N=5</b>
<b>High MAX</b>	-0.08	-0.12	-0.16	-0.14	-0.10
<b>Medium MAX</b>	0.81	0.85	0.88	0.84	0.82
<b>Low MAX</b>	0.48	0.48	0.47	0.50	0.49
<b>CAPM Alpha (High-Low)</b>	-0.56 (-1.31)	-0.60 (-1.37)	-0.63 (-1.45)	-0.64 (-1.48)	-0.59 (-1.36)

1. The three MAX portfolios were formed every month from January 1990 to December 2009.
2. In forming the three portfolios, they were ranked based on the average of the N highest maximum daily returns in the previous month MAX (N).
3. Low MAX is the portfolio of stocks with the lowest maximum multi-day returns over the previous month; High MAX is the portfolio of stocks with the highest maximum multi-day returns over the previous month.
4. The differences in average monthly returns and alphas (CAPM) between High MAX (N) and Low MAX (N) are also shown in the table.
5. Value-weighted average returns, equal-weighted average returns and the differences in both returns and alphas are reported in percentage terms.
6. The t-statistics are given in brackets.

For the value-weighted portfolios, the results of Table 4.2, Panel A showed that the high-low difference in return when sorting stocks by averaging the two highest extreme daily returns within the month increases in magnitude to -1.02% from that when sorting on average returns over the single day, which was also statistically more significant than that from the single day (N=1) with t-statistic of -2.21 compared with -1.94 for N=1. However, as we averaged over more days, the value-weighted average return difference between the high MAX and low MAX portfolios decreased in magnitude monotonically to -0.51% for averaging the five highest daily returns (N=5), with a corresponding decline in the t-statistic to -1.01. Similarly, the alpha (CAPM) differences in magnitude when sorting on returns over multiple days dropped monotonically from -1.33% for N=2 to -0.30% for N=5. However, the corresponding differences in alpha were statistically more significant than the raw return differences, especially for N = 2, 3 and 4 with the t-statistics of -3.26, -2.64 and -2.41 respectively. When we averaged the highest five daily returns, the alpha difference became highly statistically insignificant at all levels. Thus, combining the results of the raw return differences with the alpha differences in the value-weighted portfolios, averaging the highest five daily returns was not a good measure for extreme positive returns, which contradicted the expectation that MAX (5) had a strong power in estimating extreme positive returns.

For the equal-weighted portfolios, the average return differences over multiple days fluctuated around about -0.70% from N=1 to N=5; they were all statistically insignificant with t-statistics of -1.58, -1.61, -1.67, -1.70 and -1.58, respectively. The relevant alpha differences also showed an insignificant negative MAX effect between N=1 and N=5.

Thus, this evidence further corroborated that there was no evidence of a negative relationship between MAX and future returns in the equal-weighted portfolios.

## **4.4 Robustness Checks**

The single-sorting results for value-weighted portfolios provided evidence of a statistically significant negative relationship between extreme positive returns and future returns when we used risk-adjusted returns (alpha). To examine this relation more closely, we conducted two robustness tests. First we conducted a double-sort procedure using portfolio level analysis. However, the double-sort procedure had potential significant disadvantages, as discussed earlier. As a result, we also used another robustness test – cross-sectional Fama-Macbeth regressions to examine the MAX effect. Table 4.3 showed the results of the risk-adjusted returns for the value-weighted portfolios of stocks sorted by MAX after controlling for various cross-sectional variables of interest. The results of Fama-Macbeth regressions are presented in Table 4.8.

### **4.4.1 Alpha of Double-Sorted Portfolios on MAX**

In this section, we examine the alpha of value-weighted portfolios double-sorted on MAX and the control variables of interest. Table 4.3 reports the risk-adjusted returns (alphas) differences between the high MAX and low MAX portfolios and the corresponding t-statistics to test their statistical significance, after controlling for size,

book-to-market ratios, short-term reversals, momentum, illiquidity, skewness, market beta and idiosyncratic volatility.

Panel A in Table 4.3, controls for size measured by market value. For each month, we first sorted stocks into three portfolios ranked in terms of market value. Then, within each size portfolio, we allocated stocks into three portfolios according to MAX – high MAX, medium MAX and low MAX; there were a total of nine portfolios. To determine risk-adjusted returns (alphas) of portfolios sorted on MAX and size, we ran nine regressions of the excess returns of these nine portfolios on the excess market returns (see equation 1). Next, we averaged the alphas across the three size categories within each MAX category. Therefore, we obtained three portfolios with dispersion in MAX but with each portfolio containing basically all size categories effectively controlling for size. The results in Panel A showed that after controlling for size, the difference in average risk-adjusted return between the high MAX and low MAX portfolios was -1.09%, which was highly statistically significant at the 5% significance level with a t-statistic of -3.34. Thus, firm size (market value) cannot explain the high (low) expected returns to low (high) MAX stocks.

We controlled for short-term reversals in a similar way. A reversal for a stock is defined as the monthly return in the portfolio formation month. It was not surprising that stocks with extreme positive daily returns should have high monthly returns in that month. In addition, Huang et al. (2010) posited that the winner stocks were likely to be relatively

large cap stocks than the loser stocks in the portfolio formation month and they experienced strong return reversals. Thus, MAX may be a proxy for short-term reversals based on the monthly frequency. However, this was not true. After controlling for the monthly returns in the portfolio formation month, Panel B of Table 4.3 showed that the high-low difference in alpha was -0.92% per month, and it was statistically significant with a t-statistic of -2.83. This evidence indicated that short-term reversals cannot account for the negative MAX effect.

Panel C of Table 4.3 provides the results after controlling for book-to-market ratios. The difference in risk-adjusted return (alpha) between the high MAX and low MAX portfolios was -1.04% per month, which was highly statistically significant with a t-statistic of -3.88. Hence, the book-to-market ratio cannot explain the negative relationship between MAX and future stock returns.

Panel D of Table 4.3 shows the results when we control for momentum measured by the cumulative returns over the past 11 months before the portfolio formation month. The results showed that the risk-adjusted return (alpha) difference between the high MAX and low MAX portfolios was -0.87% per month, which was statistically significant with a t-statistic of -2.70. Hence, we rule out momentum as a possible explanation for the low returns to stocks with high MAX.

**Table 4.3 Alphas of Double Sorted Portfolios on MAX**

Panel A Double sort on Size (market value) and MAX				
Portfolio	High MAX	Medium MAX	Low MAX	High - Low
BIG	-0.71 (-2.53)	-0.27 (-1.51)	0.00 (0.00)	-0.71 (-1.94)
MED	-2.17 (-4.36)	-1.09 (-2.72)	-0.71 (-2.47)	-1.46 (-2.53)
SMA	-1.12 (-1.89)	0.13 (0.27)	-0.03 (-0.07)	-1.10 (-1.57)
AVE	-1.34 (-4.86)	-0.41 (-1.86)	-0.25 (-1.41)	-1.09 (-3.34)
Panel B Double sort on Reversal and MAX				
Portfolio	High MAX	Medium MAX	Low MAX	High - Low
HREV	-0.79 (-1.74)	0.00 (0.00)	-0.09 (-0.32)	-0.70 (-1.30)
MREV	-0.55 (-1.57)	-0.50 (-2.27)	-0.12 (-0.33)	-0.43 (-0.85)
LREV	-2.45 (-4.97)	-0.54 (-1.55)	-0.82 (-2.04)	-1.63 (-2.56)
AVE	-1.26 (-5.01)	-0.35 (-2.02)	-0.34 (-1.69)	-0.92 (-2.83)
Panel C Double sort on Book-to-Market Ratio and MAX				
Portfolio	High MAX	Medium MAX	Low MAX	High - Low
HBTM	0.22 (0.51)	0.87 (2.32)	0.87 (3.10)	-0.65 (-1.24)
MBTM	-0.75 (-1.96)	-0.10 (-0.37)	-0.01 (-0.04)	-0.74 (-1.65)
LBTM	-1.65 (-4.62)	0.03 (0.12)	0.07 (0.35)	-1.72 (-4.19)
AVE	-0.73 (-3.19)	0.27 (1.54)	0.31 (2.22)	-1.04 (-3.88)

**Table 4.3 (continued)**

Panel D Double sort on Momentum and MAX				
Portfolio	High MAX	Medium MAX	Low MAX	High – Low
HMOM	-1.32 (-2.92)	-0.25 (-0.77)	-0.06 (-0.18)	-1.26 (-2.20)
MMOM	-0.84 (-2.36)	-0.26 (-1.00)	-0.03 (-0.10)	-0.81 (-1.74)
LMOM	-1.43 (-3.06)	-1.30 (-3.39)	-0.88 (-2.07)	-0.55 (-0.87)
AVE	-1.20 (-4.84)	-0.60 (-3.19)	-0.32 (-1.55)	-0.87 (-2.70)
Panel E Double sort on Illiquidity and MAX				
Portfolio	High MAX	Medium MAX	Low MAX	High – Low
HILLIQ	-2.09 (-4.24)	-0.67 (-1.87)	-0.52 (-1.50)	-1.57 (-2.62)
MILLIQ	-1.24 (-3.42)	-0.30 (-1.22)	-0.10 (-0.37)	-1.15 (-2.58)
LILLIQ	-0.91 (-2.64)	0.17 (0.83)	0.04 (0.25)	-0.95 (-2.54)
AVE	-1.41 (-6.03)	-0.27 (-1.68)	-0.19 (-1.28)	-1.22 (-4.39)
Panel F Double sort on Total Skewness and MAX				
Portfolio	High MAX	Medium MAX	Low MAX	High – Low
HSKEW	-2.07 (-4.14)	-0.34 (-1.03)	-0.48 (-1.53)	-1.58 (-2.68)
MSKEW	-1.26 (-3.07)	0.04 (0.14)	-0.12 (-0.46)	-1.15 (-2.37)
LSKEW	-1.47 (-3.43)	-0.06 (-0.19)	-0.65 (-1.67)	-0.82 (-1.42)
AVE	-1.60 (-6.19)	-0.12 (-0.63)	-0.42 (-2.22)	-1.18 (-3.71)

**Table 4.3 (continued)**

Panel G Double sort on Market Beta and MAX				
Portfolio	High MAX	Medium MAX	Low MAX	High – Low
HBETA	-1.48 (-2.84)	-0.16 (-0.42)	-0.08 (-0.29)	-1.39 (-2.33)
MBETA	-0.95 (-2.56)	-0.01 (-0.04)	-0.26 (-0.33)	-0.69 (-0.79)
LBETA	-1.63 (-3.43)	-0.53 (-1.76)	-0.72 (-2.15)	-0.91 (-1.57)
AVE	-1.36 (-5.10)	-0.23 (-1.22)	-0.36 (-1.17)	-1.00 (-2.47)

Panel H Double sort on Idiosyncratic Volatility and MAX				
Portfolio	High MAX	Medium MAX	Low MAX	High – Low
HIVOL	-2.17 (-4.07)	-2.04 (-4.37)	-0.85 (-2.16)	-1.32 (-1.98)
MIVOL	-0.57 (-2.03)	-0.02 (-0.08)	-0.22 (-0.90)	-0.35 (-0.95)
LIVOL	0.21 (1.26)	-0.05 (-0.28)	-0.30 (-0.90)	0.51 (1.37)
AVE	-0.84 (-4.03)	-0.71 (-3.71)	-0.46 (-2.40)	-0.39 (-1.36)

1. The table reports the risk-adjusted returns measured by the CAPM alphas from the regressions of each return series of the MAX portfolios on the excess market returns.
2. The risk-adjusted returns are presented in percentage terms.
3. The t-statistics are given in brackets.
4. All portfolios are value weighted.
5. The sample period covers from January 1990 to December 2009.

Panel E in the Table 4.3 shows the results when we control for illiquidity measured by the ratio of the absolute monthly return to the corresponding monthly trading volume. The alpha difference between the high MAX and low MAX portfolios was -1.22% and it was highly statistically significant with a t-statistic of -4.39. This shows that a negative relationship between MAX and future stocks still held after controlling for illiquidity.

When we controlled for skewness in Panel F, the result showed that the alpha difference between the high MAX and low MAX portfolios was -1.18%, which was highly significant with a t-statistic of -3.71. Hence, we found that skewness cannot explain the negative relationship between MAX and future stock returns.

Panel G of Table 4.3 reports the results when we control for market beta. The average risk-adjusted return difference between the high MAX and low MAX portfolios was -1.00% per month with a t-statistic of -2.47. Again, MAX determined the cross-section of future stock returns with large return difference and the corresponding t-statistic significance. Thus, exposure to market risk (beta) is not an explanation of the negative MAX effect.

Our last control variable was idiosyncratic volatility. Panel F of Table 4.3 showed that controlling for idiosyncratic volatility reduced the explanatory power of MAX significantly. The high-low difference in alpha between the high MAX and low MAX

portfolio reduced from -1.13% (Table 4.1, Column 4) to -0.39% per month with a t-statistic of -1.36. Hence, the idiosyncratic volatility effect appeared to be able to explain the negative MAX effect. To further explore this phenomenon, we examined the cross-sectional correlation between extreme returns and idiosyncratic volatility as well as the relationship between idiosyncratic volatility and future returns.

Table 4.4 showed that the average cross-sectional correlation between MAX (maximum daily returns) and idiosyncratic volatility was 0.92. This meant they were highly positively correlated, i.e., stocks with high maximum daily returns tended to have high idiosyncratic volatility in the same month.

**Table 4.4 Time-Series Average of Cross-Sectional Correlation**

	<b>MAX</b>	<b>IVOL</b>
<b>MAX</b>	1	
<b>IVOL</b>	0.922	1

1. The table reports the correlation of time series between idiosyncratic volatility and extreme returns (MAX) by computing simple average IVOL and average MAX every month using all stocks.
2. The sample period is January 1990 and December 2009.

Then we used a single sort on IVOL, which was similar to that given in Table 4.1 for MAX, to examine if idiosyncratic volatility can predict future returns. The results in

Table 4.5 showed that for the value-weighted portfolios, the average raw returns increased from -0.74% to 0.85% per month, as we moved from high IVOL to low IVOL. The return difference between the high IVOL and low IVOL portfolios was -1.59% per month, which was highly statistically significant with  $-3.58$ . Likewise, the risk-adjusted return (alpha) difference of -1.69% was highly statistically significant with a t-statistic of  $-3.58$ . Thus, a negative idiosyncratic volatility effect existed in the value-weighted portfolios, which was consistent with the findings of U.S. stock market in Ang et al. (2006) and Bali et al, (2011), even though they sorted stocks into quintiles and deciles respectively. For the equal-weighted portfolios, both the return difference between the high IVOL and low IVOL portfolios of -0.41% and the corresponding alpha difference of -0.31% were statistically insignificant. Hence, there was no idiosyncratic volatility effect in the equal-weighted portfolios. This evidence supported the results of both Bali and Cakici (2008) and Bali et al. (2011). Bali et al. (2011) explained that the absence of the IVOL effect in the equal-weighted portfolios was attributed to measurement issue for smaller stocks. This implied that the idiosyncratic volatility effect was only observed in the large stocks as evidenced by the value-weighted portfolios.

Based on a strong positive correlation between maximum daily returns and idiosyncratic volatility and a negative IVOL effect in the value-weighted portfolios, it was not surprising that the average risk-adjusted return (alpha) difference between the high MAX and low MAX portfolios declined in absolute value from -1.13% (Table 4.1) to -0.39% after controlling for IVOL (Panel H of Table 4.3).

**Table 4.5 Monthly Returns and Alphas on Stock Portfolios Sorted by IVOL**

<b>Portfolio</b>	<b>Value-weighted Average return</b>	<b>Value-weighted Alpha</b>	<b>Equal-weighted Average Return</b>	<b>Equal-weighted Alpha</b>
<b>High IVOL</b>	-0.74	-1.61	-0.37	-0.15
<b>Medium IVOL</b>	0.45	-0.41	0.14	0.33
<b>Low IVOL</b>	0.85	0.08	0.04	0.15
<b>High-Low Difference</b>	-1.59 (-3.58)	-1.69 (-3.58)	-0.41 (-0.99)	-0.31 (-1.04)

1. The three IVOL portfolios were formed every month from January 1990 to December 2009.
2. Low IVOL is the portfolio of stocks with the lowest idiosyncratic volatility; High MAX is the portfolio of stocks with the highest idiosyncratic volatility.
3. The last row presents the differences in average monthly returns and the differences in CAPM Alpha between High IVOL and Low IVOL portfolios.
4. Value-weighted and equal-weighted average returns, alphas, and high-low difference are reported in percentage terms.
5. The t-statistics are given in brackets.

To explore the relationship between maximum daily returns and idiosyncratic volatility more closely, we used a reverse sort to examine the relationship between IVOL and future returns after controlling for MAX. In Table 4.6, we first sorted stocks into three portfolios based on the maximum daily returns in the previous month (MAX). Then within each MAX portfolio, we sorted the stocks based on IVOL. Thus, the high (low) IVOL portfolios contained stocks with the highest (lowest) IVOL. For the value-weighted portfolios, the average raw return difference between the high IVOL and low IVOL portfolios after controlling for MAX was -1.06% per month, which was highly

statistically significant with a t-statistic of -3.07. The average risk-adjusted return (alpha) difference between the high IVOL and low IVOL portfolios was -1.17% per month with a t-statistic of -3.54. This result was partly against the findings of Boquist (2010), who documented that extreme returns explained a portion of the negative relationship between IVOL and subsequent stock returns. In Boquist's (2010) study, he first found a significantly negative relationship between IVOL and subsequent stock returns. Then, he removed stocks with the most extreme 10% of returns (either positive or negative) to calculate IVOL by using Fama and French 3-factor model, and found no significantly negative IVOL effect at the 5% level. We suggest two reasons why our results differ from Boquist's (2010). First, our evidence showed that extreme returns were highly correlated with IVOL, so it is probable that there were not sufficient stocks with high IVOL in Boquist's (2010) study to test the IVOL effect after he took away some stocks with extreme positive returns. Second, we focused only on whether stocks with extreme positive returns explained the negative IVOL effect, whereas Boquist (2010) looked at stocks with extreme returns either positive or negative. Thus, we conclude that maximum daily return did not account for the negative idiosyncratic volatility effect in the value-weighted portfolios.

For the equal-weighted portfolios, both the average raw returns and alpha differences between the high IVOL and low IVOL portfolios after controlling for MAX turned positive and were both statistically insignificant. This was consistent with Bali et al.'s (2011) finding.

**Table 4.6 Monthly Returns and Alphas on Stock Portfolios Sorted by IVOL after Controlling for MAX**

<b>Portfolio</b>	<b>Value-weighted Average Return</b>	<b>Value-weighted Alpha</b>	<b>Equal-weighted Average Return</b>	<b>Equal-weighted Alpha</b>
<b>High IVOL</b>	-0.53	-1.38	-0.12	0.08
<b>Medium IVOL</b>	-0.003	-0.82	0.06	0.24
<b>Low IVOL</b>	0.53	-0.21	-0.13	0.01
<b>High-Low Difference</b>	-1.06 (-3.07)	-1.17 (-3.54)	0.01 (0.04)	0.07 (0.35)

1. Double-sorted, value-weighted and equal-weighted three portfolios were formed every month from January 1990 to December 2009.
2. In the table we sorted stocks based on idiosyncratic volatility after controlling for MAX.
3. We first sorted the stocks into three portfolios based on MAX. Then within each MAX portfolio, we sorted stocks into three portfolios based on IVOL.
4. The last row presents the differences in average monthly returns and the differences in CAPM Alphas between High IVOL and Low IVOL portfolios.
5. Value-weighted and equal-weighted average returns, alphas, and high-low differences are reported in percentage terms.
6. The t-statistics are given in brackets.

According to our portfolio sorting results, we suggest that the MAX effect among large stocks we documented in Table 4.1 can be explained by the IVOL effect. Thus, there was no MAX effect among large stocks. In contrast, there seemed to be a significantly negative IVOL effect among large stocks, as evidenced by the value-weighted portfolios (Table 4.5).

In summary, though there appeared to be a negative relationship between alphas and MAX for value-weighted portfolios, suggesting the presence of a MAX effect in large stocks, this relationship can be explained by the apparent negative IVOL effect documented in this study. Hence our results suggested that there was no MAX effect among large stocks. Our portfolio analysis results for equal-weighted portfolios also suggested that there was neither a MAX effect nor an IVOL effect among small stocks. Given the limitations of the portfolio sorting method, as discussed in Chapter three, we investigated this issue further using cross-sectional Fama-MacBeth regressions.

#### **4.4.2 Cross-Sectional Fama-Macbeth Regression Results**

In this section, we investigated the cross-sectional relationship between MAX and expected stock returns using the Fama-Macbeth (1973) regressions for the periods January 1990 to December 2009. Table 4.7 presents descriptive statistics of each variable. The measures for all variables were introduced in the last chapter. The mean monthly return was 0.0347%. The low mean monthly stock return indicated that the Hong Kong stock market was affected by both the Asian and global financial crises that happened in 1997 and 2008, respectively. The median monthly return was zero due to the very small mean monthly return. The mean MAX was 8.47% and the median was 6.07%.

**Table 4.7 Variables descriptive statistics for the sample data  
January 1990 to December 2009**

Variables	Mean	Std dev.	Median	Min	Max	Skew	Count
Returns	0.000347	0.198	0	-3.398	3.427	0.4487	110732
MAX	0.0847	0.0885	0.0607	0	2.949	5.784	110732
Log (MV)	20.563	1.826	20.322	14.403	28.779	0.662	110732
IVOL	0.0304	0.0252	0.0237	0	0.562	3.719	110732
REV	-0.00064	0.204	0	-3.398	3.427	0.388	110732
BETA	0.705	1.345	0.653	-48.619	42.605	0.963	110732
ILLIQ	-0.0542	4.163	0	-820.36	231.049	-115.295	110732
SKEW	0.161	1.406	0.197	-4.690	4.690	-0.402	110732
BTM	1.578	2.429	1.124	-50	100	13.596	110732
MOM	-0.0324	0.708	0.0119	-5.201	5.579	-0.221	110732

1. This table presents the descriptive statistics of each variable from January 1990 to December 2009.
2. Returns are monthly raw returns. MAX is the maximum daily return in the previous month. Log (MV) is measured by the natural logarithm of market value scaled by millions of dollars. IVOL stands for idiosyncratic volatility estimated in section 3.5.3. The short-term reversal (REV) is the monthly return in the portfolio formation month. BETA is market beta computed in section 3.5.2. ILLIQ represents the illiquidity scaled by  $10^5$ . SKEW is total skewness estimated in section 3.5.7. BTM stands for book-to-market ratio and MOM is momentum measured by the cumulative monthly returns over 11 months before the portfolio formation month.
3. The observations in the sample periods for each variable are trimmed to match each other.

The mean natural logarithm of market value (millions of dollars) was 20.563 and the mean idiosyncratic volatility was 3.04%. The mean for other variables – short-term reversal (REV), systematic risk (BETA), illiquidity (ILLIQ) scaled by  $10^5$ , skewness (SKEW), book-to-market ratios (BTM) and intermediate-term momentum (MOM) were 0.064%, 0.705, -0.0542, 0.161, 1.578 and -3.24% respectively.

Table 4.8 reports the results of the monthly Fama-Macbeth (1973) regressions during the sample period. The first line in Table 4.8 showed that the average estimated coefficient on MAX alone was -0.071, with a robust t-statistic of -2.31. This implied the existence of a strong negative MAX effect. This result conflicts with the evidence of Table 4.1 that the MAX effect did not exist in the equal-weighted portfolios, since cross-sectional regressions put equal weight on each raw return observation. The explanation for this conflicting evidence could be that in the portfolio analysis we focused only on the difference between the high MAX and low MAX portfolios and in the process we lost a lot considerable information through portfolio aggregation. Aggregation through portfolio level analysis also necessarily limited the range of values for MAX, which could partly explain the lack of an observed MAX effect at the portfolio level. With Fama-Macbeth regressions we made use of all the information provided by the data.

In contrast to the strong predictive power of MAX on future returns, the average coefficients on the individual control variables were almost all insignificant. The average slope on size ( $\log(MV)$ ) alone was -0.001, which was insignificant with a t-statistic of -0.86. The insignificant relationship between size and returns was consistent with previous research showing that size is not important in predicting stock returns after the 1980s (Wong, 2011). Lam (2002) also found that size ( $\ln(MV)$ ) was insignificantly related to average returns with a t-statistic of 1.0086 from June 1984 to June 1997 in the Hong Kong stock market.

The average slope on REV was 0.006 with a t-statistic of 0.78, which indicated that short-term reversals had no predictive power for expected stock returns. The positive relationship between BETA and the cross-section of future returns supported the fundamental theory of the CAPM, which implied that investors subjected to higher systematic risks earn higher rates of return. However, the insignificant beta in determining future returns with a t-statistic of 0.96 was consistent with most previous evidence. In addition, Bali et al. (2011) posited that any results for beta could be subject to a significant amount of measurement error, since the measure of monthly beta was based on daily data. The average coefficient of ILLIQ was -0.002, which was also not statistically significant. The negative relationship between illiquidity and expected returns contrasted with the findings of illiquidity in other stock markets. This was because a negative relationship between illiquidity and returns had no theoretical meaning because it showed that stocks that were traded more infrequently produced lower future returns. However, this finding was similar to the evidence in Wang and Di Iorio (2007), who suggested that more frequently traded stocks earned higher returns in the Chinese A-share market. The coefficient on SKEW was negative, and it was insignificant with a t-statistic of -1.06. The negative sign of skewness in the regression indicated that positively skewed assets generated low expected returns, consistent with a preference for assets with positively skewed return distributions (Bali & Murray, 2011), albeit skewness had no effect on future returns using daily data. The average slope on BTM was highly statistically positively significant with a t-statistic of 5.29, which suggested a strong explanatory power of this variable. This finding corroborated the performance of book-to-market ratio in other stock markets, which indicated that value stocks (high BTM)

produced higher abnormal returns than growth stocks (low BTM). The average slope on MOM was 0.003, but insignificant with a t-statistic of 0.9. Combining the results of momentum with short-term reversals, their highly insignificant positive relationships with future returns indicated that past returns in monthly frequency cannot capture variation in the cross-section of expected stock returns in the Hong Kong stock market.

The last result of Table 4.8 shows the regression using the full set of control variables in addition to MAX. The average slope of MAX was -0.15 with a highly significant t-statistic to -4.83. This result meant that when we controlled for all variables simultaneously, there was still a strong negative MAX effect, thereby indicating a robust MAX effect based on our Fama-Macbeth regressions. This evidence was consistent with the findings of Bali et al.' (2009) Fama-Macbeth regressions in the U.S. stock market. From the results of our relevant control variables, it was not surprising to see most variables such size, idiosyncratic volatility, short-term reversals, market beta, illiquidity, skewness were highly insignificantly related to future stock returns because those variables already showed an insignificant relationship with returns when running the regressions on these variables alone. The book-to-market variable (BTM) still indicated a highly significant explanatory power on stock returns with a t-statistic of 6.36. The performance of momentum in the full variables regression showed that it can significantly capture the variation of stock returns, which conflicted with the findings from running the regressions on momentum (MOM) alone; the reason for this could be that momentum may interact with other cross-sectional variables to influence the stock returns.

We also paid attention to the idiosyncratic volatility effect in the regressions. When we ran the regression on IVOL alone, the average slope on IVOL was -0.189 with a t-statistic of -1.60, which was not statistically significant. This indicated that idiosyncratic volatility did not influence future returns or, at least, cannot predict one-month expected stock returns. This evidence not only supported the results of Table 4.8 that there was no idiosyncratic volatility effect in the equal-weighted portfolios, but it was also broadly consistent with the performance of idiosyncratic volatility in Huang et al. (2010) and Bali et al. (2011).

Interestingly, when we added MAX together with IVOL in the regression, the negative relationship between idiosyncratic volatility and expected returns became positive, similar to the findings of Bali et al. (2011) for the U.S. stock market. The IVOL coefficient changed from -0.189 to 0.048, although it was not significant, with a t-statistic of 0.4. In order to further test whether MAX potentially reverses the negative relationship between idiosyncratic volatility and future returns, we added other control variables except MAX to the regression together with IVOL. The result showed that the relationship between idiosyncratic volatility and future returns remained negative with the average slope of IVOL of -0.210 and was marginally statistically significant at the 10% level with a t-statistic of -1.82. But when we added MAX in the full-specification regression that negative relationship was reversed and it was insignificant, with a t-statistic of 1.1. This evidence was consistent with the results of the reverse sort on MAX and IVOL in the equal-weighted portfolios reported in Table 4.6. Thus, the apparent MAX effect could potentially reverse the negative relationship between one-month

lagged idiosyncratic volatility and the cross-section of expected stock returns in the Hong Kong stock market.

In summary, the firm-level cross-sectional regressions showed strong evidence of a statistically significant negative relationship between the extreme positive returns measured by maximum daily returns in the previous month (MAX) and the cross-section of expected stock returns. This implied that a strong MAX effect may exist among small stocks as the Fama-Macbeth regressions placed equal weights on all observations. This evidence supported the findings of Bali et al. (2011) regarding the MAX effect using cross-sectional regressions in the U.S. stock market. Surprisingly, we found that some well-known cross-sectional factors including firm size, short-term reversals and momentum cannot determine the variation of future returns in the Hong Kong stock market. Market beta that had a positive relationship with future returns was consistent with the implication of the traditional CAPM, but its highly insignificant influence showed that market beta cannot predict the expected returns. More importantly, we found that the MAX effect could potentially reverse the puzzling negative relationship between one-month lagged idiosyncratic volatility and expected returns in the regressions. This evidence confirmed the results of the reverse sorts on MAX and IVOL in the equal-weighted portfolios (Table 4.6).

**Table 4.8 Average Coefficients and T-Statistics from Month-by-Month Regressions of Hong Kong Stock Returns on One-Month Lagged MAX and Control Variables**

Model	MAX	MV	IVOL	REV	BETA	ILLIQ	SKEW	BTM	MOM	Adjusted R2
1	-0.071 (-2.31)									1.90% (9.83)
2		-0.001 (-0.86)								1.60% (8.07)
3			-0.189 (-1.60)							2.10% (8.93)
4				0.006 (0.78)						1.30% (7.3)
5					0.001 (0.96)					1.10% (6.3)
6						-0.002 (-1.38)				0.10% (1.92)
7							-0.001 (-1.06)			0.30% (5.94)
8								0.006 (5.29)		1.00% (5.15)
9									0.003 (0.09)	2% (6.84)
10	-0.086 (-3.81)		0.048 (0.40)							2.70% (10.95)
11		-0.001 (-0.76)	-0.21 (-1.82)	-0.016 (-1.74)	0.001 (0.6)	-0.037 (-1.1)	-0.001 (-0.87)	0.006 (6.4)	0.009 (2.97)	9.40% (12.61)
12	-0.121 (-3.7)	-0.001 (-0.96)		0.005 (0.52)	0.002 (1.51)	-0.033 (-1.01)	0 (-0.67)	0.006 (6.39)	0.009 (2.88)	9.50% (13.22)
13	-0.075 (-2.64)					-0.001 (-1.31)				1.70% (9.28)
14	-0.071 (-2.47)	-0.001 (-1.24)								3.40% (11.95)
15		-0.001 (-0.93)	0.123 (1.10)	0.005 (0.54)	0.001 (1.05)	-0.034 (-1.03)	0.00 (-0.77)	0.006 (6.36)	0.009 (2.91)	9.90% (13.34)

1. The firm-level cross-sectional regression of the return on the one-month lagged variables of interest including MAX and eight control variables in every month from January 1990 to December 2009.
2. In each model, the table presents the time series averages of slope coefficients in the cross-sectional regression.
3. The t-statistics are presented in brackets.
4. Size (measured by the natural logarithm of market value scaled by millions of dollars), our measure of illiquidity (scaled by  $10^5$ ), reversal (the monthly return in the portfolio formation month) and momentum (the cumulative monthly returns over 11 months before the portfolio formation month).

## 4.5 Conclusion

This chapter documented the results from an examination of the relationship between extreme positive returns (MAX) and the cross-section of expected returns through portfolio analyses as well as cross-sectional Fama-Macbeth regressions. First, we found that there was a statistically significant negative relationship between maximum daily return over the past month (MAX) and expected stock returns based on the results of alphas of the single-sorted on MAX. This was because alpha was a more valid measure of returns in our study. However, we did not find evidence of the negative MAX effect in the equal-weighted portfolios.

We then conducted a robustness test by controlling for other cross-sectional effects using the alpha of the double-sorting method. The results indicated that controlling for size, short-term reversals, book-to-market ratios, momentum, illiquidity, skewness and market beta (systematic risk) cannot explain the low (high) returns to stocks with high (low) MAX. However, controlling for idiosyncratic volatility could explain the MAX effect. Thus, we concluded that there seemed to be no MAX effect among large stocks in the value-weighted portfolios. Of special interest, we found a strong idiosyncratic volatility effect among large stocks, as shown by the value-weighted portfolios. The MAX effect cannot explain this idiosyncratic volatility effect for large stocks.

Finally, due to the limitations of the portfolio sorting approach, we also conducted another robustness test - firm-level Fama-Macbeth regressions. The results provided strong evidence of a statistically significant negative relationship between MAX and the expected stock returns, which implied that a strong MAX effect may appear among small stocks. Moreover, the negative MAX effect was still significant when we controlled for multiple variables simultaneously. This evidence also corroborated the evidence documented in Bali et al. (2011) for the U.S. stock market. We also found that MAX could potentially reverse the puzzling negative idiosyncratic volatility effect in the Hong Kong stock market.

# **Chapter 5 Conclusions**

## **5.1 Introduction**

This chapter concludes this study. Section 5.2 summarises the main results and their corresponding implications. Section 5.3 provides the conclusions of this study in terms of our main findings. Section 5.4 points out the limitations and the contributions we make to asset pricing. The final section recommends future research directions.

## **5.2 Results and Implications**

This section summarises the results from the single-sorting portfolio analysis, double-sorting portfolio analysis and cross-sectional Fama-Macbeth (1973) regressions and the corresponding implications of these findings.

### **5.2.1 Results with Regard to Objective One and Implications:**

When we sorted portfolios on MAX, the results indicated that high MAX portfolio had lower value-weighted raw returns than low MAX portfolios, suggesting a negative MAX effect. More importantly, high MAX portfolios also had lower risk-adjusted returns (alpha) than low MAX portfolios, further confirming the negative MAX effect.

In contrast, there was no evidence of the negative MAX effect in the equal-weighted portfolios. The results from the single-sorted equal-weighted portfolio analysis showed that both average raw return and alpha differences between the high MAX and low MAX portfolios were not statistically significantly negative. Since the value-weighted portfolios were dominated by large stocks and the equal-weighted portfolios place equal weights on all observations, the evidence from the single-sort analysis implied that the MAX effect seemed to be largely present only in large stocks.

However, when we controlled for well-known cross-sectional effects using a double-sort procedure, we found that though cross-sectional effects due to size, short-term reversals, book-to-market ratios, momentum, illiquidity, skewness and market beta cannot explain the MAX effect; controlling for idiosyncratic volatility eliminated the MAX effect previously observed in value-weighted portfolios. Thus we concluded that there was no MAX effect for large stocks.

In addition to portfolio analysis, we also conducted Fama-Macbeth regressions to determine the relationship between MAX and future returns more closely. The results of the Fama-Macbeth regressions indicated the presence of a strong negative MAX effect.

However, the evidence of a strong negative MAX effect based on the Fama-Macbeth regressions was in conflict with the previous results that the MAX effect did not exist in

the equal-weighted portfolios. Since the regression puts an equal weight on each raw return observation that was similar to the formation of equal-weighted portfolios, these two results should be identical. The explanation for this phenomenon, as discussed earlier, could be that we can make use of all available information provided by our data in the Fama-Macbeth regressions, whereas we only focused on the difference between the high MAX and low MAX portfolio in the portfolio analysis and lost much information through aggregating stocks into portfolios in the process. Thus, we suggest that the Fama-Macbeth regression results are more reliable than the portfolio sorting approach.

In conclusion, according to the results of a series of tests on MAX, we suggest that there is a strong negative MAX effect on the Hong Kong stock market based on the Fama-Macbeth regressions, but they appear more likely to occur among small stocks. This finding broadly corroborates the evidence in the U.S. stock market documented in Bali et al. (2011). The MAX effect in our study could be due to the investors' preference for small stocks with lottery-type payoffs leading them to overpay for these stocks which then resulted in lower future stocks returns. The evidence suggests that investors can systematically increase returns by buying small stocks with low MAX and short-selling small stocks with high MAX.

### **5.2.3 Results with Regard to Objective Two and Implications:**

The single-sort results on idiosyncratic volatility showed that the differences in the value-weighted raw returns and risk-adjusted returns between the high IVOL and low IVOL portfolios were negative and statistically significant. This implied that there was a strong negative IVOL effect in the value-weighted portfolios. However, we found that there was no IVOL effect in the equal-weighted portfolios as evidenced by the insignificant raw return and alpha differences between the high IVOL and low IVOL portfolios. This was similar to the findings of Bali and Cakici (2009) and Bali et al. (2011) for the U.S. stock market. In addition, the absence of an IVOL effect in the equal-weighted portfolios was supported by the Fama-Macbeth regressions. Thus, based on both portfolios analysis and the Fama-Macbeth regressions, we documented a negative IVOL effect for large stocks and none for small stocks in the Hong Kong stock market.

We controlled for MAX to determine if the MAX effect could explain the IVOL effect in value-weighted portfolios. The results showed that even after controlling for MAX, the negative IVOL effect still persisted. However, for the equal-weighted portfolios, the results in Table 4.6 indicated that the differences in both average returns and alphas between the high IVOL and low IVOL portfolios turned positive after controlling for extreme returns, though they were not significant. This result was also confirmed by the Fama-Macbeth regressions. Running Fama-Macbeth regressions only on IVOL showed a negative IVOL effect but when we introduced MAX into the equation the coefficient of IVOL effect turned positive. Thus, these results implied that the MAX effect could reverse the puzzling negative IVOL effect in terms of both portfolio analysis and the

Fama-Macbeth regressions, but the phenomenon seemed to only happen among small stocks.

### **5.3 Conclusions**

For various reasons, a certain number of investors, especially retail investors, were willing to pay more for stocks with extreme positive returns. Such behaviour caused these stocks to produce lower future returns. Stocks with extreme positive returns that had low future returns were viewed as lottery-type tocks. Bali et al. (2011) documented that there was a statistically significant negative relationship between extreme positive returns measured by maximum daily returns in the previous month (MAX) and future returns in the subsequent month in the U.S. stock market. Our findings broadly supported the evidence of the MAX effect based on the Hong Kong stock market. Our Fama-Macbeth regressions document a statistically significant negative MAX effect on the Hong Kong stock market, but this effect appeared more likely to occur among small stocks as the regressions placed equal weights on all observations. This result was robust to control for our numerous control variables of interest. In contrast, we found no MAX effect for large stocks based on portfolio analysis, because the idiosyncratic volatility effect can explain the negative MAX effect. One noticeable point was that the results from the equal-weighted portfolio analysis contradicted the evidence of the MAX effect from the Fama-Macbeth regressions. Due to the limitations of portfolio analysis, we think the Fama-Macbeth regressions results were more reliable than the portfolio sorting approach.

Of special interest, we found that there was a negative idiosyncratic volatility effect for the value-weighted portfolios and none for the equal-weighted portfolios, which implied that an idiosyncratic volatility effect seemed to appear among large stocks and not among small stocks in the Hong Kong stock market. The absence of an idiosyncratic volatility effect for small stocks was confirmed by the Fama-Macbeth regressions. Bali et al. (2011) found that the inclusion of MAX variable reversed the negative idiosyncratic volatility effect documented in Ang et al. (2006, 2009). We also documented that the MAX effect cannot account for the idiosyncratic volatility effect for the value-weighted portfolios but could potentially lead to a positive relationship between one-month lagged idiosyncratic volatility and future stock returns evidenced by both the equal-weighted portfolios and the Fama-Macbeth Regressions.

In conclusion, we documented the significance of extreme positive returns in the cross-sectional pricing of stocks, but this effect was largely observed only in small stocks in the Hong Kong stock market. Kumar (2009) showed that certain groups of individual investors preferred lottery-type stocks that exhibited low prices and high idiosyncratic volatility. Thus, we interpreted that our results showed that poorly diversified individual investors preferred small stocks with extreme positive returns, overpaying for these stocks in the process leading to lower future returns. Future studies could investigate if the low returns to high MAX stocks we found for small stocks in our study are also present in other stock markets.

## **5.4 Limitations**

### **5.4.1 Sample Size**

The sample stocks in this study were collected directly from the DataStream database. By the end of December 2010, there were 1,244 listed companies in the Hong Kong Stock Exchange (main board) but only 860 stocks were available in our study. This limitation was affected by the data source, the DataStream database. Another limitation regarding the sample size was that the sample stocks in this study did not cover the listed companies in the Growth Enterprise Market (GEM) in the Hong Kong Stock Exchange. There were two reasons for this: first, the GEM was opened in 1999, so the sample period was not long enough to conduct this research; second, there were only a few listed stocks in GEM available in DataStream at the time we obtained our data.

### **5.4.2 Length of Sample Period**

This study covered the period from January 1990 to December 2009, which consisted of 20 years (240 months). Compared with the previous study of Bali et al. (2011) for the U.S. stock market, which covered approximately 44 years, from July 1962 to December 2005, the sample period in this study was shorter, but the limitation of the length of sample period was attributable to the data source in DataStream. For example, there were only a few sample stocks available in 1980s in DataStream to form portfolios to accurately test the MAX effect.

### **5.4.3 Lack of Quintile or Decile Portfolios Analysis**

In this study, we chose to allocate sample stocks into the three portfolios, rather than the quintile or the decile portfolios, as a result of the limitations of sample size. Quintile or decile portfolio formations were generally employed by most scholars to study asset pricing, i.e., quintile portfolios in the studies of Fu (2009) and Ang et al. (2006, 2009) or the decile portfolios in the study of Bali et al. (2011). Thus, it could be better to sort stocks into quintile or decile portfolios when comparing relevant studies.

## **5.5 Recommendations for Future Research**

According to the limitations mentioned in the previous section, there are several recommendations for future scholars interested in the MAX effect on a cross-section of expected stock returns. First, we found that the number of sample stocks available in DataStream were not sufficient when compared with the total number of the listed companies in the Hong Kong stock market. Thus, we recommend future studies choose an alternative data source for collecting sample data in order to improve the sample size.

Second, if future researchers were able to obtain a larger number of sample stocks from the Hong Kong stock market than in this study, or choose a larger stock market, such as the Japanese stock market or Shanghai stock market to examine the MAX effect, we advise them to sort stocks into quintile or decile portfolios. These methods for portfolio analysis were consistent with the methods from most previous studies regarding asset

pricing i.e., the quintiles adapted by Ang et al. (2006, 2009), Bali and Cakici (2009) and Fu (2009); the deciles employed by Bali et al. (2011) and Fama and French (1992). Thus, the results will be more comparable with previous relevant studies.

Third, for the robustness tests including both double-sorted portfolio analysis and Fama-Macbeth regressions, we used control variables of interest to examine the MAX effect. Future scholars may add more control variables like price-to-earnings ratios or co-skewness, which are both tested extensively to be proxies for risk factors, to the robust test.

Finally, we suggest that scholars may also estimate extreme positive returns over longer periods as an alternative measure of lottery-type payoffs for stocks. Like the methods adopted by Bali et al. (2011), MAX portfolios can be formed based on the highest daily returns averaged over the past three, six or twelve months. Longer past periods may also be used for MAX (N) based on the average of the N (N=1, 2, 3, 4 and 5) largest daily returns. Thus, different proxies for lottery-type payoffs for stocks may provide further evidence of the phenomenon that investors who preferred stocks exhibiting extreme positive returns led to these stocks producing lower future returns.

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