



# **Are Extreme Returns Determinants of Cross-sectional Expected Stock Returns?**

MAX effect in the Finnish market

Master's Thesis

Aalto University School of Business

Department of Finance

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10.11.2018

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### Abstract

I investigate a recently proposed asset pricing anomaly MAX effect, i.e. the extreme positive returns in the previous month, in the cross-sectional pricing of stocks in Finland. The results confirm that there exists significant negative MAX effect in the Finnish market. The equal-weighted return difference between high-MAX and low-MAX portfolios is  $-1.11\%$  per month, with corresponding alpha spread of  $-0.16\%$ . Both values are statistically significant at 5% level. However, the negative MAX effect is not robust for value-weighted portfolios. These results are consistent with previous research that the negative MAX effect in the European stock market is concentrated in small-sized companies. I conducted bivariate sorting analysis and firm-level cross-sectional regression, and conclude that the negative MAX effect is significant after controlling for size, value, skewness, momentum, short-term reversal and idiosyncratic volatility. Moreover, I discussed the relationship between the MAX effect and idiosyncratic volatility effect (IV). While both MAX and IV are negatively related to the expected future returns, MAX is not a substitute for IV. However, I did not observe a positive idiosyncratic volatility effect in the Finnish stock market after controlling for MAX, as Bali et al. (2011) recorded in their study.

Keywords: MAX effect, Extreme return, Lottery-like payoffs, Cross-sectional stock returns, Finnish Stock Market, Idiosyncratic volatility

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## 1. Introduction

The capital asset pricing model (CAPM) states that the cross-sectional expected returns are determined by the covariance between individual stock returns and the market portfolio. Under this theory, diversification is of vital importance, because investors can even out unsystematic risk. However, in reality individual investments are not well-diversified. Empirical evidence suggests that general investors pay closer attention to individual stock returns rather than merely the correlations of the cross-sectional returns.

Hundreds of firm-specific characteristics which relates to the expected stock returns have been documented so far. Fama and French (2008) recorded an overview of these characteristics. For example, Banz (1981) finds that small stocks, namely stocks with small market capitalization, have exceptionally high expected returns; Rosenberg et al. (1985) find that stocks with high book-to-market ratio have unusually high expected returns; Cohen et al. (2002) find that the more profitable the firms are, the higher expected returns are, yet Fairfield et al. (2003) show that firms which have more investments generally have lower stock returns; After stock repurchases, returns raise up (Ikenberry et al. 1995), while after stock issues, returns decrease (Loughran and Ritter, 1995); Stocks with low (high) returns over the last year tend to have low (high) returns for the next few months (Jegadeesh and Titman, 1993). These anomalies cannot be explained under the theory that returns are solely dependent on the covariance with the market.

Moreover, in recent years the relationship between the “MAX effect” and the cross-sectional expected stock returns are studied. Bali, Cakici and Whitelaw (2011) showed that American investors tend to pay more for stocks with extreme high returns, resulting in these stocks having lower future returns. Specifically, Bali et al. (2011) form portfolios from stock’s maximum daily return in the previous month (MAX) and study the returns in the following month on these portfolios. They find that MAX is significantly negatively related to the expected stock returns. For equal-weighted portfolios, the return difference between high-MAX and low-MAX is -0.65%, with the corresponding Fama-French-Carhart four factor alpha (4F-alpha) spread of -0.66% per

month. For value-weighted portfolios, the return difference is -1.03%, with -1.18% alpha difference. All return and alpha differences are statistically significant.

By this date most of the studies regarding MAX effect concern foreign stock markets, but there is few evidence from Finland. Annaert et al. (2013) included Finland in their research as they were studying the MAX effect in 13 European countries, discovering that MAX is negatively related to subsequent stock returns in Europe. Additionally, Aboulamer et al. (2016) find a positive relation between MAX and the following month returns in the Canadian equity market, which is contrary to Bali et al.'s (2011) finding. Similarly, Haykir (2018) conclude in his study that the MAX effect does not exist in the Turkish equity market. Because of these contradictory findings, it is of importance to further study the MAX effect and also in the Finnish market.

In this thesis, I investigate the relationship between MAX effect and the expected stock returns in the Finnish market over the sample period between 1990 and 2017. The results verify that the MAX effect is also significantly negatively related to the cross-sectional expected returns in Finland. From my analysis, the equal-weighted return difference between high- and low-MAX portfolios is -1.11% per month and the alpha spread is -0.16%. Both spreads are statistically significant. My main focus in this thesis is at 4F-alphas because it accounts for the systematic risk factors such as size, value and momentum (Nartea et al., 2014). The alpha spread is narrower comparing to that of Bali et al. (2011) which is probably due to the narrower range in MAX by forming stocks into 3 portfolios in this thesis instead of 10 portfolios as Bali et al. (2011) employed. However, unlike the results from Bali et al. (2011), I did not find significantly negative return and alpha differences for the value-weighted portfolios. These results are similar to Annaert et al.'s (2013) findings, where they suggest that the negative MAX effect in the European stock market is mainly among small-sized firms. I further suggest that household investors cause the negative MAX effect in the Finnish market to a large extent. This suggestion is in line with Aboulamer and Kryzanowski (2016) who conducted bivariate sorting tests in Canada using MAX and the level of institutional holdings. They suggested that in Canada the MAX effect is most common among stocks with low institutional ownership. Moreover, Kumar (2009) states that individual investors have a relatively greater preference for lottery-like assets.

Further, I investigate the controversial relationship between the MAX effect and some of the cross-sectional variables, namely size, value, skewness, momentum, short-term reversal and idiosyncratic volatility. Firstly, bivariate sorting analysis is conducted. After controlling for each cross-sectional variables, the MAX effect is still significantly negative, indicating that the MAX effect is not a substitute for these effects. However, I acknowledge that double-sorting portfolio analysis has its disadvantages. Firstly, portfolio analysis fails to reveal the collective effects of the cross-sectional variables. Secondly, it cannot explain the dependencies of the variables. Therefore, firm-level cross-sectional regression is constructed. I confirm that the MAX effect on its own negatively affect the cross-sectional expected returns. And that especially that MAX effect is not a substitute for idiosyncratic volatility (IV). I find that the negative MAX effect is enhanced after controlling for IV, as Bali et al. (2011) explored. However, I did not find that IV turns positive after controlling for MAX as suggested by Bali et al. (2011).

My thesis contributes to the literature concerning MAX in two ways. Firstly, survivorship bias free samples from a less discussed market (Finland) are used to test the relationship between MAX and expected returns. Bali et al. (2011) report that stocks with extremely high returns in the previous month (MAX) leads to lower returns in the following month. Similarly, I find that expected return differences between high- and low-MAX portfolios are negative. Secondly, I propose an alternative relationship among idiosyncratic volatility (IV), extreme returns (MAX) and the future returns than Bali et al. (2011). They report that MAX remains negative and significant after controlling for IV. In this wise, I also find that the significantly negative relationship between MAX and expected returns stays when IV is controlled. However, Bali et al. (2011) find that the negative relationship between IV and expected returns become significantly positive after controlling for MAX. Yet from my analysis, I I do not find any significant positive relation between IV and future returns when MAX is controlled.

My thesis is structured in the following way. Section Two covers the previous literature concerning MAX effect. Section Three describes the data, defines the variables and the methods used in this thesis. In the fourth section discusses the main results from univariate- and bivariate-sorting portfolio analysis and from firm level cross-sectional regressions. In the same section, I also study the persistence of the MAX effect, the

characteristics of the MAX portfolios, and the relation between idiosyncratic volatility and MAX effect. Finally, Section Five concludes the thesis.

## 2. Literature Review

Asset pricing model has been extensively studied for decades, especially to find the determinants of the cross-sectional expected stock returns. So far, hundreds of cross-sectional variables have been reported, and one of which is the MAX effect.

Bali et al. (2011) report that the extremely high returns over the past month (MAX) is negatively related to the stock returns in the following month in the U.S. equity market. To be specific, they investigate the US stock market returns from July 1962 to December 2005, and they found that stock returns within the high-MAX group is -1.03% per month lower than stocks within the low-MAX group. They further sort stocks on the average of two to five highest daily returns within the previous month, and get similar negative MAX effects. Moreover, they find that the MAX effect stays significantly negative after various variables, such as size, value, momentum, short-term reversal and illiquidity, are controlled.

There are two branches of research concerning the MAX effect after it is first discovered (Haykir, 2018). One set of studies try to explore the existence of the MAX effect worldwide. Annaert et al. (2013) study 13 European countries, and find a significantly negative MAX effect. However, the negative MAX effect only exists in equal-weighted portfolios, but not in value-weighted portfolios. Annaert et al. (2013) suggest that the negative MAX effect mainly happens in small-sized companies in Europe. Nartea et al. (2014) prove that the negative MAX effect happens in the South Korean stock market, which suggests that the MAX effect also exists in developing market. Zhong and Gray (2016) find a negative MAX effect in the Australian stock market. In addition, Aboulamer et al. (2016) conducted their research in Canadian market. They, however, find MAX is positively related to the following month returns, which is contrary to Bali et al.'s (2011) finding. Similarly, Haykir (2018) conclude in his study that the MAX effect does not happen in Turkish equity market.

Another set of literature seeks to discover why the MAX anomaly exists. Plenty of studies seek empirical evidence that the MAX anomaly occurs because of investor's

irrational behaviour. Based on Mohrschladt and Baars (2018), the existing behavioural explanations of MAX effect can be attributed to two categories: evaluation bias and judgment bias.

Under evaluation bias, decision makers evaluate risk using “transformed probabilities”. Tversky and Kahneman’s (1992) cumulative prospect theory (CPT) offers a strong explanation in this area. CPT suggests that investors overreact towards assets with a small probability of a large positive return (Tversky and Kahneman, 1992). Under this theory, Bali et al. (2011) suggest that investors have a preference for lottery-type stocks, and therefore increase the prices of high-MAX stocks beyond their fundamental value. Similarly, Barberies and Huang (2008) also suggest that investors prefer lottery-like stocks, which then become overvalued. The Optimal Expectations Framework (Brunnermeier and Parker, 2005) is also consistent with the evaluation bias. In this framework, decision makers tend to overestimate the probabilities where their investments pay off well, in order to maximize their current utility flows. As a result, the average utility is reduced *ex post*, which can be seen in two aspects -- First, investors under-diversify their portfolios; Second, investors can be risk-seeking when facing in lottery-type assets.

Judgement bias differs from evaluation bias that investors’ focus is not on the past realized returns, instead, individuals tend to focus on the strength or extremeness of the new information. Judgement bias creates overreaction when new information is high in strength and low in weight (Griffin and Tversky, 1992). Therefore, investors tend to overreact towards the strong positive information that generates the extremely high daily return, resulting in the overvaluation of the stock and the reduction of the returns in the following month. Moreover, Griffin and Tversky (1992) show that individuals usually underreact if the information is very reliable and valid. This strength-weight judgment bias implies that investors in general should overreact towards extreme positive news, while they should not do so if the positive information has high reliability. In this area, Daniel et al.’s (1998) provides strong explanations based on psychological studies – firstly, individuals overestimate their ability to evaluate private information signals; secondly, investors’ confidence changes in a biased way based on the decision outcomes. As a further support, Cheon and Lee (2017) find that the MAX effect is stronger in countries with higher levels of individualism.

In Mohrschladt and Baars's (2018) study, while evaluation biases affect investors' behaviour concerning MAX returns, judgment bias is a more important driving force for the MAX effect. They presented three arguments—Firstly, TK-measure, which reflects how appealing a stock is for investors who follows cumulative prospect theory (Barberies et al. 2016), is applied and found that high-MAX stocks are considered unattractive by investors who evaluate the daily returns of the previous month. Therefore, the hypothesis under evaluation bias that investors prefer high-MAX stocks are rejected. Secondly, Mohrschladt and Baars (2018) noticed that the overvaluation starts immediately at the realization day of MAX. Under evaluation bias, the overvaluation is from buying pressure of investors who have observed the attractive MAX return. As a result, the prices of high-MAX stocks would increase directly after the MAX observation and lead to low returns afterwards. However, empirical evidence suggests immediate price reversals. Thus, the authors propose that the phenomenon is due to an overreaction towards the news that generated the MAX return. Thirdly, the authors found that MAX effect reverses if the MAX return is accompanied with an earnings announcement. If investors act according evaluation bias, they are expected to always overreact on high-MAX days, pushing the return so high that the subsequent returns become low. However, the authors find that investors actually underreact when they receive earning announcement together with the MAX return. This observation is in line with the strength-weight judgement bias where individuals tend to underreact if the extreme news is high in weight, i.e. information is reliable and valid. To sum up, Mohrschladt and Baars (2018) give more credit to judgement bias than evaluation bias as the driving force behind the MAX effect.

There are plenty of articles suggesting that MAX could be a proxy for idiosyncratic volatility. As previous studies shown that idiosyncratic volatility is negatively related to future expected returns. Therefore, it is possible that the negative MAX effect is caused by the idiosyncratic volatility effect. However, Bali et al. (2011) proved this suggestion to be incorrect. Firstly, they find that MAX is still significantly negatively related to the expected future returns after idiosyncratic volatility is controlled. Secondly, the negative idiosyncratic volatility effect turns significantly positive after controlling for MAX. Based on these two observations, Bali et al. (2011) propose that both idiosyncratic volatility effect and MAX effect exist in stock markets at the same time, and that the idiosyncratic volatility does not drive behind the MAX effect.

It is also suggested that skewness effect could be the cause for the negative MAX effect. Golec and Tamarkin (1998) show that gamblers prefer positive skewness instead of risk as conventional financial theory suggests. Moreover, Mitton and Vorkink (2007) find that compared with diversified investors, less-diversified investors often choose stocks with noticeably higher average skewness. Therefore, it is also possible that the negative MAX effect is just another form of skewness effect. This claim is also rejected by Bali et al. (2011), who find consistent negative MAX effect after controlling for skewness.

### 3. Data and Methods

#### 3.1. Data Selection

All data for the period of June 1990 to July 2017 are obtained from Thomson Reuters DataStream (TDS) database. According to Schmidt et al. (2011), the Thomson Reuters DataStream dataset best represent statistically significant company and data item from January 1985 forward. Therefore, the sample period (June 1990 to July 2017) is set to have a broad coverage of stocks in the markets. The sample contains both active shares and delisted shares, which include companies that cease to exist due to mergers, or bankruptcy, to control for survivorship bias. I download the end-of-month return index which includes dividends and account for stock splits. I calculate book-to-market ratio (B/M) by dividing 1 by the MTB. Prior to year 2002, all data that are denominated in the old currency Markka is converted by DataStream into synthetic euro. And the risk-free rate is calculated as the weighted average of 3-month interbank offer rate.

Inspired by Annaert et al. (2013), I use similar methods to correct possible errors in DataStream. First, I correct issues with decimal errors. For example, a return index value is 56.50 for day  $t$  and should stay the same for the following day; however, DataStream gives a value of 565.0, a “right-decimal error” as Annaert et al. (2013) mentioned. Because of this error, daily return becomes 900% instead of the real value 0%. Similarly, Data Stream might give a value of 5.65 instead of 56.50, as a result of “left-decimal error”. The daily return becomes -90% instead of the true value 0%. I correct the decimal error by excluding all returns which are above 400% (a 50% true return accompanied by right-decimal error) and below -85% (a 50% true return accompanied by a left-decimal error). Further, according to Newey and West (1987), I

use adjusted t-statistics which correct both autocorrelation and heteroscedasticity of error-terms. This will enhance the robustness of my tests.

### 3.2. Construction of variables

I sort stocks based on the maximum daily return in the previous month (MAX). This I do in a monthly basis. I form three portfolios using 33<sup>th</sup> and 66<sup>th</sup> percentiles as breakpoints. The returns and the four-factor Fama-French-Carhart alphas (4F-alpha) of each portfolio are calculated in the following month. The 4F-alpha is computed based on the following four-factor Fama-French-Carhart model (1) (Fama and French, 1993 and Carhart, 1997):

$$R_{i,t} - R_{f,t} = \alpha_i + b_i (R_{m,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + m_i WML_t + \epsilon_t \quad (1)$$

Where  $R_{i,t}$  is the return of stock  $i$  in the month  $t$ ;  $R_{m,t}$  is the market return in the month  $t$ ;  $R_{f,t}$  is the risk-free rate in the month  $t$  and is calculated as the weighted average of 3-month interbank offer rate;  $SMB_t$  is the difference in the daily returns between Small and Big portfolios at month  $t$ ; Similarly,  $HML_t$  is the return difference between High- and Low-value portfolios, which is the firm's B/M six months prior;  $WML_t$  is the cumulative return for the previous 11 months starting 2 months prior (Jegadeesh and Titman, 1993); and  $\epsilon_t$  is the error term. The construction of risk factors SMB, HML and WML as proposed by Fama and French (1993) and Carhart (1997) is explained in detail in the following paragraphs.

In order to obtain market-wide risk factors, Fama and French (1993) introduced Size factor (SMB) based on the return difference in portfolio between stocks with small market capitalization and big market capitalization. Also, Fama and French (1993) discovered Value factor (HML), the return spread between high book-to-market stocks and low book-to-market stocks. Further, Carhart (1997) proposed Momentum factor (WML), which is calculated as the return difference between high past performing stocks (winner) and low past performing stocks (loser) portfolios. I follow these methods to construct the factors SMB, HML and WML.

I sort all stocks into two groups, small (S) and big (B), according to size, which is defined as the firm's market capitalization at the end of month t-1. Similarly, in order to construct the HML factor, all stocks are sorted each month into three groups, low (L), medium (M) and high (H), according to their value, which is the firm's B/M six months prior. Thus six portfolios are formed each month.

I construct the factors SMB and HML for month t-1 as follows:

$$SMB_{t-1} = \left( \frac{r_{t-1}^{\frac{S}{L}} + r_{t-1}^{\frac{S}{M}} + r_{t-1}^{\frac{S}{H}}}{3} \right) - \left( \frac{r_{t-1}^{\frac{B}{L}} + r_{t-1}^{\frac{B}{M}} + r_{t-1}^{\frac{B}{H}}}{3} \right) \quad (2)$$

$$HML_{t-1} = \left( \frac{r_{t-1}^{\frac{S}{H}} + r_{t-1}^{\frac{B}{H}}}{2} \right) - \left( \frac{r_{t-1}^{\frac{S}{L}} + r_{t-1}^{\frac{B}{L}}}{2} \right) \quad (3)$$

$r_{t-1}^{X/Y}$  represents the portfolio return which belongs to both Size group X (either S or B) and Value group Y (either H, M or L) at month t-1.

In order to construct the momentum factor, I calculate the mean return from month t-12 to month t-2 for each portfolio formed in month t-1, and use this mean return to form the momentum groups, namely loser (L), medium (M) and winner (W). I also construct two size groups monthly. Thus six portfolios are formed each month. WML is the return spread between the two winner portfolios and the two loser portfolios:

$$WML_t = \left( \frac{r_t^{\frac{S}{W}} + r_t^{\frac{B}{W}}}{2} \right) - \left( \frac{r_t^{\frac{S}{L}} + r_t^{\frac{B}{L}}}{2} \right) \quad (4)$$

$r_t^{X/Z}$  represents the return of the portfolio which belongs to both Size X (either S or B) and Momentum Z (either W, M or L).

### 3.3. Breakpoints

In each of the sort mentioned above, breakpoints are needed to divide the stocks into different portfolios. In Fama and French's (1993) work, many stock exchanges are included in their sample. Therefore, NYSE is used to calculate breakpoints, and then apply this breakpoints to their whole sample, in order to minimize the effect of microcaps and small stocks (Fama and French, 1993). In this study, I calculated the breakpoints from the whole sample. I use 80<sup>th</sup> percentile as a breakpoint to separate the small and big stocks. Additionally, I calculate the 35<sup>th</sup> and 70<sup>th</sup> percentiles as

breakpoints to separate the low, medium and high value portfolios. However, I use the 30<sup>th</sup> and 70<sup>th</sup> percentiles for the three value groups. I do not use exactly the empirical mean breakpoints because the 30<sup>th</sup> and the 70<sup>th</sup> percentiles are used more commonly in similar studies and they are very close to the empirical breakpoints (Schmidt et al. 2015). I also apply this approximation procedure to momentum portfolios, which I use 30<sup>th</sup> and 70<sup>th</sup> percentiles.

### 3.4. Methodology

A 3x3 bivariate-sorting methodology is employed in order to control the various cross-sectional effects, which include size, value, skewness, momentum, short-term reversal and idiosyncratic volatility. First, each cross-sectional variable is grouped into three portfolios. Within each portfolio, I further divide the stock returns into three more groups based on MAX. As a result, I form portfolios with different MAX values but similar in cross-sectional effects.

Bivariate sorting analysis inherits a couple of disadvantages. Firstly, it cannot reveal the effects of the characteristics simultaneously. Secondly, it is unable to explain the dependencies of the variables. Therefore, a firm-level cross-sectional regression is conducted to solve those problems.

Inspired by Bali et al. (2011), I form the cross-sectional regression model as follows:

$$R_{i,t+1} = \lambda_0 + \lambda_1 MAX_{i,t} + \lambda_2 SIZE_{i,t} + \lambda_3 VALUE_{i,t} + \lambda_4 MOM_{i,t} + \lambda_5 REV_{i,t} + \lambda_6 IV_{i,t} + \varepsilon_{i,t+1} \quad (5)$$

The variable definitions are described below:

*SIZE<sub>i,t</sub>*: Size variable for company i is defined as the company's market capitalization at the end of the previous month t;

*VALUE<sub>i,t</sub>*: Value variable for company i is the company's book-to-market ratio six months prior (t-6);

*MOM<sub>i,t</sub>*: Momentum variable for firm i at month t is the stock's 11-month past return, starting from 2 month prior, namely the returns from month t-12 to month t-2 (Jegadeesh and Titman, 1993);

$REV_{i,t}$ : Short-term reversal variable is the stock's return in the previous month t-1;

$IV_{i,t}$ : Idiosyncratic volatility is calculated as the standard deviation of daily residuals from the Fama-French three-factor model (6) at the end of the previous month t-1.

$$R_{i,t-1} - R_{f,t-1} = \alpha_i + b_i (R_{m,t-1} - R_{f,t-1}) + s_i SMB_{t-1} + h_i HML_{t-1} + \epsilon_{t-1} \quad (6)$$

And

$$IV_{i,t} = \sqrt{Var(\epsilon_{i,t-1})} \quad (7)$$

## 4. Empirical Results

I use univariate sorting analyses to study whether the extreme positive return in the previous month (MAX) is one of the determinant of cross-sectional expected stock returns in the Finnish equity market. I confirm that the MAX has a significant negative effect on the expected returns among equal-weighted portfolios in Finland; in value-weighted portfolios, however, the negative relationship between MAX and the expected stock returns is not significant. Further, I demonstrate the persistence of MAX and summarize the characteristics of the MAX portfolios. Bivariate sorting analysis and cross-sectional regression are performed to investigate the relationship between the MAX effect and various cross-sectional effects. I conclude that the cross-sectional variables which are used in this thesis are not the driving forces for the negative MAX effect. Further, the relationship between MAX effect and idiosyncratic volatility is discussed in detail, where I reject the claim that MAX is just a substitute for idiosyncratic volatility. Yet I do not find that idiosyncratic volatility turns significantly positive when MAX is controlled, thus the relationship between IV, MAX and future returns discovered in this thesis are different than that of Bali et al. (2011).

### 4.1. Univariate sorting

First of all, I conduct the univariate sorting analysis. I sort stocks into three portfolios based on the extreme positive returns from the previous month (MAX). The average monthly returns and 4F-alphas of equal-weighted (EW) and value-weighted (VW)

portfolios are calculated and presented in Table 1. HMAX portfolio includes stocks with the highest MAX from previous month and LMAX portfolio has stocks with lowest MAX. The last row reports the return differences between high- and low-MAX portfolios, and the corresponding p-values of the Newey-West t-test are reported in the parentheses.

Table 1

	Equal-weighted Portfolios		Value-weighted Portfolios	
	Average Return(%)	4F-Alpha(%)	Average Return(%)	4F-Alpha(%)
HMAX	0.3797	-0.0512	0.2244	-0.0255
MMAX	1.3133	0.0814	0.7169	0.4062
LMAX	1.4897	0.1129	0.5167	0.2205
HMAX-LMAX	-1.1101 (0.0171)	-0.1641 (0.0456)	-0.2924 (0.3477)	-0.2460 (0.1929)

*Table 1. Monthly returns and 4F-alphas from univariate analysis.*

*This table records the monthly returns and the 4F-alphas of equal- and value-weighted portfolios of Finnish stocks which are sorted by extreme positive returns in the previous month (MAX). HMAX contains stocks with the highest MAX from previous month and LMAX portfolio has stocks with lowest MAX. The last row reports the return spreads between high- and low-MAX portfolios, and the corresponding p-values of the Newey-West t-test are recorded in the parentheses.*

Table 1 shows that the average return for equal-weighted high-MAX portfolio is lower than that of the low-MAX portfolio. Thus the negative MAX effect is presented. The average return difference is -1.11% per month with 5% significance level. The result agrees with Bali et al. (2011) who report a -0.65% return difference with 10% significance level. Further, the alpha spread under my analysis is -0.16% per month for equal-weighted portfolios, and is also significant at the 5% level. This thesis focus mainly on the alpha spread, because it controls for the basic risk factors such as size, value and momentum, and thus better describes the negative MAX effect (Nartea et al., 2014). In comparison, Bali et al. (2011) report an equal-weighted alpha spread of -0.66% per month. My alpha spread is narrower comparing to that of Bali et al. (2011). It is probably due to the narrower range in MAX by sorting stocks into 3 portfolios in this thesis instead of 10 portfolios as Bali et al. (2011) employed. In Bali et al.'s (2011)

study, the average returns for the lower deciles are quite close in value, but the high MAX decile shows a significant drop in average returns. My results are similar, the average return for high MAX portfolio is 0.38%, comparing to around 1.35% for Medium- and Low-MAX portfolios.

However, the MAX effect is not significant in value-weighted portfolios as is shown from Table 1. Both return and 4F-alpha differences are negative, but they are not statistically significant. High-MAX portfolio does not show a significant steep drop in average returns compared with medium- and low-MAX portfolios. Moreover, I cannot reject the hypothesis that the average returns for all three MAX portfolios are equal with p value of 0.35. Similarly, the hypothesis that the alphas of all three portfolios are equal is not rejected with p value of 0.19. I conclude that unlike Bali et al.'s (2011) finding, the MAX effect in value-weighted portfolios is weak in the Finnish equity market.

The fact that the negative MAX effect is significant in equal-weighted portfolios but not in value-weighted portfolios indicates that the MAX effect is most common in small-sized companies in Finland. Annaert et al.'s (2013) discovered similar phenomenon from their European sample. Kumar (2009) also states that the lottery-type stocks are mainly from small companies.

Furthermore, I hypothesize that the MAX effect in Finland is largely caused by individual investors. Small companies give individual investors an advantage over institutional investors. For one thing, most small companies are under regulations which makes it difficult for institutional investors to buy or sell large block of stocks from them. For the other, many small-sized companies have little analyst coverage. Therefore, it is possible that individual investors cause the negative MAX effect in the Finnish stock market. This is in line with Kumar's (2009) finding, that individual investors, compared to institutional investors, have a larger propensity to buy lottery-type stocks. Kumar finds that household investors make unevenly more investments in stocks with low price, high idiosyncratic volatility and high skewness when comparing to institutional investors. Additionally, stocks which are held predominantly by household investors are those with highest book-to-market ratio, illiquidity, and volatility, and those stocks present slightly negative average monthly returns compared with other stocks (Ang et al., 2013). These characteristics can influence directly on the

relationship between MAX and expected future returns. Aboulamer and Kryzanowski (2016) conducted tests in which they sorted their Canadian sample using extreme positive returns from the previous month (MAX) and the degree of institutional ownership. They note that after MAX is controlled, the 4F-alphas are the lowest for the lowest institutional holding quintile in both equal- and value-weighted portfolios. They suggested that the MAX effect in Canada is mainly manifested in stocks with low institutional holdings.

To conclude, I confirm that the extreme positive returns from previous month (MAX) produce significantly negative returns in the following month among equal-weighted portfolios in Finland; in value-weighted portfolios, however, the results do not indicate a significant negative relationship between MAX and the expected cross-sectional stock returns. In order to get a clearer picture of the MAX effect, I study the persistence in MAX returns and the characteristics of the MAX portfolios in the following sections.

#### 4.2.Persistence of MAX

The persistence of MAX is the premise for investors to prefer high-MAX stocks. To make sure that MAX effect does not occur randomly, I do the following analyses to test the constancy of MAX.

Table 2 records the average MAX values at the month when the portfolio is formed ( $t=0$ ) and at the month that follows ( $t=1$ ). The last two rows represent the average MAX differences between high- and low-MAX portfolios, and the p-values of the adjusted t-test respectively. It is evident that the portfolios with high-MAX tend to continue to exhibit significantly higher maximum daily returns in the following month compared to the low-MAX portfolios.

Table 2

	MAX (t=0)	MAX (t=1)
HMAX	13.2632	6.5953
MMAX	4.6201	4.1535
LMAX	3.0306	3.4199
HMAX-LMAX	10.2326	3.1754
	(5.95E-4)	(0.0122)

Table 2. MAX values in two subsequent months.

*This table reports the average MAX value for each portfolio in the month when the portfolio is formed (t=0) and in the subsequent month (t=1). Newey-West t-test are conducted, and the responding p-values are reported in the parentheses.*

Further, I examine the consistency level of MAX values by calculating a transition matrix. It records the average probability of a stock moving from one MAX group from month t=0 to another in month t=1. Table 3 displays the transition matrix. The first column in the left-hand side are the portfolios in the formation month t=0 and the first row above of the table are the portfolios of the next month t=1. For example, the unit at the cross-section of the first row and the third column shows the probability (21.98%) that a company was in the high-Max portfolio in month t=0 and moved to the low-MAX portfolio in the month t=1. If MAX is random, all probabilities are expected to be approximately 33%. However, in all diagonal cells from Table 3, the transition probabilities are above 33%, especially for the extreme groups (HMAX to HMAX and LMAX to LMAX).

From Table 3, we can see that firms which locate in high- or low-MAX groups in the formation month t=0 have large probability to stay in their groups in the following month t=1. A stock locating in the high-MAX group in month t=0 has a 53.52% probability of staying in the same group in month t=1, a 28.99% probability of moving into the medium-MAX group and a 21.89% probability of transferring into the low-MAX group. Similarly, a stock in the low-MAX group in month t=0 has a 52.66% chance of remaining in the same group in month t=1, a 27.81% chance of moving into the medium-MAX group and a 24.85% chance of transferring into the high-MAX group. These results imply that MAX is not randomly occurring phenomenon, and that it might predict cross-sectional stock returns in the future.

Table 3

		Portfolio in the following month (t=1)		
portfolio in the formation month (t=0)		HMAX	MMAX	LMAX
	HMAX	53.25%	28.99%	21.89%
	MMAX	21.61%	44.44%	33.95%
	LMAX	24.85%	27.81%	52.66%

Table 3. Transition Matrix

The transition matrix displays the average probability of a stock moving from one MAX group in time  $t=0$  to another in time  $t=1$ .

Further, I seek to measure the predictability of MAX in time-series analysis, and calculate the autocorrelations for MAX with lags of 1 to 12 months. The first-order autocorrelation of the high-MAX portfolio is 0.72, and the autocorrelations decrease gradually as the order increases. As a result, there is a high level of predictability in the time series for MAX portfolios.

Additionally, Augmented Dickey Fuller unit root test is also conducted. The hypothesis that there exists a unit root is rejected in 83.6% of the cases. Therefore, I conclude that the MAX returns do not occur randomly, instead, they are considerably persistent.

#### 4.3. The Characteristics of the MAX Portfolios

It is argued that univariate sorting analysis provides biased results because it does not take into account the characteristics of the company, such as size, book-to-market ratio and skewness etc. Therefore, I analysis the characteristics of the MAX portfolio, and report the results in the Table 4. The Table 4 below presents the calculated values respectively from left to right: market size (in millions), book-to-market ratios, skewness, momentum, short- term reversal and idiosyncratic volatility (multiplied by one hundred).

Table 4

	SIZE(€10 <sup>6</sup> )	VALUE	SKEWNESS	MOMENTUM	REV	IV(10 <sup>2</sup> )
HMAX	0.9338	0.7243	0.8618	1.1341	5.1098	9.4536
MMAX	1.3488	0.7892	0.1879	1.1692	1.0157	6.8162
LMAX	1.0421	0.8426	-0.3369	1.1892	-1.3660	6.6265
HMAX-LMAX	-0.1083	-0.1183	1.1987	-0.0551	6.4758	2.8271
	(0.3744)	(6.985E-4)	(2.4E-15)	(0.0848)	(6.2E-7)	(0.0341)

*Table 4. MAX Portfolio Characteristics*

*The table summarizes the average values of Size (Market Capitalization, in millions), Value (Book-to-Market ratio), Skewness, Momentum, Short-term Reversal and Idiosyncratic Volatility. Newey-West t-test are conducted, and the responding p-values are reported in the parentheses.*

Table 4 shows that high-MAX portfolio companies generally have smaller market capitalization, lower book-to-market ratio, higher skewness, lower returns in past 11 months, higher returns in the previous month and higher idiosyncratic volatility. The results are mostly in line with Bali et al.'s (2011) findings, except that the high-MAX portfolios in the United States having larger book-to-market ratio than low-MAX stocks.

The market size increases gradually from high-MAX to low-MAX portfolios. Fama and French (1993) has shown that companies with smaller market capitalization tend to perform better than companies with bigger market size. Therefore, the results of univariate sorting analysis are biased because of the market size is unevenly distributed among MAX portfolios. Taking this issue into account, the real return difference between high-MAX and low-MAX might be more negative and more significant.

On the other hand, the book-to-market ratios are lower in high-MAX portfolio than in low-MAX portfolio, and is statistically significant. According to Fama and French (1993), stocks with high book-to-market ratio should outperform stocks with lower value. This face would increase the return difference and its significance between high- and low-MAX portfolios in the single sorting analysis. In other words, the real return difference between high- and low-MAX might be less negative and less significant.

In summary, I find a significantly negative MAX effect for equal-weighted portfolios in the Finnish equity market, however, the MAX effect is not found in value-weighted stock portfolios. Further, I confirm that MAX is not a random phenomenon. The consistency of MAX returns is the building ground for investors to prefer high MAX

stocks. The analysis of characteristics of the MAX portfolios provides further insights about the MAX effect. However, it is impossible to study the effect of one single factor without further analysis, therefore, I conduct a bivariate sorting analysis and firm-level cross-sectional regression analysis, which are presented in the following sections.

#### 4.4. Bivariate sorting

In this section, the relationship between MAX and the future expected returns is investigated by controlling for various variables. As shown in Table 4 above, stocks with high MAX values tend to be small in size, low in B/M value, high skewness, and they tend to have lower returns in past 11 months but have higher returns in the month prior, and they also tend to have high idiosyncratic volatility. It is well studied that characteristics such as low-Book-to-Market ratio stocks, high skewness, previous month's winners and those stocks with high idiosyncratic volatility tend to have low returns in the subsequent months. Therefore, the argument that the MAX effect could be substitute for these cross-sectional effects has its ground.

Therefore, I conducted a series of double sorting analysis to control for these cross-sectional variables, which include Size, Value, Skewness, Momentum, Short-term Reversal and Idiosyncratic Volatility. I first sort stocks into three groups based on the control variables. Then in each group, I sort stocks further into three portfolios based on the extreme positive return from the previous month (MAX). So, there are in total 9 portfolios (3\*3) regarding one control variable. Inspired by Ang et al. (2009), I focus on the 4F-alpha spreads because they accounts for the systematic risk factors, such as size, value and momentum. The results are summarized in Table 5.

Table 5

	HMAX	MMAX	LMAX	HMAX-LMAX	
Panel A. Double sort on size and MAX					
BIG	-0.01287	-0.02497	0.07110	-0.08397	(0.3568)
MED	-0.08230	0.11581	0.18081	-0.26310	(0.0403)
SMA	-0.05521	0.12081	0.09456	-0.14977	(0.0191)
AVE	-0.04013	0.07050	0.08250	-0.16561	(0.0184)
Panel B. Double sort on value and MAX					
HBM	0.0227	0.0755	0.0932	-0.0705	(0.0445)

MBM	-0.1874	-0.1905	-0.1308	-0.0566	(0.0267)
LBM	-0.1538	-0.2121	0.2003	-0.3541	(0.1428)
AVE	-0.1062	0.0657	0.1542	-0.1604	(0.0271)
Panel C. Double sort on skewness and MAX					
HSK	0.01589	0.03613	0.07798	-0.06209	(0.0155)
MSK	0.0957	-0.07097	0.09669	-0.00099	(0.0249)
LSK	-0.1368	0.1714	0.1141	-0.2509	(0.0414)
AVE	-0.0728	0.0355	0.14513	-0.10466	(0.0179)
Panel D. Double sort on momentum and MAX					
WIN	-0.0685	0.0693	0.08535	-0.15385	(0.0352)
MED	-0.05153	0.0719	-0.0351	-0.01643	(0.0498)
LSR	-0.14048	0.0409	0.1837	-0.32418	(0.0373)
AVE	-0.08684	0.0607	0.07798	-0.16482	(0.0093)
Panel E. Double sort on short-term reversal and MAX					
WIN	-0.08964	0.08648	0.05828	-0.14792	(0.0072)
MED	-0.0236	0.0523	0.1691	-0.1927	(0.0432)
LSR	-0.02256	0.1518	0.1555	-0.17806	(0.0376)
AVE	-0.04527	0.09686	0.12763	-0.17289	(0.0238)
Panel F. Double sort on idiosyncratic volatility and MAX					
HIV	-0.09748	-0.07564	-0.08364	-0.01384	(0.0089)
MIV	-0.05729	0.1523	0.126964	-0.18425	(0.0428)
LIV	-0.05703	0.0753	0.131495	-0.18852	(0.3317)
AVE	-0.0706	0.050653	0.058273	-0.12887	(0.0371)

*Table 5. 4F-alphas of bivariate sorting analysis*

*Table 5 records the 4F-alphas of equal-weighted portfolios of Finnish stocks where their previous month's extreme positive returns (MAX) and various control variables are the sorting variables. HMAX and LMAX are composed of the stocks with the highest and lowest MAX returns within each control variable group. Newey-West t-test are conducted, and the responding p-values are reported in the parentheses.*

Panel A double sorts stocks on MAX and Size (in millions). The last column of Panel A shows that the 4F-alpha spreads for medium- and small-size groups are negative and significant at the 5% level. For the big size group, the alpha difference is negative but not significant at any conventional level. This is in line with our previous results that the negative MAX effect exists for small-sized stocks, whereas the relationship between MAX and expected returns is weak for large-sized stocks. Further, it is evident that the average return difference (-0.1656%, p=0.0184) between high- and low-MAX after size

being controlled is more significantly negative than that (-0.1641%,  $p=0.0456$ ) under univariate sorting in Table 1. The reason can be that MAX effect is enhanced due to controlled size effect. Since high-MAX stocks are generally small stocks, and under standard size effect small stocks would suggest high returns. Under univariate sorting, the MAX effect is diluted by the Size effect, however, after controlling for size the MAX effect is enhanced.

Panel B records the results for portfolios double-sorted on MAX and Value. The 4F-alpha differences for both high- and medium-B/M companies are negative and significant at 5% level, yet it is not significant for low-B/M companies. It implies that the MAX effect is strong among high value companies yet weak among low value companies. According to Fama and French (1993), stocks with high book-to-market ratio should outperform stocks with lower book-to-market ratio. This observation would increase the return difference and its significance between high-MAX and low-MAX portfolios in the single sorting analysis. In other words, after controlling for value, the MAX effect should be reduced. Therefore the fact that, the average alpha spread from Panel B is still significantly negative at -0.1604% per month, indicates that the value effect does not cause the negative MAX effect.

Panel C double-sorts stocks on Skewness and MAX. The 4F-alpha differences for all skewness levels are negative and significant. Compared with the alpha spread in univariate sorting analysis, the total average alpha difference in Panel C is smaller in magnitude, but it is still significantly negative, at -0.1047% per month. Similar to value effect, skewness effect would enlarge the return spreads between high- and low-MAX portfolios in the univariate sorting analysis. Therefore, the significantly negative alpha spread after skewness is controlled shows that skewness effect is also not the driving force behind the MAX effect.

4F alphas from portfolios sorted on both Momentum and MAX is recorded in Panel D. The 4F-alpha differences for all momentum groups are negative and significant. Bali et al. (2011) report their alpha difference is smaller in magnitude in double-sorting analysis than in single-sorting analysis, yet in my sample, the alpha difference is interestingly larger for double sorts even though the difference is quite small. More importantly, the average alpha spread between high- and low-MAX portfolios is negative (-0.1648% per month) and statistically significant ( $p=0.0093$ ) after

Momentum is controlled, showing that the momentum effect does not cause the MAX effect.

Portfolios sorted on both Short-term Reversal and MAX are reported in Panel E. The 4F-alpha spread for WNR (high short-term reversal) group is highly significant (at 1% level), and significant (at 5% level) for MED (medium short-term reversal) and LSR (low short-term reversal) groups. This implies that the negative MAX effect is strongest for high short-term reversal group and weaker for medium and low short-term reversal groups. As Bali et al. (2011) point out, stocks with extremely high daily returns also tend to have positive monthly returns, therefore, MAX could be a substitute for the short-term reversal effect. However, this proves to be wrong. The average alpha spread from Panel E is negative (-0.1781% per month) and significant ( $p=0.0238$ ), proving that the negative MAX effect still exists after short-term reversal effect being controlled.

The last Panel F contains the 4F-alphas for portfolios sorted on both Idiosyncratic Volatility and MAX. The negative MAX effect is statistically significant in high- and medium- idiosyncratic volatility portfolios, but insignificant in stocks with low idiosyncratic volatility. However, it can be shown from the last column in Panel F that average alpha spread at -0.1289% per month, and is statistically significant ( $p=0.0371$ ). It shows that the negative MAX effect is not a substitute for the idiosyncratic volatility effect neither. More detailed analysis between Idiosyncratic Volatility and MAX is discussed later in the thesis.

#### 4.5. Firm-level cross-sectional regression

Although bivariate sorting analysis provides an easy way to study MAX effect beyond the other characteristics, it does not sufficiently control for the variables. Firstly, the bivariate sorting analysis cannot report the concurrent effects of MAX and the variables. Secondly, it cannot explain the interactions between the variables. Instead, firm-level cross-sectional regression is able to explain these simultaneous effects and dependencies.

The cross-sectional regression is conducted monthly. The slope coefficients of each variable are reported, as well as the p-value of their Newey-West adjusted t-statistics.

Following Bali et al. (2011), my firm-level cross-sectional regression model is:

$$R_{i,t+1} = \lambda_0 + \lambda_1 MAX_{i,t} + \lambda_2 SIZE_{i,t} + \lambda_3 VALUE_{i,t} + \lambda_4 MOM_{i,t} + \lambda_5 REV_{i,t} + \lambda_6 IV_{i,t} + \varepsilon_{i,t+1} \quad (8)$$

Where  $R_{i,t+1}$  is the return for stock  $i$  in month  $t+1$ . The explanatory variables such as extreme positive daily return in the previous month (MAX), book-to-market ratio (B/M), and idiosyncratic volatility (IV) are the value from the previous month (month  $t-1$ ), market capitalization (SIZE) is the book-to-market ratio 6 months prior, short-term reversal (REV) is the return from month  $t-2$ , and momentum variable (MOM) is calculated over the 11-month period ending in 2 months prior. Table 6 summarizes the results of the regression.

Table 6

Regression	MAX	SIZE(10 <sup>6</sup> )	B/M	WML	REV	IV(10 <sup>2</sup> )
1	-0.09367 (0.044)					
2		-0.08936 (0.013)				
3			0.63 (1.2E-4)			
4				0.14 (0.017)		
5					-0.091 (0.021)	
6						-0.006 (0.043)
7	-0.0712 (0.037)	-0.054 (0.033)	0.59 (1.2E-4)	0.14 (0.017)	-0.091 (0.019)	0.0013 (0.673)

Table 6. Firm-level cross-sectional regression

*This table reports slope coefficients from firm-level cross-sectional regression. Rows 1 to 6 show the slope coefficients when each corresponding variable is the only variable in the regression. Row 7 contains the coefficients from the regression with all variables Newey-West t-test are conducted, and the responding p-values are reported in the parentheses.*

In regression 1, I use MAX as the only variable. A negative and significant relation between MAX and expected returns is recorded, with coefficient of -0.0937 and the p-

value of 0.044. Rows 2 to 6 show the slope coefficients when each corresponding variable is the only variable in the regression. The results are mostly consistent with previous research: size has significantly negative coefficient, book-to-market ratio and momentum are significantly positively related to future expected returns, short-term reversal and idiosyncratic volatility have significantly negative relations with returns in the following month.

The coefficients from the regression with all variables are recorded in the 7<sup>th</sup> row of Table 6. The coefficient of MAX becomes more negative when taking the characteristics of the high MAX stocks into consideration. The slope coefficient changes to -0.071 with p-value of 0.037. Compared with the MAX slope coefficient in the univariate regression model 1, the MAX coefficient in the full regression model 7 is less negative. It is shown earlier that high-MAX stocks have generally small book-to-market value, small average return in the past 11 months, and high return in the past months and have high idiosyncratic volatility. Therefore, controlling for these characteristics would increase the high-MAX return premium. Although market capitalization has reverse effect, it cannot offset the effects caused by other variables.

The firm-level cross-sectional regression reinforces the conclusion I mentioned earlier that the negative MAX effect is not caused by cross-sectional variables such as size, value, momentum, short-term reversal and idiosyncratic volatility. My findings are consistent with Bali et al. (2011), who report a negative and statistically significant MAX coefficient in the univariate portfolio regression (regression 1); and in the full specification model (regression 7) they measure even more negative MAX slope coefficient with higher t-statistics.

#### 4.6. MAX effect and idiosyncratic volatility

It is argued that MAX effect might be a substitute for idiosyncratic volatility effect. Previous literature has shown that stocks which have high idiosyncratic volatility (IV) has lower expected returns on average than stocks which have the lower IV (Ang et al., 2009). From Row 6 in Table 6 which is posted above, the slope coefficient for idiosyncratic volatility is significantly negative related to the expected return, which proves that IV has negative effect on the cross-sectional returns in my sample as well. Moreover, as Table 4 shows, high MAX stocks generally have higher idiosyncratic

volatility (IV). Therefore, it is possible that the negative MAX effect is in fact just a substitute for the idiosyncratic volatility effect. In this section, I study specifically the relationship between MAX effect and idiosyncratic volatility (IV).

First of all, I test whether IV would affect the negative relationship between MAX and expected returns. As has discussed earlier regarding Panel F in Table 5, the average alpha spread (-0.1288% per month) is significantly negative after controlling for idiosyncratic volatility, which indicates that idiosyncratic volatility does not affect the MAX effect. Secondly, I do another bivariate sorting analysis but with an opposite sorting order. I first sort stocks into three groups based on the MAX and then within each MAX group I rank stocks using the idiosyncratic volatility as sorting variable. As a result, the 4F-alpha spread between high-IV and low-IV is positive but insignificant with the value of 0.08% and p-value of 0.33. It can be inferred that when MAX is taken into account, the effect of IV weakens. However, definitive decisions cannot be made based on the insignificant results from this analysis. Therefore, I further analyse the problem from the firm-level cross-sectional regression.

Table 7

Regression	MAX	SIZE( $10^6$ )	B/M	WML	REV	IV( $10^2$ )
1	-0.09367 (0.044)					
2		-0.08936 (0.013)				
3			0.63 (1.2E-4)			
4				0.14 (0.017)		
5					0.091 (0.021)	
6						-0.006 (0.043)
7	-0.0905 (0.011)					0.0011 (0.654)
8	-0.0712 (0.037)	-0.054 (0.033)	0.59 (1.2E-4)	0.14 (0.017)	0.091 (0.019)	0.0013 (0.673)

Table 6. Firm-level cross-sectional regression—MAX and IV

*This table reports slope coefficients from firm-level cross-sectional regression. Rows 1 to 6 show the slope coefficients when each corresponding variable is the only variable in the regression. Row 7 records the regression with MAX and Idiosyncratic Volatility as explanatory variables. Row 8 contains the coefficients from the regression with all variables. Newey-West t-test are conducted, and the responding p-values are reported in the parentheses.*

Table 7 reports the coefficient from firm-level cross-sectional regression. The difference between Table 7 and Table 6 is that one more regression with MAX and Idiosyncratic Volatility as explanatory variables are recorded in the 7<sup>th</sup> row of Table 7. As Table 6, the 1<sup>st</sup> row until the 6<sup>th</sup> row represent regressions with only one explanatory variable; and the 8<sup>th</sup> row shows the regression with all variables. From Row 6, a negative and significant IV slope coefficient is found with value of -0.006 and p-value of 0.043. Therefore, I confirm IV is negatively related to expected returns as proposed by Ang et al. (2006). It is intriguing to notice from the 7<sup>th</sup> row that the coefficient of IV becomes positive (0.0013) when MAX is added to the regression, although it is not significant. Meanwhile, the coefficient of the MAX changes slightly from -0.094 to -0.0905. In the full regression model 8, MAX has less negative coefficient (-0.071) but significant with p-value of 0.037, while IV stays positive but insignificant. These data are consistent with the findings of the double sorts in Table 5 that MAX effect is not a substitute for idiosyncratic volatility effect.

In summary, idiosyncratic volatility is negatively related to the cross-sectional expected returns in the Finnish market, but when MAX effect is controlled, this negative relationship between IV and future return weakens. My results agree mostly with Bali et al. (2011), who find that MAX stays significantly negative after IV is controlled. Bali et al. (2011) also find that the negative relationship between IV and expected returns turns to significantly positive when controlling for MAX, but I do not find such changes in my analysis. The argument that MAX is just a manifestation for idiosyncratic volatility effect can be proven to be incorrect.

## 5. Conclusion

Over the last few decades, it has been discovered that individual investments are not well-diversified as suggested by the classic Capital Asset Pricing Model (CAPM). Bali et al.'s (2011) paper showed that American investors tend to pay more for stocks that exhibit extremely high positive returns, and that these stocks have lower returns in the future. Specifically, Bali et al. (2011) report that the extreme positive returns in the previous month (MAX) is negatively related to the subsequent stock returns in the American stock market. Thus the MAX effect is introduced as one of the cross-sectional anomalies into finance literature. The subsequent studies concerning MAX effect show diverse results in different economic areas in the world, and few study has covered the Finnish equity market. Therefore, it is of value to examine the MAX effect again and also in Finland. In this thesis, I study whether the extreme positive returns in the previous month (MAX) negatively affect the cross-sectional expected returns in the Finnish market. I report a return difference of -1.11% per month between high-MAX and low-MAX portfolios and a corresponding alpha spread of -0.16%, both of which are statistically significant at 5% level. Thus the thesis provides an evidence that the negative MAX effect does exist in the Finnish stock market. Bali et al. (2011) find significantly negative MAX effect in both equal- and value-weighted portfolios in the U.S. However, the MAX effect in Finland is only shown in equal-weighted portfolios. The possible explanation might be that the MAX effect is most common in small-sized companies in Finland. Furthermore, I suggest that the MAX effect in Finland is largely caused by household investors. Small companies give individual investors an advantage over institutional investors. For one thing, most small companies are under regulations which makes it difficult for institutional investors to buy or sell large block of stocks from them. For another, many small-sized companies have little analyst coverage. Therefore, it is possible that the individual investors cause the negative MAX effect in the Finnish stock market.

The persistence of MAX is the premise for investors to prefer high-MAX stocks. Therefore, I further seek to test that MAX effect does not occur randomly. Firstly, I compare the average MAX values in each MAX groups at the formation month and at the following month. The result show that high-MAX continues to exhibit significantly

higher maximum daily returns in the following month compared to the low-MAX portfolios. Secondly, I use a transition matrix, which reports the probabilities of stock movement among three MAX levels from the previous month to the next, to further examine the level of persistence in MAX values. If MAX returns are random, I expect all probabilities to be approximately 33%. However, the extreme groups (high-MAX to high-MAX, low-MAX to low-MAX) are always above 33%. It also implies that the MAX returns do not follow a random walk. I further calculate the autocorrelations for MAX with lags of 1 to 12 months, and the result shows that there is a high level of predictability in the time series for each MAX portfolio. Additionally, Augmented Dickey Fuller unit root test is conducted. The existence of a unit root is rejected in 83.6% of the cases. Therefore, I conclude that the MAX returns do not occur randomly, instead, they are noticeably persistent.

After analysing the characteristics of the MAX portfolios, I find that high-MAX portfolio companies have in average smaller market size, lower book-to-market ratio, higher skewness, lower returns in past 11 months, higher returns in the previous month and higher idiosyncratic volatility. It is well studied that stocks with low Book-to-Market ratio stocks, low returns for the past 11 months, previous month's winners and those stocks with high idiosyncratic volatility tend to have low returns in the months followed. Therefore, the argument that the MAX effect could be a substitute for these cross-sectional effects has its ground. Because it is impossible to study the effect of MAX returns separately from other characteristics in the univariate sorting analysis, I conduct a bivariate sorting analysis and a cross-sectional regression analysis. As a result, I find a significantly negative MAX effect after controlling for variables such as size, value, skewness, momentum, short-term reversal and idiosyncratic volatility. For the relationship between idiosyncratic volatility and MAX specifically, I conclude that although IV has negative relationship with future returns, and that MAX and IV are correlated, MAX is not a substitute for idiosyncratic volatility. Nevertheless, I did not find that the negative relationship between IV and future return turns significantly positive after controlling for MAX as Bali et al. (2011) stated.

The results indicate that in theory investors in the Finnish stock market could increase their portfolio returns by short-selling high-MAX stocks and buying low-MAX stocks.

But why the MAX effect is not arbitrated away? Bali et al. (2011) suggest that the characteristics of the high-MAX stocks, such as small size, can lead to high transaction costs when enforcing the investing strategy. Besides, investor and institutional restrictions, unwillingness or inability towards short-selling can make it difficult to benefit from MAX effect in practice.

It would be of value to test if Finnish companies with higher institutional ownership are less affected by MAX than firms with lower institutional ownership. Inspired by Aboulamer and Kryzanowski (2016), I would double sort my sample data using institutional ownership levels and MAX as sorting variables. Then, in the lowest institutional holding portfolio, I would calculate the 4F-alpha difference between high- and low-MAX groups. As comparison, I also conduct analysis in the higher institutional ownership portfolios, and calculate the alpha spreads between high- and low-MAX portfolios. Unfortunately, due to time restriction, I am unable to find official or publicly available database containing institutional holdings in Finland which is similar to the 13F filings required by the SEC in the America nor can I approximate the level of institutional investors from investor managers' US mail as Aboulamer and Kryzanowski (2016) used in Canadian market. It is an area for future study.

Moreover, the existence of MAX effect suggests that investors in the Finnish market are biased as the investors in the America. According to Mohrschladt and Baars (2018), while both evaluation bias and judgement bias play important roles behind the MAX effect, they imply different financial implications. Under evaluation bias, investors prefer lottery-like stocks, thus always pushing the subsequent returns lower. Under judgement bias, however, investors might over- or under-react based on the information they get. Thus, the managers who provide financial information can possibly lead the direction of the mispricing (Mohrschladt and Baars, 2018). Thus it is important to test which of the two behavioural biases explains the MAX effect more convincingly. It is of future research to investigate the role judgment bias and evaluation bias play behind the MAX effect.

## References

- Aboulamer, A., Kryzanowski, L., 2016. Are idiosyncratic volatility and MAX priced in the Canadian market? *Journal of Empirical Finance*, 37, 20 - 36.
- Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. *The Journal of Finance*, Vol. 61, Issue. 1, 259 - 299.
- Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: international and further US evidence. *Journal of Financial Economics*, Vol. 91, 1 - 23.
- Annaert, J., De Ceuster, M. and Versteegen, K., 2013. Are extreme returns priced in the stock market? European evidence. *Journal of Banking & Finance*, 37, 3401 - 11.
- Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, 99 (2), 427 - 446.
- Barberis, N. and Huang, M., 2008. Stocks as lotteries: the implications of probability weighting for security prices. *American Economic Review*, Vol. 98, Issue 5, 2066 - 2100.
- Barberis, N., Mukherjee, A., and Wang, B., 2016. Prospect Theory and Stock Returns: An Empirical Test. *The Review of Financial Studies*, Vol. 29, Issue. 11, 3068 - 3107.
- Banz, Rolf W., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics*, Vol. 9, 3-18.
- Brunnermeier, M. K. and Parker, J. A., 2005. Optimal expectations. *American Economic Review*, Vol. 95, Issue 4, 1092-1118.
- Brunnermeier, M. K., Gollier, C. and Parker, J. A., 2007. Optimal beliefs, asset prices, and the preference for skewed returns. *American Economic Review*, Vol. 97, 159 - 165.
- Carhart, M.M., 1997. On persistence in mutual fund performance. *The Journal of Finance*, Vol. 52, 57 - 82.
- Cheon, Y., Lee, K.H., 2014. Maxing out globally: MAX-premium, uncertainty avoidance, and the cross section of expected stock returns. Working paper. Seoul National University.
- Cohen, Randolph B., Paul A. Gompers, and Tuomo Vuolteenaho, 2002. Who underreacts to cash flow news? Evidence from trading between individuals and institutions. *Journal of Financial Economics*, Vol. 66, 409 – 462.
- Conrad, J., Kapadia, N., Xing, Y., 2014. Death and jackpot: Why do individual investors hold overpriced stocks? *Journal of Financial Economics*, Vol. 113, Issue 3, 455 - 475.
- Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. *Journal of Finance*, Vol. 53, Issue. 6, 1839 - 1885.
- Fairfield, Patricia M., Scott Whisenant, and Terry L. Yohn, 2003. Accrued earnings and growth: Implications for future profitability and market mispricing. *The Accounting Review*, Vol. 78, 353-371.
- Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, Vol. 33, 3 - 56.

- Fama, E.F., French, K.R., 2008. Dissecting anomalies. *The Journal of Finance*, Vol. 63, 1653 - 1678.
- Golec, J. and Tamarkin, M., 1998. Bettors love skewness, not risk, at the horse track. *Journal of Political Economy*, Vol. 106, 205 - 225.
- Griffin D., and Tversky A., 1992. The Weighing of Evidence and the Determinants of Confidence. *Cognitive Psychology*, Vol. 24, 414 - 435.
- Han, B. and Kumar, A., 2013. Speculative retail trading and asset prices. *Journal of Financial and Quantitative Analysis*, Vol. 48, 377 - 404.
- Haykir Ozakan., 2018. Does MAX Anomaly Exist in Emerging Market: Evidence from the Turkish Stock Market? *International Journal of Economics and Financial Issues*, Vol. 8, Issue. 2, 148 - 153.
- Ikenberry, D., Josef L., and Theo V., 1995. Market under-reaction to open market share repurchases. *Journal of Financial Economics*, Vol. 39, 181 - 208.
- Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, Vol. 48, Issue. 1, 65 - 91.
- Kumar, A., 2009. Who gambles in the stock market? *The Journal of Finance*, Vol. 64, Issue. 4, 1889-1933.
- Loughran, Tim., and Jay R. Ritter., 1995. The new issues puzzle, *The Journal of Finance*, Vol. 50, 23 - 51.
- Mitton, T. and Vorkink, K., 2007. Equilibrium under diversification and the preference for skewness. *Review of Financial Studies*, Vol. 20, 1255 - 1288.
- Mohrschladt Hannes., and Baars Maren., 2018. An Alternative Behavioral Explanation for the MAX Effect. Available at SSRN: <https://ssrn.com/abstract=3214438> or <http://dx.doi.org/10.2139/ssrn.3214438>
- Nartea G.V., Wu, J., Liu, H., 2014. Extreme returns in emerging stock markets: evidence of a MAX effect in South Korea. *Applied Financial Economics*, Vol. 24, No. 6, 425 - 435.
- Newey, W.K., West, K.D., 1987. Hypothesis testing with efficient method of moments estimation. *International Economic Review*, Vol. 28, Issue. 3, 777 - 787.
- Rosenberg, B., Kenneth R., and Ronald L., 1985. Persuasive evidence of market inefficiency. *Journal of Portfolio Management*, Vol. 11, 9 - 17.
- Tversky, A., Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, Vol. 5, 297 - 323.
- Zhong, A., Gray, P., 2016. The MAX effect: An exploration of risk and mispricing explanations. *Journal of Banking and Finance*, Vol. 65, 76 - 90.