Do Past Extreme Returns Explain the Future Performance?

MAX Effect Evidence from the Nordic Countries

Abstract

I examine MAX effect, i.e. negative relation between high maximum daily returns in the past month and returns in the next month, in the Nordics. Bali et. al. (2011) first find the MAX effect in U.S.A. I examine the MAX effect in the Nordics because of lack of evidence in the Nordics and the Aboulamer et. al (2016) recent contradictory finding in Canada. I confirm the previous results about MAX effect. I find negative cross-sectional relation between high maximum returns in past month and returns in the next month after controlling for variables: beta, size, book-to-market ratio, momentum, short term reversal and illiquidity. My results are also robust for idiosyncratic volatility puzzle i.e. negative relation between high idiosyncratic volatility and returns introduced by Ang et. al (2009), in fact the idiosyncratic volatility puzzle seems to overturn to positive effect after controlling MAX. The effect is consistent with investors preference for lottery-like stocks which lead to over-demand, higher prices and lower expected returns for high MAX stocks.

Bachelor’s Thesis

Aalto University School of Business

Department of Finance

Anton Kokljuschkin

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Aalto University

School of Business

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1 Introduction

Although asset pricing models have been examined in finance for decades there is still no consensus for perfect asset pricing model. It is unknown which factors perfectly determine changes in cross-sectional expected stock return. One of the recently proposed variables to the asset pricing models is the MAX effect i.e. the negative relation between the past month maximum returns and the next month returns. Bali et. al. (2011) find first this negative relation in the U.S.A. and Annaert et. al (2013) confirm the results in Europe. The only Nordic country in their sample is Finland and that too with minority weight. The most recent finding about MAX effect is Aboulamer et. al. (2016) research from Canada. They find the positive (opposite) relation between past month maximum returns and the next month returns. Because of the contradictory findings in Canada and the lack of evidence in the Nordics it is important to examine MAX effect again and also in the Nordics.

The first theory about asset pricing dates back to the year 1738 when Bernoulli published the famous St Petersburg paper which discovered that investors prefer to increase the wealth and the same time minimize the risk. This becomes a leading idea in finance, and remains all the way to the 1950s when Markovitz (1952) revolutionizes the whole field of finance by publishing the article Portfolio Selection. (Dimson, 1999.) The first mathematical capital asset pricing model was introduced in 1960s when William Sharpe (1964) and John Lintner (1965) introduce the capital asset pricing model (CAPM). For this revolutionary work Sharpe received Nobel Prize later in 1990. (Fama, French ,2004.) CAPM assumes that investors have quadratic utility functions and returns are normally distributed (Berk, 1997). Under these assumptions expected returns can be calculating as a covariance of the returns and the market portfolio. The biggest advantage of CAPM is that it offers easy and intuitive explanation for the expected returns.

Although CAPM is a revolutionary model and can be seen as the start of modern era of finance, its empirical evidences are quite weak. However, Black (1972) version of the model was a big success. In the late 1970s researchers begin to develop complicated models with more variables than just market beta. Variables like size, momentum and different price ratios start to appear in asset pricing models together with beta. (Fama, French, 2004.)

Although Fama French four-factor model is a widely used and accepted model for estimating predicted stock returns, usually when more explaining power to the model is needed it gets more variables, like idiosyncratic volatility or illiquidity of the stock. Often new effects and variables are judged to be the results of data mining and pure statistical coincidences. The best way to prove these allegations wrong is to test the effect in different markets in different time periods. (Annert et. al., 2013.) This is one of the objectives of this thesis. Clearly MAX effect needs more research before it can be widely accepted and used globally in the asset pricing model. This thesis brings new evidence in the new market about the existence of MAX effect which will further strengthen the position of the MAX in the asset pricing models.

I start my research by doing univariate portfolio analysis. I construct a decile portfolio by ranking companies based on the daily maximum returns in the past month. The lowest daily maximum returns in each month are placed in the first portfolio and the highest daily maximum returns in each month are placed in the last, tenth portfolio (i.e. the higher maximum daily return in each month, the higher portfolio number). The portfolios are constructed in the beginning of each month from January 1991 to December 2015. I construct both value-weighted (VW) and equal-weighted (EW) portfolios. Bali et al. (2011) report statistically and economically significant results in U.S.A. They measure a monthly difference of -1.03 % in value-weighted and -0.65% difference between the highest MAX decile and the lowest decile portfolio. I measure the monthly difference of -0.36% (VW) and 0.25% (EW) between the HIGH (10) and LOW (1) portfolios. However, my results are far from significant. I also do multiday univariate portfolio analysis which increases the differences between portfolios. When ranking is based on the average of the three highest daily return within the past month (MAX (3)), the value-weighted portfolio difference increases to -0.77% but still remain insignificant.

Portfolio analysis has its own advantages. It is very intuitive and a simple way to calculate returns, but it destroys a lot of data about the characteristics of the company. High MAX portfolio companies obviously do not represent the whole universe of stocks. High MAX stocks are usually small companies with low book-to-market. Because of the shortcomings of portfolio analysis I also do firm-level cross-sectional regressions. Bali et. al. (2011) find negative and significant relation between MAX and return after controlling the variables such as size, book-to-market ratio, momentum, market beta, illiquidity and past month return. I also find negative and significant results in my firm-level cross-sectional regression when controlling with the same variables. The results are also robust to winsorizing MAX both at the 99% level and 95% level. In fact, the effect is even stronger and more significant after doing so. Finally, I examine Ang et. al. (2009) idiosyncratic volatility puzzle together with maximum effect. I find some indication about the existence of the idiosyncratic volatility puzzle in my sample although the results are not significant. After controlling idiosyncratic volatility with the maximum daily returns the effect disappears and even turn to opposite (positive) direction. Therefore, the results are also robust to idiosyncratic volatility puzzle and even some indication is found that idiosyncratic volatility is just a proxy for MAX and not other way around.

The rest of my thesis is structured as follows: In the second Section I will go through the previous literature about my subject and cover the theory about MAX effect. In the third Section I cover the data and the construction of variables. In the fourth Section I will go through the results for both portfolio analysis and firm level cross-sectional regressions. The fourth Section also covers the persistence of the MAX effect and characteristics of each of the portfolio companies. In the fifth Section I review the idiosyncratic volatility puzzle and the MAX effect together. In the sixth Section I conclude the thesis and go through the results and conclusions of the thesis.

2 Literature review

The MAX effect is consistent with previous research about the investors' biased and irrational behavior e.g. propensity to buy lottery-like stocks i.e. stocks with tiny low probability to huge win and high probability to small loss. Kumar (2009) reports that people's lottery-like preferences affect their investment decisions. The irrational preference is in line with the theory of attention effect introduced by Barber and Odean (2008). They showed that investors are more likely to buy stocks with high attention which can be i.e. extreme daily return or appearance in the daily news or unusual trading volume. It is also consistent with Tversky and Kahneman (1992) Cumulative Prospect theory which claims that people over-estimate the probability of very unlikely winnings and under-estimate the probability of probable winnings.

After all, in the context of stock-markets this denotes that people prefer stocks with lottery-like characteristics which can lead to over-demand of these stocks, i.e. higher prices and lower expected returns.

Bali et al. (2011) publish an article *Stocks as lotteries and the cross section of expected returns* which introduces the MAX effect i.e. the negative correlation between high maximum returns and future returns which continue the research about investors preference about assets with lottery-like payoffs. They find the effect when trying to find reasons behind Ang. et. al (2009) idiosyncratic volatility puzzle i.e. negative relation between idiosyncratic volatility and future returns. Instead of finding the effect behind the puzzle they find that idiosyncratic volatility puzzle is proxy for MAX effect. Bali et. al (2011) examine this investors irrational propensity by comparing returns between stocks with high daily returns in the past month to stocks with low daily maximum returns in the past month. They find economically and statistically significant results. High daily maximum return stocks have over 1% higher returns monthly compared to lower daily maximum returns stocks.

If this phenomenon exists, why it is not arbitraged away? Few explanations have been discovered. Benefiting from this phenomenon requires short-selling stocks with high maximum returns in the past month. Like previous research has showed investors or institutions restrictions, unwillingness or inability might prevent short-selling stocks which in practice makes impossible to directly benefit from MAX effect. Also the characteristics of the high MAX return stocks e.g. small size can lead to high transaction costs when executing the investing strategy. (Bali et. al., 2011.)

3 Data

3.1 Sample

The data is downloaded from Thomson DataStream (TDS). My sample contains in total 2094 companies from all Nordic countries: Finland (226 companies), Sweden (924), Norway (546), Denmark (364) and Iceland (34). My data series begins from 1.1.1985 and ends 31.12.2015. The sample includes both listed and de-listed companies which will minimize the effect of survivorship bias. If all required financial ratios or data were not available in Datastream companies are excluded in the final sample. The final regressions comprise 228 764 monthly company observations. In the portfolio analyses time-series are shorter because of the lack of available European Fama-French factors data in Kenneth R. French's website. The univariate and bivariate portfolio analyzes time-series are from November 1991 to December 2015. Market portfolio is constructed by myself because no suitable Nordics market portfolio was available. It has been constructed as a value-weighted portfolio of all Nordics stocks available in Datastream. I also calculate risk-free rate by myself as a weighted average of 3-month interbank offer rate (see Appendix A). Fama French Carhart four-factor model factors are from Kenneth French's website.

3.2 Construction and adjustments of the variables

All the returns are calculated by using Datastream Total Return Index (RI) which takes into consideration both dividends and splitting issues (see Appendix A). I use daily values for calculating both daily maximum returns and monthly returns for each company. Monthly book-to-market ratios (taking inverse of market-to-book ratio) and market capitalizations are both downloaded directly from Datastream by converting all of the values to euros with Datastream's own currency converter. All my variables are defined more specifically in Appendix B.

I use the same methods to correct possible errors in Datastreasm than Annaert et al. (2013); Ince and Porter (2006) and Schmidt et al. (2011). First, I correct issues with decimal errors i.e. decimal point moves to right (left) e.g. first day return index value is 82.20 and although value should remain the same in the next day Datastream gives a value of 822.0 (8.22). Because of this error daily return get value of 900% (-90%) instead of the real value of 0%. I correct decimal error by excluding all returns which are above 400% or below -85% which are (-) 50% true return accompanied by left (right) decimal error. Annaert et. al (2013).

Secondly, when calculating monthly MAX returns for each company I require at least 15 observations per month. In average there are 20 trading per month, so if more than five values are missing in $month_t$ MAX(N) is set missing. By doing this I ensure that MAX values do not contain just series of zeros which would distort the results.

Inspired by the previous research about the MAX effect all the t-statistics which are presented in the thesis are adjusted t-statistics presented by Newey and West (1987). This adjustment corrects the both autocorrelation and heteroscedasticity of error-terms. This will make my results robust and also more comparable with previous research.

4 Results

4.1 Univariate portfolio analysis

Univariate portfolio analysis, i.e. sorting stocks to the portfolios based on one variable: past month maximum daily return (MAX), includes my whole sample, 2094 sample companies from Nordics but the time series is shorter because Fama-French-Carhart 4 factor factors are only available from November 1990 onward. Other weakness of the analysis is that Iceland is not officially included in Europe portfolio in Kenneth French's website when estimating Fama French factors but because of similarity and minority of the Islandic stocks in my sample I use the same Fama-French factors for Icelandic companies as well. Portfolios are constructed by ranking the companies in deciles based on the past month maximum daily return so that portfolio 1 (LOW) consists the companies that have low daily maximum returns in the past month_{t-1} and other way around portfolio 10 (HIGH) consists companies that have high daily maximum in the past month_{t-1}. In average each portfolio has 71 companies. I have to exclude 7 months (See Appendix A) because of too much 0 % maximum daily returns in past month which leaded the issue where there are not any stocks in some portfolio when other has 170 stocks. This would prevent me from calculating averages because of any data was not available from these months. This exclusion however does not affect the overall results at all. By doing so every portfolio has the same amount stocks in every month (if divisible by ten).

Table 1
Univariate portfolio analysis
Portfolios are constructed by ranking stocks based on the maximum daily return within past month. Portfolio 1 (10) consists the stocks with the lowest (highest) maximum daily returns. Portfolios are constructed every month from November 1991 to December 2015. Table include both equal-weighted (EW) and value-weighted (VW) portfolios. FF4 alpha columns presents Fama-French-Carhart four-factor model alphas. The last rows present the difference between tenth and first portfolio raw returns and four-factor alphas and below that in the parentheses the Newey-West (1987) adjusted t-statistics.

Equal-weighted portfolio			Value-weighted portfolio		
Portfolio	Average monthly raw return	FF4 alpha	Portfolio	Average monthly raw return	FF4 alpha
1 (LOW)	1.41 %	0.92	1 (LOW)	1.47 %	0.96
2	1.25 %	0.77	2	1.07 %	0.49
3	1.32 %	0.88	3	1.18 %	0.66
4	1.26 %	0.90	4	1.04 %	0.67
5	1.24 %	0.88	5	1.21 %	0.58
6	1.33 %	1.02	6	1.20 %	0.80
7	0.96 %	0.75	7	1.19 %	0.85
8	0.95 %	0.71	8	1.21 %	0.90
9	1.09 %	0.89	9	0.91 %	0.79
10 (HIGH)	1.66 %	1.38	10 (HIGH)	1.11 %	0.69
(10-1) difference	0.25 %	0.24	(10-1) difference	-0.36 %	-0.50
T-statistics	(0.31)	(0.34)	T-statistics	(-0.71)	(-1.08)

Table 1 presents the overall result of univariate portfolio analysis. Table presents the average monthly raw returns and four-factor alphas for each portfolio. Last two rows present the hedge (10-1) portfolio return and below in the parentheses its Newey-West (1987) adjusted t-statistics. The raw return and four-factor alpha difference between 10 (HIGH) and 1 (LOW) portfolio is negative only in the value-weighted portfolio. Both value-weighted and equal-weighted differences are insignificant. Value-weighted raw return difference between portfolios 10 (HIGH) and 1 (LOW) is -0.36% but only with t-statistic of -0.71. Four-factor alpha difference is -0.50 but insignificant with t-statistics of -1.08. In equal weighted portfolios results are opposite than in the value-weighted portfolio. The difference between portfolios 10 (HIGH) and 1(LOW) is 0.25% with the t-statistics of 0.75. Four-factor alpha difference is also positive but insignificant. The difference is 0.24 with t-statistics of 0.34.

Both equal- and value-weighted portfolios behave quite randomly and any clear pattern is not found. In the both cases the highest average return can be found in the far end of the portfolios either in the first (1 (LOW)) portfolio or in the last (10 (HIGH)) portfolio. My findings are somewhat different than Bali et. al. (2011) report. They find the clear decreasing pattern for four-factor alphas starting from the first (1) portfolio. They also report significant negative raw return and four-factor alpha differences in the value-weighted and significant four-factor alpha in the equal-weight portfolio. However, my value-weighted raw returns and four-factor alphas are quite close the ones than Bali et. al. (2011) report although my results were insignificant.

4.2 Univariate portfolio analysis for MAX (2) and MAX (3) portfolios

I also do univariate portfolio analysis for averages of 2 and 3 highest daily maximum returns to which are presented in Table 2. Returns are calculated by using same methods than above but instead of just ranking the companies based on the highest daily return in the past month they are ranked now based on the average of the two or three highest daily returns within month. Portfolios are marked as a MAX(N) where N denotes the number of returns that are included when calculating average ie. MAX (2) portfolios are ranked by the average of two highest return. MAX (1) column consists the same data than above and it has attached only to make comparison easier.

MAX (2) and MAX (3) portfolio returns are mostly in line with MAX (1) returns but the differences between 10-1 portfolios increase in both value- and equal-weighted portfolios. The difference between raw return increases from -0.36% in MAX (1) value-weighted portfolio to -0.77% in MAX (3) portfolio ranking. This is mostly because of lower returns in 10(HIGH) portfolio.

Equal-weighted portfolios behave mostly in the same way than value-weighted portfolios. The difference increases (the value decreases) and finally even turns into negative in MAX (3) portfolio. Even the difference turns to negative, the t-statistics decreases even further. The four-factor alpha difference behave also in the same way but like raw return, the difference remains insignificant as well.

Table 2
Univariate multiday portfolio analysis
Portfolio are constructed by ranking the stocks based on the average of the N highest daily maximum returns(MAX(N)) within the past month. Portfolios are constructed every month from November 1991 to December 2015. Table consists both equal-weighted (EW) and value-weighted (VW) weighting methods. Portfolio 1 (10) consists the lowest (highest) multiday within past month. The last rows present the difference between tenth and first portfolio raw return and four-factor (4F) alphas and below the difference in the parentheses the Newey-West (1987) adjusted t-statistics.

Equal-weighted portfolio monthly returns				Value-weighted portfolio monthly returns			
Portfolio	MAX(1)	MAX(2)	MAX(3)	Portfolio	MAX(1)	MAX(2)	MAX(3)
Panel A: Average equal portfolio returns for univariate sorts on MAX(N)				Panel B: Average value weighted portfolio returns for univariate sorts MAX(N)			
1(LOW)	1.41 %	1.61 %	1.61 %	1(LOW)	1.47 %	1.42 %	1.42 %
2	1.25 %	1.39 %	1.42 %	2	1.07 %	1.20 %	1.24 %
3	1.32 %	1.34 %	1.30 %	3	1.18 %	1.23 %	1.26 %
4	1.26 %	1.36 %	1.33 %	4	1.04 %	1.14 %	1.02 %
5	1.24 %	1.25 %	1.28 %	5	1.21 %	1.06 %	1.05 %
6	1.33 %	1.24 %	1.22 %	6	1.20 %	1.22 %	1.03 %
7	0.96 %	1.17 %	1.19 %	7	1.19 %	1.18 %	1.26 %
8	0.95 %	1.10 %	1.04 %	8	1.21 %	1.13 %	1.29 %
9	1.09 %	0.91 %	1.25 %	9	0.91 %	1.22 %	1.30 %
10(HIGH)	1.66 %	1.72 %	1.51 %	10(HIGH)	1.11 %	0.88 %	0.65 %
(10-1) difference	0.25 %	0.11 %	-0.11 %	(10-1) difference	-0.36 %	-0.53 %	-0.77 %
T-statistics	(0.31)	(0.14)	(-0.13)	T-statistics	(-0.71)	(-0.96)	(-1.30)
(10-1) 4F-alpha	0.24	0.07	-0.13	(10-1) 4F-alpha	-0.50	-0.55	-0.81
T-statistics	(0.34)	(0.11)	(-0.20)	T-statistics	(-1.08)	(-1.11)	(-1.40)

Clearly the difference between 10 (HIGH) and 1(LOW) portfolio increases when taking averages of multiple maximum returns rather than just ranking based on the single highest daily return. This finding is consistent with the Bali et. al. (2011), although this review does not produce significant results. Bali et. al. (2011) find significant results also in the MAX (2) and MAX (3) portfolios. After all the univariate portfolio analysis gives tiny indication of the possible MAX effect in the Nordics especially in the value-weighted portfolios but any significant evidence of the effect is not found in this analysis.

After all I do not find any significant evidence for the negative relation between past month maximum daily returns and next months returns. I find negative differences between 10(HIGH) and 1 (LOW) value-weighted portfolios but none of them is significant. My most significant finding is MAX (3) hedge (10-1) portfolio alpha difference -0.81 with t-statistics of -1.40 which is not convincing at all. My insignificant results might be due to weaknesses and shortcomings about my analysis which I mention earlier. My data period is also over 60 years shorter than Bali et. al. (2011) have, which is due to availability of the data. Their sample is also notably larger (consists all NYSE, Amex and Nasqaq stocks) Annaert et. al. (2013) neither do not find statistically significant results in the univariate portfolio analysis in Europe. Although portfolio analysis is intuitive and easy way to measure the returns it has its own shortcomings and e.g. it does not take into account characteristics of the companies which I review in the next chapter.

4.3 Characteristics of the portfolio companies

Like mentioned earlier portfolio analysis does not take into account the characteristics of the company (size, book-to-market ratio, beta etc.) but only the maximum returns of the stocks. If the 1(LOW) and 10 (HIGH) portfolio companies do not represent the whole universe of stocks the results are clearly biased. I report the characteristics of the portfolio companies in the Table 3. The values are calculated by taking median values for each portfolio in each month and after this taking averages for the monthly values for each portfolio. Below are presented the calculated values from left to right: average monthly returns (in percentage), daily maximum return in month (in percentage), market betas, market values (in millions), book-to-market ratios, momentum which is defined as a returns in the last 11 months (starting from 2 months backwards), short- term reversal which is defined as a past month return, measure for illiquidity (scaled down to 10^5) and idiosyncratic volatility (multiplied by one hundred). All the variables are defined more specifically in Appendix B.

Table 3 presents that 10 (HIGH) portfolio companies have in average smaller market value, lower book-to-market rate, higher returns in the past month but lower returns in past 11 months and their shares are less illiquid and have higher idiosyncratic volatility. Market betas are quite low in both LOW and HIGH portfolios but the pattern is decreasing. These findings mostly in line with Bali et al. (2011) and Annaert et. al. (2013) excluding the market beta.

Table 3
Characteristics of the MAX (1) portfolios
Portfolios are constructed by ranking stocks based on the maximum daily return within past month. Portfolios are constructed every month from January 1985 to December 2015. Portfolio 1 (10) consists the stocks with the lowest (highest) maximum daily returns. Table presents the average of the monthly median values for each variable. Variables from left to right: monthly return (in percent), maximum daily return (in percent), the market beta, the market value of the company (in million euros), the book-to-market ratio, the cumulative return over the last 11 months (MOM), return in the past month (REV), calculated illiquidity value (scaled by 10^5) and idiosyncratic volatility. All the variables are defined in Appendix B.

Portfolio	R	MAX_{t-1}	BETA	SIZE (€ 10^6)	BM	MOM	REV	ILLIQ (10^5)	IVOL (10^2)
1 (LOW)	0.82	1.75	0.15	235.8	0.67	0.89	-1.95	6.05	1.34
2	0.89	2.59	0.16	301.6	0.62	0.43	-1.01	4.97	1.56
3	0.82	3.20	0.15	283.8	0.63	0.44	-0.49	4.61	1.69
4	0.67	3.80	0.14	248.0	0.62	0.71	0.31	4.39	1.80
5	0.65	4.43	0.14	200.6	0.60	0.24	0.85	4.30	1.94
6	0.51	5.18	0.12	173.2	0.59	0.37	1.43	4.23	2.08
7	0.30	6.12	0.11	122.6	0.60	0.19	1.84	4.09	2.25
8	0.02	7.46	0.09	91.6	0.57	0.23	2.69	3.94	2.54
9	-0.45	9.80	0.07	59.6	0.56	0.06	4.20	3.88	2.96
10 (HIGH)	-1.44	16.48	0.04	28.7	0.51	-0.11	8.76	3.38	4.03

10 (HIGH) portfolio companies are on average almost nine times smaller than 1(LOW) portfolio companies. There is also clear decreasing pattern (if excluding 1 (LOW) portfolio) between market values and portfolios. Like Fama-French three-factor model has shown, companies with smaller market capitalization tend to perform better than companies with higher market capitalizations. The results of univariate portfolio analysis are biased because of the unequal market capitalization distribution. Taking into account this issue the difference be might be more significant and the difference between 10 (HIGH) and 1 (LOW) be more negative.

The book-to-market ratios also are lower in 10 (HIGH) portfolio companies than 1 (LOW) portfolio companies. 10 (HIGH) portfolio companies have almost 25 % lower book-to-market ratios than in the 1 (LOW) portfolio companies. As well as the market capitalization, stocks with lower book-to-market should also perform better than stocks with higher book-to-market ratios according to Fama-French three factor model. This observation as well should increase the difference and significance of the returns even further when taking account characteristics of the company.

However, also other characteristics like momentum and market beta together with above mentioned characteristics also affect the expected returns of the stocks in the different directions. It is impossible to guess the overall effect of these factor without any regression. I do the firm-level cross sectional regression and it is presented in the next section 4.4.

4.4 Firm- level cross-sectional regression

Portfolio analysis does not give any significant results which might be due to above mentioned shortcomings of univariate portfolio analysis. Portfolio analysis is easy and demonstrative way to measure returns but there are also obvious disadvantages as well. First, and most importantly portfolio analysis fails to reveal the relations behind the characteristics simultaneously so it destroys lot of data which are crucial when wishing to get overall picture of the effect. Secondly, it fails to explain the dependencies of the variables, although it is possible to explain something about reasons, characteristics and dependencies with detected average characteristics. Firm-level cross-sectional regression instead is capable to explain these dependencies.

Following by Bali et. al. (2011) my final econometric regression model is:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}MAX_{i,t} + \lambda_{2,t}BETA_{i,t} + \lambda_{3,t}SIZE_{i,t} + \lambda_{4,t}BM_{i,t} + \lambda_{5,t}MOM_{i,t} + \lambda_{6,t}REV_{i,t} + \lambda_{7,t}ILLIQ_{i,t} + \varepsilon_{i,t+1}. \tag{1}$$

Where $R_{i,t+1}$ which is my dependent variable is the raw return in percentage for stock i in month_{t+1} in percentage. MAX which is my variable of interest is the daily maximum return within month in percentage. All of the explanatory variables: maximum return in the month (MAX), market beta (BETA), market capitalization (SIZE), book-to-market ratio (BM), momentum term (MOM), short-term reversal (REV) and illiquidity of the stock ((ILLIQ) scaled by 10^5) are one month lagged value and are all defined more precisely in Appendix B. Following by Annaert et. al. (2013) all the explanatory variables are winsorized at the 0.5% and 99.5% levels to eliminate the outliers in the sample. MAX 99 (95) is MAX variable which is winsorized at the 99% (95%) level only in the sense of robustness check. The regression consists all the 2094 Nordic companies in my sample from January 1985 to December 2015 including totally 372 months of data when excluding missing data there are 228 764 data points. Time-series averages of the slope coefficients $\lambda_{i,t}(i = 1, 2, 3 \dots 7)$ are reported in the first line and below in the parentheses are Newey-West (1987) adjusted t-statistics. Regression are made by using the single maximum return within month (MAX (1)). Table 4 reports the results of the regression.

Table 4
Firm-level cross-sectional regressions
I run firm-level cross-sectional regression in each month from January 1985 to December 2015. MAX is the maximum daily return in the past month. MAX 99 (95) is the maximum return in the past month winzorizing at the 99% (95%) level. All the controlling variables are also lagged values and are defined in the Appendix B. Slope coefficients of time-series average of the cross-sectional regression is reported in the first row and below that in the parentheses their associated Newey-West (1987) adjusted t-statistics.

Model #	MAX95	MAX99	MAX	BETA	SIZE	BM	MOM	REV	ILLIQ
1			-0.023						
			(-1.60)						
2				-1.10					
				(-7.74)					
3					-0.162				
					(-5.28)				
4						1.25			
						(20.43)			
5							0.032		
							(11.96)		
6								0.025	
								(4.76)	
7									-0.0015
									(-6.58)
8			-0.032	-0.53	-0.086	1.27	0.032	0.030	-0.0020
			(-2.25)	*(-4.00)*	*(-3.29)*	*(20.28)*	*(11.98)*	*(6.06)*	*(-9.14)*
9	-0.042								
	(-2.18)								
10		-0.027							
		(-1.72)							
11		-0.036		-0.532	-0.089	1.27	0.032	0.030	-0.0020
		(-2.37)		*(-4.03)*	*(-3.4)*	*(20.28)*	*(11.98)*	*(6.07)*	*(-9.3)*
12	-0.053			-0.55	-0.090	1.26	0.032	0.030	-0.0021
	(-2.81)			*(-4.12)*	*(-3.21)*	*(20.12)*	*(11.99)*	*(6.00)*	*(-9.66)*

In the univariate regression (#1), i.e. running regression using only one variable (MAX), I find negative but insignificant relation between MAX and returns with slope coefficient of -0.023 and with the Newey-West (1987) adjusted t-statistics of -1.60. Slope coefficients of the control variables are reported in the rows (2) ... (6). Slope coefficients of the control variables are mostly in line with previous research: size has negative and significant, book-to-market has positive and significant and momentum has positive and significant slope coefficients. Bali et. al (2011) also report negative BETA slope coefficient but their result was insignificant. Annaert et. al (2013) in turn reported negative relation between illiquidity and return. Surprisingly short-term reversal has a positive and significant slope coefficient.

The most interesting model is found on the eighth (#8) row in the Table 4 where is reported the full specification model which is our main target. After adding 6 more explanatory variables in addition to MAX the slope coefficient of the MAX turns to more negative and also statistically significant. The slope coefficient increases to -0.032 with Newey-West (1987) adjusted t-statistics of -2.25. The explanation for the increasing slope coefficient is the same, to which I referred earlier and what Table 3 signaled as well. When taking into account the characteristics of the high MAX stocks, the effect and significance of results increase even more.

MAX99 (95) variables indicates MAX variable which is winzorized at the 99% (95%) level. Like last four rows (# 8-12) show, the economic effect of MAX is even larger when winsorizing MAX further. When winsorizing at the 99% level, MAX slope coefficient increases to -0.036 and become more significant with t-statistics of -2.37. Even more when winsorizing at the 95% level, the slope coefficient increases to -0.053 and become even more significant with t-statistics of -2.81. The same increasing slope coefficient and significance when winzoring at the higher level can be found in the univariate regression of MAX99 (#10) and MAX95 (#11).

After all, I do not find any significant results from the univariate regression except when winzorizing MAX at the 95% level. MAX95 alone is statistically significant with the slope coefficient of – 0.042. Instead after controlling for variables like: size, book-to-market, beta, momentum, short-term reversal and illiquidity MAX is statistically significant with the slope coefficient of -0.032. My results are also robust when winsorizing maximum daily returns at the 99% and at the 95% level, in fact they become even more significant. My findings are also consistent with previous research except Bali et. al. (2011) report negative and statistically significant results in the univariate portfolio regression (#1 model). In the full specification model they measure even larger slope coefficient with higher t-statistics. Bali et. al (2011) also find that effect becomes even more larger when winsorizing at the 99% or at the 95% level.

4.5 Stability of MAX

If the MAX is not stable i.e. former behavior does not predict to the forthcoming behavior, then there are no any reason investors to prefer high MAX stocks and even less if these stocks turn to have lower expected returns as well. To make sure that MAX effect is not just a randomly occurring phenomenon I do transition matrix which shows the movements of the stocks between portfolios. Table 5 presents the overall results of the transition matrix. It shows that companies that were in 10 (HIGH) or 1 (LOW) portfolios in the past $month_{t-1}$ very likely stays in these portfolio in the next $month_t$. In the left hand side in the first column are the portfolio numbers in the past $month_{t-1}$ and the above of the table in the first row is the portfolio where the company belong in the next $month_t$ e.g. second (2) row and third (3) column shows the probability (14, %) that company was in the second (2) portfolio past $month_{t-1}$ and in the next $month_t$ moved to third (3) portfolio. The Table 5 describes the movement of the companies between different MAX (1) portfolios.

When the company was in the past $month_{t-1}$ in 10 (HIGH) portfolio there is 35.6% probability that it remains in the same portfolio in the next $month_t$ and even more 68.1 % probability to belong in the highest third (8, 9 or 10 (HIGH)) of the portfolios. Companies in the other end have almost the same numbers: when the company was past $month_{t-1}$ in the 1 (LOW) portfolio there is 29.1 % probability to belong also in the next $month_t$ in the same portfolio and like above 58.9% probability to belong in the first third (1 (LOW), 2 or 3) of the portfolios. Also every value on the diagonal matrix which indicates the probability that company remains in the same portfolio are over 10%. These results imply that large movements between different ends of the deciles are very rare eg. probability that stock will move from 10 (1) portfolio to first (last) portfolio is only 5% (6.1%). Most importantly the largest probabilities to staying in the same portfolio can be found exactly for both end of the portfolios: 1(LOW) portfolio and 10 (HIGH) portfolios which are under observation.

Table 5
Transition matrix
The matrix presents the average probability that stock$_i$ will transfer from the portfolio in the first column to the portfolio in the first row i.e. first column represents the the portfolio t-1 and first row represent the portfolio in time t. Table contain every MAX (1) portfolio movement from January 1985 to December 2015.

		Portfolio in the next month$_t$									
	Portfolio	1 (LOW)	2	3	4	5	6	7	8	9	10 (HIGH)
Portfolio in the previous month$_{t-1}$	1 (LOW)	29.1 %	17.0 %	12.8 %	10.7 %	8.7 %	6.8 %	5.4 %	4.1 %	3.0 %	2.3 %
	2	17.1 %	16.9 %	14.5 %	12.3 %	10.3 %	9.3 %	7.4 %	5.6 %	4.3 %	2.3 %
	3	13.1 %	14.6 %	14.4 %	12.7 %	11.8 %	10.1 %	8.4 %	6.7 %	5.2 %	3.0 %
	4	11.0 %	12.7 %	12.8 %	12.9 %	12.0 %	11.0 %	9.7 %	8.3 %	6.2 %	3.5 %
	5	8.0 %	11.2 %	11.9 %	12.2 %	12.3 %	12.3 %	10.3 %	9.6 %	7.5 %	4.6 %
	6	6.7 %	9.1 %	10.6 %	11.4 %	11.9 %	12.6 %	11.9 %	10.7 %	9.1 %	6.1 %
	7	5.4 %	7.6 %	8.9 %	10.2 %	11.3 %	12.1 %	13.6 %	11.9 %	11.3 %	7.6 %
	8	3.9 %	5.7 %	7.2 %	8.8 %	10.0 %	11.2 %	13.3 %	14.7 %	14.4 %	11.0 %
	9	3.0 %	4.5 %	5.6 %	6.4 %	8.0 %	10.1 %	12.0 %	15.0 %	18.0 %	17.3 %
	10 (HIGH)	3.4 %	2.1 %	3.0 %	3.6 %	4.9 %	6.2 %	8.7 %	12.9 %	19.6 %	35.6 %

5 MAX effect and idiosyncratic volatility

Ang et. al (2009) find that stocks with high idiosyncratic volatility globally has in average lower future returns than stocks with the lower idiosyncratic risk. Like Table 3 report, stocks with high maximum daily returns has also higher idiosyncratic volatility. MAX might just be proxy for idiosyncratic volatility puzzle. In this chapter we discuss about the MAX effect together with idiosyncratic volatility.

In my sample MAX is highly correlated with the IVOL. Correlation between MAX and IVOL is 0.84 which is the first signal that the MAX might be just a proxy of idiosyncratic volatility. I also do the same univariate portfolio analysis for IVOL than I did earlier to MAX (Table 1). Stocks with low idiosyncratic volatility are placed in the 1(LOW) portfolio and stocks with high idiosyncratic volatility are placed in the 10 (HIGH) portfolio. The detailed results have left out. I find negative difference between 10 (HIGH) IVOL portfolio and 1(LOW) IVOL portfolios. The difference between value-weighted 10 (HIGH) IVOL portfolio and 1 (LOW) IVOL portfolio is -0.84% and four-factor alpha difference is -0.93 with Newey and West (1987) adjusted t-statistics of -1.65. In the equal-weighted portfolio the same difference does not occur, in fact the both four-factor alpha and raw return difference is positive and insignificant. Seems like the idiosyncratic puzzle only exist in the value-weighted portfolio which is consistent with the previous research. Clearly higher idiosyncratic volatility stocks behave also in the same way than high MAX stocks i.e. they have lower return in the next month.

Table 6
Bivariate portfolio analysis
In Panel A portfolios are constructed by first ranking stocks based on idiosyncratic volatility and then within these portfolios based on maximum daily return within month. In Panel B portfolios are constructed by first ranking stocks based on maximum daily returns within month and then within these portfolios based on idiosyncratic volatility. Table contains both equal-weighted (EW) and value-weighted (VW) weighting methods. Last rows present the average raw return and Fama-French-Carhart four factor (4F) alpha difference between tenth (10) and first (1) portfolio and below these in the parentheses are presented Newey-West (1987) adjusted t-statistics. Portfolios are constructed in every month from November 1991 to December 2015.

Portfolio	EW	VW	Portfolio	EW	VW
Panel A: Sorted by MAX controlling for IVOL			Panel B: Sorted by IVOL controlling for MAX		
1(LOW)	1.58 %	1.18 %	1(LOW)	1.09 %	0.87 %
2	1.29 %	1.26 %	2	1.10 %	1.20 %
3	1.30 %	0.94 %	3	1.24 %	1.25 %
4	1.13 %	1.30 %	4	1.00 %	0.99 %
5	1.17 %	1.07 %	5	1.26 %	1.33 %
6	1.16 %	0.92 %	6	1.28 %	1.33 %
7	1.24 %	1.03 %	7	1.09 %	1.09 %
8	1.20 %	1.24 %	8	1.20 %	0.93 %
9	1.13 %	1.10 %	9	1.29 %	0.87 %
10(HIGH)	0.87 %	1.01 %	10(HIGH)	1.51 %	0.91 %
(10-1) difference	-0.71 %	-0.17 %	(10-1) difference	0.42 %	0.03 %
T-statistics	(-3.73)	(-0.42)	T-statistics	(1.30)	(0.07)
(10-1) 4F- alpha	-1.12	-0.64	(10-1) 4F- alpha	0.06	-0.19
T-statistics	(-5.68)	(-1.49)	T-statistics	(0.19)	(-0.45)

To analyze more about the relation between idiosyncratic volatility and high maximum returns I do bivariate portfolio analysis i.e. evaluate the performances of the portfolios which are ranked based on two variables: IVOL and MAX. Table 6 presents the results of the bivariate portfolio analysis. In the Panel A I first construct 10 portfolios by ranking stocks based on idiosyncratic volatility and after that in each IVOL portfolio I rank stocks based on the maximum daily return in each month by using same methods than above. The raw return difference between equal weighted portfolio is -0.71% with t-statistics of -3.73. 10-1 portfolio 4-factor alpha is -1.12 and significant with t-statistics of -5.68. In the value-weighted portfolio the difference is smaller and insignificant. The raw return difference between tenth and first portfolio is only -0.17% with the t-statistics of -0.42. Four-factor alpha is also negative but insignificant with value of -0.64 with t-statistics of -1.49. In the value-weighting portfolio returns we see that after controlling IVOL the raw return difference has reduced for previously reported ones. Surprisingly in the equal-weighted portfolio the difference between the tenth and first portfolio increases. Keeping still mind that results were not significant earlier.

I also do same bivariate portfolio analysis but with the reverse sorting order. I use same methods but now I first rank stocks based on the maximum daily returns within month and after that rank these within portfolio by the idiosyncratic volatility so that stocks with lowest (highest) idiosyncratic volatility locate in the 1 (10) portfolio. The results for the equal weighted portfolios are opposite than Table 5A presents. The raw return difference in the equal-weighted portfolio between first and tenth portfolio is 0.42% with t-statistics of 1.30 The four-factor alpha is as well positive and insignificant with the value of 0.06 with t-statistics of 0.19. The value-weighted results are mainly same than in the Table 5A. The difference is 0.03% with t-statistics of 0.07 but the four-factor alpha is negative but insignificant with value of -0.19 and the t-statistics of -0.45. The raw return difference is in both equal- and value-weighted portfolios are smaller than previously reported in univariate portfolio analysis.

In both value-weight bivariate portfolio the raw return decreases and when sorting by IVOL and controlling for MAX the difference become positive. When taking account MAX, the effect of IVOL clearly decreases. However, too far-reaching conclusions cannot be made because of insignificance of the results and shortcomings of portfolio analysis that were introduced earlier. I do firm-level cross-sectional regression again but now also taking account idiosyncratic volatility.

Table 7
Firm-level cross-sectional regression with IVOL
I run firm-level cross-sectional regression in each month from January 1985 to December 2015. MAX is the maximum daily return in the past month. All the controlling variables are also lagged values and are defined in the Appendix B. Slope coefficients of time-series average of the cross-sectional regression is reported in the first row and below that in the parentheses their associated Newey-West (1987) adjusted t-statistics.

Model #	MAX	IVOL	BETA	SIZE	BM	MOM	REV	ILLIQ
1	-0.023							
	(-1.60)							
2		-0.012						
		(-0.24)						
3	-0.067	0.18						
	(-2.28)	*(1.67)*						
4	-0.075	0.18	-0.47	-0.053	1.30	0.032	0.030	-0.0021
	(-2.48)	*(1.66)*	*(-3.42)*	*(-2.14)*	*(20.16)*	*(11.91)*	*(6.26)*	*(-9.26)*

Table 7 presents the results of the firm-level cross-sectional regression with IVOL which is scaled by 10^2. Like second row (#2) shows there are negative although insignificant relation between past month idiosyncratic volatility and next month returns. The slope coefficient of the IVOL is -0.012 with Newey-West (1987) t-statistics of -0.24. When adding the MAX in the regression (#3) the slope coefficient of the IVOL turn to positive with the value of 0.18 and more significant with the Newey-West (1987) adjusted t-statistics of 1.67. In the same time the slope coefficient of the MAX increases to -0.067 with the Newey-West (1987) adjusted t-statistics of 1.67. The same effect can also be detected in the full model (#4). MAX has even more positive slope coefficient with the value of -0.075 and with the t-statistics of -2.48 and IVOL remains positive but insignificant. These are consistent with the findings of the bivariate portfolio analysis (Table 6). In alone, between idiosyncratic volatility and future returns has a negative relation but after taking account MAX effect this relation weakens or disappears. I do not find the same idiosyncratic volatility puzzle that Ang. et. al. (2009) report. Although it seems that idiosyncratic volatility might have a positive relation with future returns after controlling also MAX. However, I do not find any significant results. Arguments that MAX is just a proxy for IVOL can be proven to be incorrect.

My results are consistent with the Bali et. al. (2011) findings. They also report that MAX remain also negative and significant after controlling for IVOL. They find positive and significant relation between IVOL and future returns and report that IVOL is just a proxy for MAX. They also report positive relation between minimum return in previous month and next month returns i.e. the lower minimum return in past month the higher returns in next month. I find the opposite results in my sample i.e. the higher minimum return in past month the lower return in the next month. These results are significant only in the full specification model.

6 Conclusion

In this thesis I have studied MAX effect i.e. negative relation between the past month maximum daily returns and next month returns in the Nordics from January 1985 to December 2015. My sample includes overall 2094 stocks from every Nordic country: Denmark, Finland, Iceland Norway and Sweden. I measure the relation both with portfolio analysis and with firm-level cross-sectional regressions.

Portfolio analysis do not give any statistically significant results which might be due the shorter time period or the shortcomings of the portfolio analysis. Instead in the firm-level cross-sectional regression I find negative and statistically significant relation between previous month maximum returns and next month returns after controlling MAX for variables such: size, book-to-market ratio, market beta, momentum, short-term reversal and illiquidity. Results are also significant when winzorizing maximum returns at the 99% and 95% percent level.

I also find the Ang et. al. (2009) idiosyncratic volatility puzzle relation after doing univariate portfolio analysis to IVOL. After doing firm-level cross-sectional regression for the idiosyncratic volatility the puzzle disappears. After adding also MAX to the regression slope coefficient of the IVOL turns to positive and remained insignificant. Based on these findings we can refute the allegation that MAX effect is just a proxy for idiosyncratic volatility. However unlike Bali et. al. (2011), I do not find enough evidence in my thesis that idiosyncratic volatility is a proxy for MAX effect.

After all, these findings are in line with previous research about investors preference toward lottery-like stocks which is caused by propensity to over-estimate the small probabilities to huge profits. This lead to over-demand of lottery-like stocks and therefore higher prices and lower expected returns of the lottery-like stocks.

The implication of this thesis can be separated in the academic ones and the practical ones. In academic perspective my results confirm the Bali et. al. (2011) and Annert et. al. (2013) previous results about MAX effect also in the Nordic markets. This result is another evidence on behalf of the global existence of the MAX effect and step toward to the wider usage of MAX in the asset pricing models. In the practical perspective, benefiting directly for this effect requires short-selling. Even transactions costs and/or unwillingness or restrictions prevent directly benefiting from this effect, investors still should be aware of the MAX effect and how these kind of vulnerabilities might be harmful when trading and making investing decisions.

In the further research it will be important to confirm the results in the Nordics also with longer time period to get complete understanding of the existence of the MAX effect. The existence of the effect should also be examined in the other markets where it has not been discovered yet e.g. in Asia. In addition, it would be interesting to examine if the effect is stronger among the stocks with high/low institutional ownership rate or with countries that have high gambling preferences.

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Appendix A

TOTAL RETURN INDEX:

$$RI_t = RI_{t-1} * \frac{PI_t}{PI_{t-1}} * (1 + \frac{DY_t}{100} * \frac{1}{N})$$

Where: RI_t = Return index on day t

PI_t = Price index on day t

DY_t= Dividend yield % on day t

N = Number of working day (= 260)

MARKET PORTFOLIO:

Value-weighted portfolio constructed by all Nordic companies available from TDS.

RISK-FREE RATE:

Helsinki Interbank Offered Rate (HELIBOR) change to EURIBOR 1998 onward,
Stockholm Interbank Offered Rate (STIBOR)
Reykjavik Offered Rate (REIBOR)
Norwegian Interbank Offered Rate (NIBOR)
Copenhagen Interbank Offered Rate(CIBOR).

EXCLUDED MONTHS IN THE UNIVARIATE PORTFOLIO ANALYSIS:

8/1991, 3/1992 and 7-12/1992.

Appendix B: Variable definitions

Following by Bali et. al (2011) I used almost same variable with some adjustments:

MAX:

Highest daily return within month. $MAX_{i,t} = \max(R_{i,d}) \quad d = 1,2,3, \dots, D_t$

Where: $(R_{i,d})$= Return on stock i in day d, D_t= number of trading day in the month t.

BETA:

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

Where: Where: $(R_{i,d})$= Return on stock i in day d, $(R_{m,d})$= Market return[1] in day d, $r_{f,d}$= risk-free rate[2] on day t.

SIZE:

Market value is measured as a natural logarithm from the value I downloaded from TDS. Market value (MV) is defined as a end of the previous (t-1) month value from TDS. All market values are converted to euros.

[1] Market portfolio: Value-weighted portfolio constructed by all Nordic companies available from TDS

[2] Risk-free rate: Country-weighted average of 3-month interbank offered rate (See Appendix A)

BM:

Book-to-market is measured as a natural logarithm from the value I downloaded from TDS. Book-to-market (BM) is defined as a inverse number from market-to-book value which was available from TDS.

MOM:

Intermediate-term momentum which is measured by following Jegadeesh and Titman (1993). Momentum variable is defined as a cumulative return on previous 11 month starting from 2 months backwards (t-2) i.e., the cumulative return from t-12 to month t-2.

REV:

Short-term reversal which is measured by following Jegadeesh and Titman (1990) and Lehmann (1990). REV is defined as a return on previous (t-1) month.

ILLIQ:

Illiquidity of stock is measured by following Amihud (2002). I defined stocks illiquidity as absolute monthly stock return divided monthly trading volume in euros.

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

Where: $R_{i,t}$ = return in stock i in month t, $VOLE_{i,t}$ = monthly trading volume in euros.

IVOL:

Idiosyncratic volatility is measured by assuming single-factor return-generating process (CAPM) for each individual share: $R_{i,d} - r_{f,d} = \alpha_i + \beta_i (R_{m,d} - r_{f,d}) + \varepsilon_{i,d}$

Where: $\varepsilon_{i,d}$ = Idiosyncratic volatility on day t.

$IVOL_{i,t} = \sqrt{var(\varepsilon_{i,d})}$

Where: $IVOL_{i,t}$ = Monthly idiosyncratic volatility in month t.