

# The MAX effect and what drives it

## – *Evidence from the Swedish stock market*\*

Karl Hellgren\* & Alexander Helmy\*

18 May 2015

Stockholm School of Economics  
Department of Finance  
Bachelor Thesis

### Abstract

Inspired by previous findings on the cross-sectional relationship between extreme positive daily stock returns and subsequent negative returns in the US and euro-zone markets, we search for its presence in the Swedish market. We argue that this effect, known as the MAX effect, is mainly driven by individual investors seeking lottery-like payoffs. This makes Sweden an interesting object of study due to its high share of individual investor market participation. We find a monthly return difference for stocks in the 1<sup>st</sup> and 10<sup>th</sup> MAX deciles of -1.14%, controlling for known factors such as size, book-to-market, momentum, short term reversal and illiquidity. The MAX effect is also robust for various measures of skewness. To further explore if individual investors drive this effect we use a unique data set to examine individual investor purchasing behavior. We find some indications that individual investors are behind the effect, but cannot exclude the possibility that institutional investors also contribute.

**Tutor:** Jungsuk Han

**Keywords:** MAX effect, lottery-type stocks, cross-sectional return predictability, individual investor purchasing behavior

---

\* 22567@student.hhs.se

\* 22738@student.hhs.se

\* We extend our gratitude to our tutor Jungsuk Han for his insights and guidance. We would also like to acknowledge the help of Erik Eklund and Mikael Nilsson for providing us with valuable resources. Last but not least – a thank you to our fellow peers at the Stockholm School of Economics.

## Contents

1. Introduction.....	4
2. Data.....	6
3. Univariate portfolio-level analysis.....	8
3.1. Robustness.....	10
3.2. The persistence of MAX.....	11
4. Firm-level cross-sectional regression .....	12
4.1. Introduction and model specification.....	12
4.2. Variable definitions.....	13
4.3. Result .....	15
4.4. Max and skewness.....	16
5. MAX and individual investors .....	19
5.1. Model specification.....	20
5.2. Results.....	20
6. Conclusion .....	22
6.1. Limitations and future research .....	22
7. References .....	24
Appendix A .....	27

“The next best thing to a fortune is the chance of a fortune”

— *Chance, New Statesman and Nation, June 6, 1931*

## 1. Introduction

In finance, the field of asset pricing has puzzled researchers for decades. Despite very extensive research it is still not known exactly what affects the price of an asset. The Fama-French-Carhart (Fama and French, 1993; Carhart, 1997) four factor model is well accepted as a model for explaining return variation. In the model, expected return is predicted on a firm's exposure to the market, the firm's size, book-to-market ratio and momentum. Several other factors have been added to the model to help further the explanatory power, such as illiquidity and reversal.

The MAX effect is potentially one such factor. The MAX effect is the tendency of stocks which have had an extreme positive return in a day within a month to underperform in the subsequent month. The literature argues that certain investors have an abnormal preference for these stocks, due to their lottery-like payoffs. The abnormal preference causes investors to overpay for the stocks and this is why they underperform in the subsequent month. The reasons for this kind of purchasing is not rational, in the same way gambling or betting it is not rational. Kumar (2009) presents evidence that some investors exhibit a preference for lottery-type stocks. The cumulative prospect theory (Tversky and Kahneman, 1992) modeled by Barberis and Huang (2008), explains this behavior as a result of overweighting small probability outcomes. In the MAX context this would mean that an investor will put too much weight on the probability of another extreme return.

Bali and Cakici (2008); Bali et al. (2011) first discover the MAX effect in the US stock market in an attempt to explain recent findings by Ang et al. (2006, 2009) that idiosyncratic volatility is priced. This pricing of idiosyncratic volatility is in great contrast to the finance literature. However Bali and Cakici (2008); Bali et al. (2011) find that idiosyncratic volatility is merely a proxy for the MAX effect. Their findings have since been corroborated by Annaert et al. (2013), who find evidence of the MAX effect in the euro-zone and by Fong and Toh (2014) on the US stock market.

One may ask why MAX is not arbitrated away by informed investors. If markets are complete and all assets are traded the MAX effect would not occur since arbitrageurs would trade against the irrational investors who give rise to the phenomenon in the first place. An investor could make an arbitrage profit by short selling the high MAX stocks and buying the low MAX stocks. However there are limits to arbitrage. The high MAX stocks are generally small and illiquid thus short selling is seldom possible. Furthermore the short selling of high MAX stocks would expose the arbitrageur to considerable idiosyncratic risk.

Previous research (Bali et al., 2011; Fong and Toh 2014) have suggested that it is primarily individual investors that drive the MAX effect. To us this is also intuitive, given that individual investors are less informed than institutional investors are.

The relative amount of individual investors' stock ownership between samples should influence the MAX effect if the claim has any validity. According to research on Swedish individual investors by Guiso and Sodini (2013), the portion of individual investor direct stock ownership is among the highest in developed countries. Approximately 40% of Swedes own stocks, this makes Sweden a highly interesting country to study in order to examine what drives the MAX effect. Our results are based on a sample of all Swedish stock listed on the Stockholm Stock Exchange from January 1997 – December 2014, the data is described in great detail in the next section.

We start our research by doing a portfolio level analysis, constructing ten equally- and value-weighted portfolios based on daily maximum return (MAX), where the low MAX decile and the high MAX decile contain the stocks with the lowest and highest maximum daily return respectively. Then we evaluate the return in the subsequent month. The monthly raw return difference between the equally-weighted high MAX portfolio and the equally-weighted low MAX portfolio is -1.40 %, in other words, stocks which haven't had an extreme return outperform stock which have had an extreme return by 1.40 percentage points per month. The corresponding Fama-French-Carhart four factor alpha is -1.19%. The results are significant on standard confidence levels. In contrast with the findings of Bali et al. (2011) we do not find significant results for the value-weighted portfolios. We test the robustness of MAX by constructing the equally- and value-weighted portfolios based on the average of the three and five maximum daily returns and find that MAX is significant in the equally-weighted portfolios, however not significant in the value-weighted portfolios. This suggests that investors hold a preference for lottery-like stocks (Kumar, 2009) and that MAX is a proxy for this. If investors do hold a preference for these stocks, they should only do this if MAX is persistent, meaning that the probability of a stock which has had an extreme daily return within a month is larger in the subsequent month. If MAX is not persistent, the probability of a stock being in the high MAX portfolio in the subsequent month should be 10%, however the probability we observe is larger by a factor of three, furthermore the probability of a high MAX stock being in any of the top three decile portfolios in the subsequent month is 58%.

While sorting on portfolio level is intuitive, it also has drawbacks, for example a significant amount of information is lost in the process of aggregation. Therefore we investigate if the effect is present on the firm-level in the cross-section, by using the standard Fama and MacBeth (1973) procedure. We regress monthly return on several lagged predictors including: MAX, beta, size, book-to-market, momentum, illiquidity and short term reversal. The regression reveals that MAX is associated with a negative price in the Swedish stock market. The difference between the median of the high- and low MAX stocks is -1.14% and is highly significant.

However there could be alternative explanations of our results. Mitton and Vorkink (2007) develop a model in which investors have heterogeneous preferences for skewness in returns. In the model some investors prefer stock with positive skewness, hence they are willing to accept a lower expected return. From the portfolio level analysis we find that stock in the high MAX portfolio have significantly higher skewness in returns. Therefore we need to control that extreme positive returns are not just a proxy for skewness. We perform a battery of univariate regressions of monthly return on total, systematic, and idiosyncratic skewness. We also incorporate these measures one by one in the cross sectional model specification. The results show that MAX is neither a proxy for skewness nor is it very sensitive to controls for skewness. Furthermore skewness does not seem to be priced in the Swedish stock market. The return difference of the 5<sup>th</sup> and 95<sup>th</sup> percentile of stocks sorted on maximum return, in the cross-section, including controls for skewness, is -0.98% per month and statistically significant

Finally we assess the claim of past researchers Fong and Toh (2014) that it is mainly individual investors that are driving the effect. We use a unique data set provided by a leading Swedish retail bank that is filtered to only include buying and selling carried out by individual investors. Inspired by Barber and Odean (2008) we use this data set to investigate how individual investors react to extreme daily returns. The results from this analysis suggests that individual investors are driving the MAX effect, however limitations in the data hinders us from concluding that they are the sole drivers.

The remainder of this thesis is structured as follows: *Data*, this section describes the data and data selection in great detail. *Univariate portfolio-level analysis*, in this section we examine the MAX effect using a portfolio approach, the text is structured so that it first gives a detailed explanation of the methodology, this is followed by a review and discussion of the results. *Firm-level cross-sectional regression*, here we confirm our results from the portfolio level analysis, using a firm-level approach. First the methodology and the model is presented, secondly the results are presented and analyzed and lastly the model is extended to investigate the relation of MAX and skewness. *MAX and individual investors*, this section examines why the MAX effect occurs in the first place. In the *Conclusion*, the results and limitations of our analyses are summarized.

## 2. Data

In our analysis of the MAX effect in the Swedish market, we have used all Swedish common stocks listed on the main exchange<sup>1</sup> between 1997 – 2014. Preference shares have been excluded for comparability with our predecessors. The total number of stock in the sample is 634, on average 290 stocks per time period. Datastream does not report stocks that have been delisted. In order to

---

<sup>1</sup> All firms listed on Stockholm Stock Exchange's Small-, Mid- & Large cap, formerly A- & O list.

minimize the risk of survivorship bias, we have manually added all delisted stocks, using press releases from the NASDAQ OMX webpage<sup>2</sup>. This is also the reason for our time frame selection, no listing or delisting announcements before 1997 are easily accessible. It is not uncommon for a stock to be listed on a secondary exchange before it transfers to the main exchange. Therefore stock data before an index inclusion has been removed, furthermore we also account for index exclusions by removing stock data for stocks that have moved from the main exchange to a secondary exchange. For a complete list of all stocks, and their inclusion and exclusion date, see Appendix A – we choose to include this list since we were not able to find a similar list ourselves. It is our hope that it could be of help to other scholars in the future. The data, such as market value (MV), price-to-book value (PTBV) and total return index (TRI), was downloaded from Thomson Reuters Datastream. The data frequency used is daily.

**Table 1.** *Stock characteristics sorted on decile portfolios.*

The table presents the time-series average values for: market value in millions of Swedish kronor, stock price in Swedish kronor, book-to-market, beta, total skewness in returns, illiquidity measured as a percentage of zeros over the past 260 trading days, short term reversal, intermediate term momentum and maximum daily return within a month.

	Price	MV	BM	BETA	TSKEW	ILLIQ	REV	MOM	MAX
Low MAX	122.06	23 228	0.71	0.56	0.52	0.35	-3.54	13.66	1.36
2	122.20	23 674	0.68	0.65	0.35	0.28	-1.90	14.86	2.75
3	114.99	21 272	0.67	0.67	0.40	0.40	-1.20	14.53	3.38
4	109.95	16 570	0.65	0.67	0.40	0.33	-0.66	15.54	3.97
5	102.29	15 014	0.65	0.68	0.45	0.34	-0.04	15.03	4.61
6	92.89	12 333	0.65	0.69	0.52	0.37	0.13	15.54	5.36
7	84.53	10 036	0.63	0.73	0.55	0.42	0.97	15.02	6.29
8	76.26	8 581	0.65	0.72	0.62	0.64	1.57	13.22	7.61
9	65.85	5 486	0.66	0.71	0.76	0.73	3.73	11.82	9.85
High MAX	46.83	3 074	0.72	0.74	1.12	1.15	11.51	3.37	19.49

We have used total return index rather than adjusted prices to calculate returns. The TRI is adjusted for all corporate actions including splits and dividends, as opposed to adjusted prices which only correct for splits and reverse splits. MV has been used to construct value weighted portfolios as well as market return, which is the value weighted return of all stocks in the sample. PTBV has been used to calculate book-to-market, which is a factor in the cross sectional regressions.

Datastream has some reported issues, such as decimal jumps. We have made sanity checks of the data following Ince and Porter (2006) and Schmidt et al. (2011), by manually looking at daily

<sup>2</sup> <http://www.nasdaqomx.com/transactions/markets/nordic/corporate-actions/stockholm/changes-to-the-list>

stock returns in excess of 100 %. We have used media archives to determine the validity of these returns and have removed one such extreme return, where no proof of validity was found. Furthermore Datastream reports missing values in PTBV for 109 stocks in our sample, it appears as if this occurrence is completely random.

Fama-French-Carhart factors (FFC) for the Swedish market where sourced from Professor Stefano Marmi of Pisa University.<sup>3</sup> The factors are on a monthly basis and stretch from January 1997 until March 2013. Marmi has calculated the factors using 6 portfolios sorted on book-to-market and size, following standard FFC procedures. In the next section we put our data set to use by analyzing if MAX is present in the portfolio setting.

### 3. Univariate portfolio-level analysis

Using our carefully constructed data set we start our research by doing portfolio level analysis to obtain an initial indication on whether we can observe the MAX effect or not. Sorting the stocks into portfolios and comparing the characteristics of each portfolio is relatively simple and intuitive. Furthermore portfolio sorting does not apply any form, e.g. linear or quadratic, to the relationship between MAX and expected returns.

**Table 2.** *Returns and alphas by portfolio sorted on MAX*

Decile portfolios are formed each month for the sample period of 1997-2014 based on the maximum daily return of stocks within each month. High MAX portfolio contain the stocks in the highest decile of daily returns and Low MAX portfolio contain the stocks in the lowest decile of daily returns. The average return columns display the monthly raw return of the portfolios and is expressed in percentage. The four-factor alpha is the risk adjusted return, adjusting for size, value, momentum and market risk premium. 10-1 Hedge is the raw and risk adjusted returns obtained from having a long position in High MAX portfolio and short in Low MAX portfolio. Newey-West (1987) t-statistics for the 10-1 Hedged portfolio are presented in parenthesis. Average MAX shows the average maximum daily raw return for each portfolio.

Decile	VW Portfolios		EW Portfolios		Average MAX
	Average Return	Four-factor Alpha	Average Return	Four-factor Alpha	
Low MAX	1.27	0.49	1.56	0.82	1.36
2	1.13	0.10	1.49	0.65	2.75
3	0.94	-0.02	1.53	0.68	3.38
4	0.78	-0.35	1.36	0.46	3.97
5	0.98	-0.17	1.10	0.19	4.61
6	0.76	-0.60	1.01	0.19	5.36
7	0.80	-0.21	0.78	0.01	6.29
8	1.26	0.42	0.93	0.26	7.61
9	1.00	-0.17	0.51	-0.36	9.85
High MAX	0.80	-0.19	0.16	-0.36	19.49
10-1 Hedge	-0.47	-0.68	-1.40	-1.19	
Newey-West t-stat	(-0.68)	(-1.06)	(-2.31)	(-2.91)	

<sup>3</sup> [http://homepage.sns.it/marmi/Data\\_Library.html#Sweden](http://homepage.sns.it/marmi/Data_Library.html#Sweden)



We calculate daily returns using total return index. Based on the maximum daily return within a month we construct equally-weighted and value-weighted decile portfolios, where the Low MAX portfolio contains stocks which have had the lowest maximum daily return and the High MAX portfolio contains stocks with the highest maximum daily return. Table 1 reports stock characteristics sorted on decile portfolios.

Table 2 reports the average monthly returns after the portfolio formation month, four factor alpha and the corresponding Newey-West (1987) t-statistic for the hedged portfolio. The Newey-West (1987) t-statistic controls for both autocorrelation and heteroskedasticity. The hedged portfolio is the difference of High MAX and Low MAX one month return. The equally-weighted hedged portfolio has a raw return of -1.40 % and is significant on all standard levels. The value-weighted hedged portfolio has a raw return of -0.47 %, however, not significant. These results contradict the findings of Bali et al. (2011) on the US stock market, who find evidence of the MAX effect in equally- and value-weighted portfolios. However our findings are in some regards consistent with the findings from the euro-zone area of Annaert et al. (2013). They find statistical significance of four-factor alpha, as do we, on equally-weighted portfolios, however no other evidence of the MAX effect in the portfolio setting.

The four-factor alpha is the intercept when regressing monthly excess return on size factor (SMB), value factor (HML) and momentum factor (MOM), using the standard Fama and French (1993) and Carhart (1997) model. When adjusting returns for these systematic factors we observe an alpha for the hedged equally-weighted portfolio of -1.19% and a corresponding Newey-West (1987) t-statistic of -2.91. For the value-weighted portfolios we cannot observe the same monotonic patterns as for the equally-weighted portfolios, the hedged value-weighted portfolio has an alpha of -0.68 and a corresponding Newey-West (1987) t-statistic of -1.06, making it insignificant using standard levels of significance..

Individual investors are often poorly diversified, (Odean, 1999; Mitton and Vorkink, 2007; Goetzman and Kumar, 2008), and are expected to make mistakes that one should not expect from an institutional investor. Kumar (2009) finds that individual investors have a preference for lottery-like stocks. It has been argued by Bali et al. (2011) that these investors are the likely drivers behind the MAX effect. Therefore it follows our intuition that the MAX effect should be more prominent in Sweden due to a higher market participation of individual investors (Guiso and Sodini, 2013), compared to the US.

However intuitive, this is not what our findings in portfolio setting shows, at least not indisputably. The raw return difference and alpha difference respectively are significantly larger in Sweden compared to the findings of Bali et al. (2011). However in the more economically valid,

value-weighted portfolios we cannot see any statistical significance. A plausible explanation for this could be that we have a much smaller set of firms, with an average of 29 stocks in each decile portfolio. The implications of this is that occasionally very large stocks manage to qualify into the high MAX portfolio, these stocks however tend not to be persistent so they reverse to a more stable lower decile in the subsequent month. These stocks taint the results of the value-weighted portfolios significantly more than in the equally-weighted portfolios. The average market value for high MAX stocks in our sample subset is 3.1 billion Swedish kronor which is larger by a factor of 8.5<sup>4</sup> compared to Annaert et al. (2013). This characteristic is in line with the above explanation. Unfortunately it is not possible to compare market value directly to Bali et al. (2011) due to a large difference in the time span of the sampling period.

### *3.1. Robustness*

One may ask if one extreme daily return is enough to attract investor attention and create an increased demand for these lottery-like stocks. The subject of investor inattention has been thoroughly discussed in publications by Odean (1999); Barber and Odean (2008); Barberis et al. (1998); Daniel et al. (1998); DellaVigna and Pollet (2009); Hong and Stein (1999). These suggest that investor are inattentive to news regarding the stock or firm and infrequently update their beliefs. In the previous section we used the one day maximum return as a proxy for a lottery-like stock. However this choice is somewhat arbitrary and in light of investor inattention it might not be optimal. If investors are inattentive to news of the stock, such as an extreme daily return, a stock might need to have several extreme daily peaks in order for investors to discover these stocks. Furthermore they may need more than one observation of an extreme peak in order to categorize a stock as lottery-like. If investors only observe one extreme daily return, they might attribute this to a freak event and may not expect to see this kind of extreme return in the future. However if a stock has several peaks investors might see this as a characteristic of the stock. Given the above discussion, it may be suboptimal to construct portfolios on the daily maximum return.

For these reasons we do a robustness check of our findings to see whether MAX is still observable in the univariate portfolio analysis when changing the number of maximum daily returns. We construct decile portfolios on the average of the three and five maximum returns in each month. The robustness check concludes that MAX is persistent in the equally-weighted portfolios. With a four factor alpha difference of -1.52% and -1.53% for N=3 and N=5 respectively. It appears that the alpha difference is if anything statistically more significant for changes to the number of maximum daily returns. In the case of the value weighted portfolios, the

---

<sup>4</sup> Annaert et al. Report an average market value of 38.6 MN euro, using May 2015 exchange rate this is approximately 360 MN SEK. Some caution is advised, since the sample time frame differs in the way that ours is more recent.

return difference and the alpha difference increase in absolute numbers, also the Newey-West (1987) t-statistic increase. For the raw return in  $N=5$  the Newey-West (1987) t-statistic is -1.84 making it significant on a 10% level. We can see that the statistical and economic significance increases, this may be due to investor inattention discussed earlier. The next question we ask is whether investors are rational in forming these beliefs about a stock being lottery-like. Are previous extreme returns any guarantee of future extreme returns? This issue of persistency is examined in the next section.

**Table 3.** *Decile portfolio sorted on MAX(N)*

This table show the robustness of MAX. Portfolios are constructed every month based on the average  $N$  highest return with each month. Columns  $N=3$  (5) show the returns of portfolios constructed using the average of the three (five) maximum monthly returns for each stock. Return difference and alpha difference show the raw returns and risk adjusted return respectively of the hedged portfolio, with a long position in High MAX(N) and a short position in Low MAX(N), Newey-West (1987) adjusted t-statistic is presented in parenthesis below.

Decile	VW portfolio return			EW portfolio return		
	N=1	N=3	N=5	N=1	N=3	N=5
Low MAX(N)	1.27	1.71	1.88	1.56	1.64	1.55
2	1.13	1.10	0.83	1.49	1.47	1.53
3	0.94	1.21	1.26	1.53	1.45	1.28
4	0.78	1.31	1.19	1.36	1.15	1.30
5	0.98	0.89	1.19	1.10	1.21	1.18
6	0.76	0.84	0.93	1.01	1.05	1.21
7	0.80	1.16	0.77	0.78	1.02	0.75
8	1.26	0.96	1.08	0.93	0.63	0.82
9	1.00	1.20	0.67	0.51	0.83	0.91
High MAX(N)	0.80	0.65	0.65	0.16	0.00	-0.08
Return difference	-0.47	-1.06	-1.23	-1.40	-1.64	-1.63
Newey-West t-stat	(-0.68)	(-1.33)	(-1.84)	(-2.31)	(-2.53)	(-2.50)
Alpha difference	-0.68	-1.05	-1.19	-1.19	-1.52	-1.53
Newey-West t-stat	(-1.06)	(-1.46)	(-1.79)	(-2.91)	(-3.27)	(-3.11)

### 3.2. The persistence of MAX

It is of importance to investigate the persistence of the MAX effect. If investors sees an extreme daily return of a stock as an indication that this could be repeated in future months, they might be willing to pay a premium for these stocks. Therefore we need to examine if this belief is accurate by analyzing the persistence of extreme daily returns between months. In addition to this, we use extreme returns of stocks in month  $t$  to form portfolios and then measure the monthly return of these portfolios over the month  $t + 1$ . If MAX is not persistent, this way of predicting future MAX using MAX from past months would be incorrect.

A transition matrix is calculated to investigate whether MAX is persistent and thereby shedding light on the issues raised earlier. We construct the matrix by calculating the probability

$P_{i,j}$  that a stock in portfolio  $i$  in month  $t$  will be a constituent of portfolio  $j$  in month  $t + 1$ . If a stock's maximum daily return in a month is totally random or not persistent, all probabilities in the transition matrix are expected to be circa 10%. Table 4 shows that this is not the case. All diagonal elements in the transition matrix have values over 10%. Additionally, and more importantly, the probability of a stock in decile 10 (high MAX) to be found in the same decile the next month is 28.3% and the probability of a stock in decile 10 to end up in the deciles 8, 9 or 10 in the following month is 58.3%. For robustness, we also calculate a transitional matrix for MAX(5). For brevity we do not tabulate this, but we find that the persistence of MAX is slightly higher with this specification. Lastly we regress MAX on its lagged value in the cross-section. This regression yields a coefficient of 0.33 with a Newey-West (1987) t-statistic of 11.35. The evidence from the transition matrices and the cross-sectional regression leads us to the conclusion that the lottery-like extreme returns of certain stocks are persistent.

**Table 4.** *Month-to-month transition matrix for MAX.*

In each month we form decile portfolios based on the maximum daily return in that month (MAX). The table shows the calculated probability of a stock in portfolio  $i$  to transition to the portfolio  $j$  in the subsequent month. E.g. if a stock is assigned to decile 10 in month  $t$  (rows), the probability of that stock to being a constituent of decile 10 the following month as well is 28% (columns).

[%]	Low	2	3	4	5	6	7	8	9	High
Low	24	15	12	10	9	8	6	5	5	6
2	15	16	14	13	10	9	8	6	5	4
3	12	13	14	12	12	10	9	7	6	5
4	10	13	12	12	11	11	9	9	7	6
5	9	11	11	12	11	11	11	9	8	7
6	7	9	11	11	12	12	11	11	10	7
7	6	7	9	10	10	12	13	12	12	8
8	5	6	8	9	10	10	13	13	13	12
9	5	5	7	7	9	10	12	14	16	16
High	7	4	4	4	6	9	9	13	17	28

## 4. Firm-level cross-sectional regression

### 4.1. Introduction and model specification

Encouraged by our results in the portfolio setting we continue our research by conducting cross-sectional regressions on the firm level. Portfolio level analysis is intuitive and model free in the sense that it does not apply any kind of functional form on the relationship between MAX and stock returns. It does however aggregate firm-level data in the process of forming portfolios and thereby discards a large amount of information. Furthermore it is not possible for us to perform bivariate sorts to control for other well-known factors that affect the pricing of stocks. This is due to our limited sample size that makes the portfolios formed in a bivariate sort too small.

Therefore we turn to firm-level cross-sectional analysis to further explore the MAX effect and also how it interacts with other factors that affect the pricing of stocks. The procedure we choose to use is the Fama and MacBeth (1973) procedure, as it is the procedure used by much of the previous research on the expected return of assets in the cross-section. The MAX effect is of course our main subject of attention, but the model is expanded by adding a total of seven control variables. To be able to compare our results with Bali et al. (2011) and Annaert et al. (2013) we include the same variables as they have. However, to concentrate on the MAX effect and focus the scope of our research we choose not to include idiosyncratic volatility. Bali et al. (2011) and Annaert et al. (2013) devote quite some time on investigating and discarding the relationship between expected returns and idiosyncratic volatility first documented by Ang et al. (2006, 2009). Although this relationship is interesting, we find it unnecessary and not relevant to our study to investigate it further. The total model specification is then:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}MAX + \lambda_{2,t}BETA + \lambda_{3,t}SIZE + \lambda_{4,t}BM + \lambda_{5,t}MOM + \lambda_{6,t}REV \\ + \lambda_{7,t}ILLIQ + \varepsilon_{i,t+1}$$

where  $R_{i,t+1}$  is the monthly return in month  $t + 1$ . MAX is the maximum daily return in the previous month and BETA, SIZE, BM, MOM, REV and ILLIQ are our control factors. All variables are constructed so that they are known to a potential investor at the time  $t$ . We present the variable definitions and short explanations of them in section 4.2. The slope coefficients  $\lambda_{1,t} - \lambda_{7,t}$  are estimated in the Fama-MacBeth regressions. These slope coefficients are then examined to see which factors are associated with non-zero premiums. The time-series average of these premiums are reported and discussed in great detail in a later section.

#### 4.2. Variable definitions

**MAX(N):** We follow the definition of Bali et al. (2011) and Annaert et al. (2013). MAX(N) is the average of  $N$  number of maximum daily returns for a stock during a month  $t$ :

$$MAX(N)_{i,t} = \frac{1}{N} \sum_{n=1}^N \max(R_{i,d})$$

$$d = 1, 2, 3 \dots D_t$$

where  $R_{i,d}$  is the daily return in day  $d$  of stock  $i$ .  $D$  is the total number of trading days in month  $t$ . E.g. MAX(1) is the maximum daily return of a stock in a month, MAX(5) is the average of the 5 highest daily returns of a stock in a month.

**MARKET BETA:** Market beta is calculated using daily returns, therefore we need to account for nonsynchronous trading. This is done by regressing daily stock returns on the current, lagging and leading market return as proposed by Scholes and Williams (1977) and Dimson (1979):

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d-1} - r_{f,d-1}) + \beta_{2,i}(R_{m,d} - r_{f,d}) + \beta_{3,i}(R_{m,d+1} - r_{f,d+1})$$

where  $R_{i,d}$  is the daily return in day  $d$  of stock  $i$ .  $r_{f,d}$  is the risk-free rate on day  $d$ , calculated using the Swedish 90 day T-bill rate.  $R_{m,d}$  is the return of the market on day  $d$  calculated as the value-weighted return of all the stocks in our sample that day. Total market beta for stock  $i$  is then calculated as:

$$\widehat{\beta}_i = \widehat{\beta}_{1,i} + \widehat{\beta}_{2,i} + \widehat{\beta}_{3,i}$$

**SIZE (MV):** Since it first was discovered by Banz (1981), the size effect is widely considered as a predictor of stock returns. We follow previous research and define it as the natural logarithm of market value.

**BOOK-TO-MARKET (BM):** Just as the size effect, book-to-market is heavily documented and widely acknowledged to be an important determinant of expected cross-sectional return. We follow Bali et al. (2011) which in turn use the Fama and French (1992) definition of the book-to-market variable. Market value of equity is divided by book value of equity at the previous fiscal year end. The book value is adjusted for deferred taxes.

**SHORT-TERM REVERSAL (REV):** We use the definition of short-term reversal from Jegadeesh (1990) and use the previous month return to account for the reversal effect.

**MOMENTUM (MOM):** The momentum effect was discovered by Jegadeesh and Titman (1993). It is widely considered as an important firm-level return predictor. In later work, Fama and French (2008) defines it as the return of holding a stock  $i$  the period  $t-12$  to  $t-2$ . We follow this definition.

**ILLIQUIDITY (ILLIQ):** Inspired by Bekaert et al. (2007) and Annaert et al. (2013) we calculate illiquidity as the portion of days with zero trading over the last 260 trading days.

$$Illiq_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} (1|Vol_{i,d} = 0)$$

where  $D_t$  is the number of trading days in year  $t$  and  $Vol_{i,d}$  is the traded volume of stock  $i$  on day  $d$ .

### 4.3. Result

Each month we regress monthly return on several lagged predictors including MAX, following the Fama-MacBeth procedure. The times series average, slope coefficient  $\lambda_{i,t}$  ( $i=1, 2, \dots, 7$ ) and the corresponding Newey-West (1987) t- statistics are presented in Table 4.

**Table 4.** *Firm-level cross-sectional regression*

Each month, we regress monthly return on several lagged predictor variables including MAX in the previous month, beta, market value, book-to-market, illiquidity measure, momentum and short term reversal. The variables are defined in the section 4.2. The values in the diagonal are the times-series average slope coefficients from the univariate regressions. On the horizontal are the time-series average slope coefficients of the multivariate regression. The corresponding Newey-West (1987) adjusted t-statistic is reported in parenthesis.

MAX	BETA	MV	BM	ILLIQ	MOM	REV
-0.0836 (-3.20)						
	0.0008 (1.07)					
		0.0005 (0.75)				
			0.0070 (3.14)			
				0.0165 (0.73)		
					0.0138 (2.21)	
						0.0211 (1.89)
-0.0688 (-2.63)	0.0015 (2.02)	-0.0003 (-0.44)	0.0075 (3.80)	-0.0228 (-0.70)	0.0123 (2.80)	-0.0065 (-0.56)

When regressing monthly return on MAX in the previous month in the cross-section we notice that MAX has a negative slope coefficient  $\lambda_{i,t}$  of -0.0836 and a high Newey-West (1987) adjusted t-statistic of  $|3.20|$ . When we include the control variables, the coefficient of MAX decreases slightly and is -0.0688 and the Newey-West (1987) adjusted t-statistic is impressive at  $|2.63|$ . This is a strong indication that MAX is negatively priced in the Swedish stock market. The spread in median maximum daily return between decile 10 and 1 is approximately 13.6%, multiplying this number with the slope coefficient of MAX, we get an estimate of the monthly risk premium of -1.14%. This is consistent with the intuition that MAX is more prominent in Sweden than it is in the US. Bali et al. (2011) report a comparable risk premium of 0.69%. The value from the firm-level cross-sectional analysis is slightly lower than the alpha that what was discovered in the univariate portfolio level analysis, this could be a result of regressing on more control variables and that we do not lose information due to aggregation. We test the hypothesis that the slope

coefficient  $\lambda_{MAX}$  are the same for the Swedish and US sample and are able to reject the hypothesis at all standard significance levels. Thus we confirm that the MAX effect is more prominent in Sweden.

The univariate regressions of the control variables show results consistent with the literature, a market BETA with a low positive slope however it is not significant, ( $t=1.07$ ). BM is positive and significant, ( $t=3.14$ ). ILLIQ is positive yet insignificant, ( $t=0.73$ ), in accordance with our expectations, meaning that less liquid stock outperform more liquid stocks, due to an illiquidity premium. MOM is positive and significant ( $t=2.21$ ). MV is slightly positive which is somewhat anomalous, this would indicate that large firms outperform small firms, however the result is insignificant, ( $t=0.75$ ). We find no credible research on the size effect in Sweden, however Annaert et al. (2013) report positive, yet insignificant size effect for Benelux, Germany, France and Italy, also REV is slightly anomalous, a positive sign of the slope coefficient, which furthermore is weakly significant ( $t=1.89$ ), suggest that short term reversal does not exist in this sample. However this anomaly disappears in the full model specification. Although it appears that MAX is robust for the conventional factors in the FFC model, reversal and illiquidity, one important factor that remains to be investigated is skewness.

#### 4.4. Max and skewness

The relation between skewness and returns has engaged many researcher in the field of finance for quite some time. Kraus and Litzenberger (1976); Harvey and Siddeque (2000) find evidence that investors have an aversion to variance and a preference for positive systematic skewness, also known as co-skewness. Thus stocks that decrease the investor's skewness are less desirable and will thus have a higher expected return. Several authors argue that it is not only co-skewness but also idiosyncratic skewness that is priced. Mitton and Vorkink (2007) develop a model where certain investors have a preference for positive skewness in returns, in equilibrium idiosyncratic skewness is priced.

We define total skewness (TSKEW) in each month for stock  $i$  in month  $t$ , as the skewness in daily returns in the preceding 260 trading days:

$$TSKEW_{i,t} = \frac{1}{260} \sum_{d=1}^{D_t} \left( \frac{R_{i,d} - \mu_i}{\sigma_i} \right)^3$$

where  $R_{i,d}$  is the return of stock  $i$  on day  $d$ ,  $\mu_i$  is the average return of stock  $i$  over the past 260 trading days and  $\sigma_i$  is the standard deviation of returns of stock  $i$  over the past 260 trading days.



Following Harvey and Siddique (2000) we estimate systematic (SSKEW) and idiosyncratic skewness (ISKEW) each month using daily data over the preceding 260 trading days, using the following regression:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \gamma_i(R_{m,d} - r_{f,d})^2 + \varepsilon_{i,d}$$

where  $R_{i,d}$  is the return of stock  $i$  on day  $d$ ,  $R_{m,d}$  is the market return on day  $d$ ,  $r_{f,d}$  is the risk free rate on day  $d$ ,  $\varepsilon_{i,d}$  is the idiosyncratic return of stock  $i$  on day  $d$ . ISKEW of stock  $i$  in month  $t$ , is the skewness in the daily residual  $\varepsilon_{i,d}$  of stock  $i$ , in the 260 trading days preceding month  $t$ . Systematic skewness of stock  $i$  in month  $t$  is the estimated slope coefficient  $\gamma_{i,d}$  estimated on the last 260 trading days.

Table 1 presents the average total skewness of stocks in each decile formed on monthly maximum return. It seems as though there is a significant relation of MAX and total skewness, the average skewness for stocks in decile 10 is more than double that of decile 1. Could it in fact be that MAX is just a good proxy for skewness, and the true reason of why stocks underperform in the subsequent month, is not the MAX peak but in fact a preference for skewness in returns? We test this by correlating MAX with total (TSKEW), idiosyncratic (ISKEW) and systematic skewness (SSKEW) in the cross-section. The correlations are presented in Table 5 and are unimpressive, the monotonicity observable in Table 1 completely vanishes in the cross section. The reason for this is that portfolio level analysis discards large amounts of data through aggregation. The weak correlation indicates that MAX is not a proxy for skewness.

**Table 5.** *Correlation between MAX and skewness*

The table below reports the cross sectional correlation of MAX and TSKEW, ISKEW and SSKEW separately.

	MAX	TSKEW	ISKEW	SSKEW
MAX	1			
TSKEW	0.106	1		
ISKEW	0.091	0.942	1	
SSKEW	0.020	-0.009	-0.035	1

Following Bali et al. (2011), we also test if MAX is persistent when controlling for skewness. Therefore, we first perform univariate regressions of monthly return on TSKEW, SSKEW and ISKEW, to see if any of the skewness measures are priced. We do this following standard Fama-MacBeth (1973) procedure. Table 6 reports the slope coefficient  $\lambda$ , and the corresponding Newey-West (1987) t-statistic is reported in parenthesis. The univariate regressions indicate that skewness

is not a priced factor in the Swedish stock market. The coefficients are very close to zero for all measures of skewness and the corresponding Newey-West (1987) t-statistic is very unimpressive.

Secondly we add skewness the full model specification of the above section, we do this to see if MAX is persistent to controls for skewness. When any of the defined skewness measure are added to the model, their statistical significance increases, however they are still close to zero and not statistically significant. Boyer et al. (2010) argue that lagged skewness may not be a good predictor of future skewness, this may explain why it appears as if skewness is not priced. What is perhaps most important to notice is that MAX is persistent when controlling for skewness. The slope coefficient of MAX increases slightly, controlling for any measure of skewness. The corresponding Newey-West (1987) t-statistics are all above 2.6 which indicates a high level of significance. Thus MAX is consistent to controls for any measure of skewness. The difference in the median MAX of the 10<sup>th</sup> decile and the 1<sup>st</sup> decile is 13.6%, multiplying this number with the average slope coefficient  $\lambda_{MAX}$  in the full model specifications, yields a risk premium of 0.98%.

**Table 6.** *Cross-sectional regression, full model specification and skewness*

The table reports the slope coefficients from the Fama-Macbeth (1973) two pass regression, when regressing monthly return on total skewness (TSKEW) systematic skewness (SKEW) and idiosyncratic skewness (ISKEW). Furthermore each one of the measures of skewness is added to the full model specification, where monthly return is regressed on MAX, BETA, MV, BM, ILLIQ, MOM, REV and any measure of skewness. Newey-West (1987) adjusted t-statistics are reported in parentheses.

MAX	BETA	MV	BM	ILLIQ	MOM	REV	TSKEW	SSKEW	ISKEW
							0.0004 (0.58)		
								-0.0023 (-0.35)	
									0.0002 (0.22)
-0.0756 (-2.89)	0.0014 (1.95)	-0.0002 (-0.32)	0.0080 (4.02)	-0.0167 (-0.50)	0.0124 (2.74)	-0.0074 (-0.65)	0.0007 (0.87)		
-0.0693 (-2.70)	0.0016 (2.24)	-0.0002 (-0.32)	0.0074 (3.79)	-0.0211 (-0.63)	0.0123 (2.79)	-0.0054 (-0.47)		-0.0135 (-1.75)	
-0.0704 (-2.64)	0.0014 (1.96)	-0.0002 (-0.34)	0.0076 (3.85)	-0.0187 (-0.57)	0.0127 (2.82)	-0.0068 (-0.59)			0.0004 (0.51)

So far we have shown that MAX is priced in the Swedish stock market using a portfolio level analysis and a firm-level cross-sectional analysis. Bali et al. (2011); Annaert et al. (2013); Fong and Toh (2014) argue that it is individual investors that drive the MAX effect and not institutional investors. This is also a very intuitive explanation, individuals are proven to make many mistakes in the stock market, Odean (1999), Mitton and Vorkink (2007) for examples of common mistakes

of individual investors. However it has not been proven that it is in fact these investors that drive the effect. Therefore we turn our focus away from MAX and instead look at what drives it. In the next section we will try to do this, using a unique dataset from a leading Swedish retail brokerage firm.

## 5. MAX and individual investors

We argue that it is individual investors that mainly drive the MAX effect. In previous research Fong and Toh (2014) use SEC filings on institutional ownership of stocks to do bivariate sorts on MAX and institutional ownership. They find that although the MAX effect is the most present in the portfolio of stocks with the highest share of individual ownership, it is also statistically significant for all but the most institutionally owned stocks. We see their results as a strong indication that it is mainly individual investors that drive the MAX effect.

To shed more light on the issue we take a different approach than Fong and Toh (2014). The method we have chosen is to see if we can find any correlation between extreme daily returns of a stock in a month and individual investor purchasing behavior, more specifically their net transactions in Swedish krona (hereafter NT). This approach follows Barber and Odean (2008) who investigates what catches the attention of individual investors using transaction data from discount brokerages. In that process, they unknowingly examine the MAX effect since one of the attention-grabbers in their research is extreme daily returns. They find evidence that an extreme daily return in day  $t$  results in higher net buying by individual investors in the following day ( $t + 1$ ).

With the help from a leading Swedish retail bank that has asked to be anonymous, we have obtained a somewhat similar data set as the one Barber and Odean (2008) uses. However due to data availability it is limited to the period January 2013 – December 2014 and only contains transactions at the monthly level. It covers all stocks on the Swedish main market with information on aggregated NT for all the bank's private customers. It differs from the dataset used by Barber and Odean (2008) in that it does not contain data on total the total sum of selling and buying for each month. This is not due to data availability but to bank secrecy regulations and this limits us from calculating buy-sell imbalance<sup>5</sup>. We are fully aware that these shortcomings will significantly limit our ability to obtain robust evidence, but we do expect to at least provide some indication that the MAX effect is driven by individual investors.

---

<sup>5</sup> Barber and Odean (2008) define buy-sell imbalance for each share in each period as shares bought minus shares sold, over the total number of shares bought and sold.

### 5.1. Model specification

We need to normalize NT for all stocks since the total NT will of course be higher in absolute terms for large-cap stocks as compared to small-cap stocks. Therefore we divide the sum of NT for each stock  $i$  in month  $t$  by the average market value (MV) for that stock in month  $t$ :

$$NTofMV_{i,t} = \frac{NT_{i,t}}{MV_{i,t}}$$

This is an intuitive but somewhat crude measure of how much of the market value of each firm that has been bought or sold by individual investors. We then, as before, construct decile stock portfolios based on maximum daily return in a month. This is followed by computing the time-series average of  $NTofMV$  for each portfolio. One should note however that  $NTofMV$  and maximum daily return are from the same month  $t$ . This differs from the portfolio analysis of MAX return in section 3 where returns are calculated in the subsequent month. The rationale behind this is that the demand shock following the extreme daily return is assumed to be quite instantaneous. We would have liked to follow Barber and Odean (2008) and use  $NTofMV$  for the day after the extreme return, but as mentioned earlier this data is not available to us.

We calculate portfolio average NT both for the full sample of stocks and also for a restricted sample. The restriction is excluding the top 30 most traded stocks<sup>6</sup>. The reason for doing this is that these stocks are without competition the most bought stocks by first-time customers in our sample. Excluding them dampens the distortion effect of new customer inflow.

### 5.2. Results

The results from the portfolio analysis is reported in Table 7.  $NTofMV$  is tabulated both for the full and restricted sample, as well as the 10 – 1 portfolio differences and the corresponding Newey-West (1987) t-statistics. We notice that  $NTofMV$  is largely constant for portfolio 1 -8 but increases in portfolio 9 and spikes drastically in portfolio 10. The difference between portfolio 10 and 1 is positive for both portfolios but the magnitude is slightly larger in the restricted sample, both are significant at conventional significance levels. Using our measure of  $NTofMV$  we can see a clear relationship between MAX and individual investor NT.

---

<sup>6</sup> These are stocks in OMXS 30, an official index of the most traded stocks at the Stockholm Stock Exchange.

**Table 7.** *MAX and individual investor purchasing behavior.*

Decile Portfolios of stocks are formed each month from January 2013 to December 2014 based on maximum daily return in that month. The average net transactions divided by market value for each portfolio in the portfolio formation month is then calculated and reported. The restricted sample excludes the top 30 most traded stocks. The 10 – 1 portfolio differences are also reported as well as their corresponding Newey-West (1987) t-statistics in parentheses.

Decile	NTof MV (‰)	
	Full sample	Restricted sample
Low MAX	0.2884	0.3813
2	0.2742	0.255
3	0.1074	0.1723
4	0.2979	0.272
5	0.2267	0.1709
6	0.0475	0.2295
7	0.2921	0.2785
8	0.2086	0.3367
9	0.4889	0.3574
High MAX	1.0994	1.2834
10-1 difference	0.8110	0.9021
Newey-West t-stat	(2.36)	(2.23)

In spite of this we refrain from drawing any definite conclusions. The data suggests that MAX is to some extent driven by individual investors. But the fact that our sample is limited in time, sampling frequency and is missing data on total numbers of shares bought and sold limits the validity and explanatory power. Instead we see it as an indication and not a definite proof. Another limitation is that we have not investigated the previous findings by Fong and Toh (2014) that stocks with a moderate amount of institutional capital also are subject to the MAX effect. To control for this we would need access to a dataset containing NTs by institutional investors only, this we have not been able to obtain.

Our results on individual investor purchasing behavior cannot alone explain the drivers of the MAX effect. However several other factors also indicate that is indeed individual investors that mainly give rise to the MAX effect. Firstly our own study indicates that MAX is stronger in Sweden, a country with a very large amount of individual investor market participation. Secondly the empirical results of Barber Odean (2008) and Fong and Toh (2014) also points towards individual investors, and lastly the work of Kumar (2009). This evidence taken together, in addition to our novel results, makes us fairly confident about individual investors being the primary seekers of lottery-type MAX stocks.

## 6. Conclusion

We are able to corroborate recent findings by Bali et al. (2011) and Annaert et al. (2013) that the stocks which have had an extreme positive daily return systematically underperform in the subsequent month. The evidence is found in a carefully constructed data set of stocks on the Swedish market. Our results are robust for a battery of control variables. The MAX effect we observe is stronger in Sweden, we argue that this is due to a higher degree of individual investor market participation and their demand for lottery-like payoffs. We find some evidence in support of this notion. By looking at individual investor purchasing behavior we find that they are heavily buying stocks that have exhibited extreme positive returns. This is in line with previous studies by Barber and Odean (2008); Fong and Toh (2014).

The corroborating results we present is yet another step towards MAX becoming a recognized factor in asset pricing models. Our findings shed light on individual investors' stock purchasing behavior and show the implications of their mistakes.

### 6.1. *Limitations and future research*

To evaluate the validity and relevance of our research we have to shed light on the limitations and shortcomings of our work. First of all our sample is limited to the period 1997-2014. This is a fair bit shorter than the one used by many of our predecessors (Bali et al., 2011; Annaert et al., 2013) and also most other studies on cross-sectional asset pricing. Data availability and accuracy is a general problem for all studies on the Swedish equity market. For example, Sweden limited the inflow of foreign capital until the early 1990s (Bergström, 2002) making data prior to this questionable to use in financial studies. A longer time sample would have allowed us to study subsamples with different market conditions.

The number of firms in the sample is also smaller than many of our predecessors'. This is problematic since it limits us from doing bivariate portfolio sorts to control for well-known determinants of expected returns, such as book-to-market, size, etc. We overcome this limitation by analyzing on the firm level in the cross-section. We have included all the standard control variables in our regression model and also included skewness. There is however no guarantee that other, unknown variables are omitted and that MAX is a proxy for an asset pricing determinant not yet explored.

Another issue is the data on individual investor purchasing behavior. We are of course very grateful for the data we have kindly been provided, but nonetheless it is lacking in some regards. Sample length is even shorter here than in the firm-level cross-sectional setting due to data availability, and for legal reasons we have not been able to obtain certain metrics that would have been of interest. These metrics would include a more fine-grained aggregation, such as purchasing

data on different groups such as gender, age or disposable income. The fact that we miss a control group of institutional investors is also a shortcoming.

We have shown that the MAX effect is more prominent in Sweden than in the US and in the euro area. We argue that this is attributable to the high relative amount of market participation of individual investors. However in making this argument we assume individual investors to be homogeneous between countries, so that a Swedish individual investor would act according to the same principles as an investor from e.g. the US. There is also another explanation for why the effect seems more prominent in Sweden than in the samples of our processors, it could just be that the possibility of short selling is more restricted in our sample, or that the transaction cost associated with short selling is higher in our sample. This restricts more informed traders from correcting the mispricing caused by the MAX effect. However we have not looked in to this alternative explanation but it could serve as a good starting point for future research.

Even though we have several indications about which investors drive the anomalous returns in the high MAX stocks, we are unable to present any explicit evidence. If it is in fact as we and others have suggested, that mainly individual investors are driving the effect, it is important to know this. However, we leave this task to future scholars. Another interesting subject to study is whether the reason behind the extreme return (e.g. earnings announcement, analyst recommendations, takeover announcement, etc.) affects subsequent returns.

## 7. References

Ang, A., Hodrick, R.J., Xing, Y. & Zhang, X. 2009, "High idiosyncratic volatility and low returns: International and further U.S. evidence", *Journal of Financial Economics*, vol. 91, no. 1, pp. 1-23.

Ang, A., Hodrick, R.J., Xing, Y. & Zhang, X. 2006, "The Cross-Section of Volatility and Expected Returns", *The Journal of Finance*, vol. 61, no. 1, pp. 259-299.

Annaert, J., De Ceuster, M. & Versteegen, K. 2013, "Are extreme returns priced in the stock market? European evidence", *Journal of Banking & Finance*, vol. 37, no. 9, pp. 3401-3411.

Bali, T.G. & Cakici, N. 2008, "Idiosyncratic Volatility and the Cross Section of Expected Returns", *Journal of Financial and Quantitative Analysis*, vol. 43, no. 01, pp. 29-58.

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*, vol. 99, no. 2, pp. 427-446.

Banz, R.W. 1981, "The relationship between return and market value of common stocks", *Journal of Financial Economics*, vol. 9, no. 1, pp. 3-18.

Barber, B.M. & Odean, T. 2008, "All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors", *Review of Financial Studies*, vol. 21, no. 2, pp. 785-818.

Barberis, N. & Huang, M. 2008, "Stocks as lotteries: The implications of probability weighting for security prices", *American Economic Review*, vol. 98, no. 5, pp. 2066-2100.

Barberis, N., Shleifer, A. & Vishny, R. 1998, "A model of investor sentiment", *Journal of Financial Economics*, vol. 49, no. 3, pp. 307-343.

Bekaert, G., Harvey, C.R. & Lundblad, C. 2007, "Liquidity and expected returns: Lessons from emerging markets", *Review of Financial Studies*, vol. 20, no. 6, pp. 1783-1831.

Bergström, V. 2002, "Har globaliseringen något att göra med nedläggningen av bankomaten?" (Sveriges Riksbank, Stockholm, Sweden).

Boyer, B., Mitton, T. & Vorkink, K. 2010, "Expected Idiosyncratic Skewness", *Review of Financial Studies*, vol. 23, no. 1, pp. 169-202.

Carhart, M.M. 1997, "On Persistence in Mutual Fund Performance", *The Journal of Finance*, vol. 52, no. 1, pp. 57-82.



- Daniel, K., Hirshleifer, D. & Subrahmanyam, A. 1998, "Investor Psychology and Security Market Under- and Overreactions", *The Journal of Finance*, vol. 53, no. 6, pp. 1839-1885.
- Dellavigna, S. & Pollet, J.M. 2009, "Investor inattention and friday earnings announcements", *Journal of Finance*, vol. 64, no. 2, pp. 709-749.
- Dimson, E. 1979, "Risk measurement when shares are subject to infrequent trading", *Journal of Financial Economics*, vol. 7, no. 2, pp. 197-226.
- Fama, E.F. & French, K.R. 2008, "Dissecting Anomalies", *The Journal of Finance*, vol. 63, no. 4, pp. 1653-1678.
- Fama, E.F. & French, K.R. 1993, "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics*, vol. 33, no. 1, pp. 3-56.
- Fama, E.F. & French, K.R. 1992, "The Cross-Section of Expected Stock Returns", *The Journal of Finance*, vol. 47, no. 2, pp. 427-465.
- Fama, E.F. & MacBeth, J.D. 1973, "Risk, Return, and Equilibrium: Empirical Tests", *Journal of Political Economy*, vol. 81, no. 3, pp. 607-636.
- Fong, W.M. & Toh, B. 2014, "Investor sentiment and the MAX effect", *Journal of Banking & Finance*, vol. 46, no. 0, pp. 190-201.
- Goetzmann, W.N. & Kumar, A. 2008, "Equity Portfolio Diversification", *Review of Finance*, vol. 12, no. 3, pp. 433-463.
- Guiso, L. & Sodini, P. 2013 "Chapter 21 - Household Finance: An Emerging Field" in *Handbook of the Economics of Finance* Elsevier, pp. 1397-1532.
- Hong, H. & Stein, J.C. 1999, "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets", *The Journal of Finance*, vol. 54, no. 6, pp. 2143-2184.
- Harvey, C.R. & Siddique, A. 2000, "Conditional Skewness in Asset Pricing Tests", *The Journal of Finance*, vol. 55, no. 3, pp. 1263-1295.
- Ince, O.S. & Porter, R.B. 2006, "Individual equity return data from Thomson Datastream: Handle with care!", *Journal of Financial Research*, vol. 29, no. 4, pp. 463-479.

Jegadeesh, N. 1990, "Evidence of Predictable Behavior of Security Returns", *The Journal of Finance*, vol. 45, no. 3, pp. 881-898.

Jegadeesh, N. & Titman, S. 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency", *The Journal of Finance*, vol. 48, no. 1, pp. 65-91.

Kraus, A. & Litzenberger, R.H. 1976, "Skewness preference and the valuation of risk assets", *The Journal of Finance*, vol. 31, no. 4, pp. 1085-1100.

Kumar, A. 2009, "Who Gambles in the Stock Market?", *The Journal of Finance*, vol. 64, no. 4, pp. 1889-1933.

Mitton, T. & Vorkink, K. 2007, "Equilibrium underdiversification and the preference for skewness", *Review of Financial Studies*, vol. 20, no. 4, pp. 1255-1288.

Newey, W. & West, K. 1987, "A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix", *Econometrica*, vol. 55, no. 3, pp. 703-08.

Odean, T. 1999, "Do investors trade too much?", *American Economic Review*, vol. 89, no. 5, pp. 1279-1298.

Schmidt, P.S., Schrimpf, A., von Arx, U., Wagner, A. & Ziegler, A. 2011, "On the Construction of Common Size, Value and Momentum Factors in International Stock Markets: A Guide with Applications", Center of Economic Research at ETH Zurich.

Scholes, M. & Williams, J. 1977, "Estimating betas from nonsynchronous data", *Journal of Financial Economics*, vol. 5, no. 3, pp. 309-327.

Tversky, A. & Kahneman, D. 1992, "Advances in prospect theory: Cumulative representation of uncertainty", *Journal of Risk and Uncertainty*, vol. 5, no. 4, pp. 297-323.

**Appendix A.** All stocks listed on Stockholm stock exchange main list, 1997-2014. Stock names are reported by their names as of 2015.05.01.

Name	Inclusion date	Exclusion date			
AARHUSKARLSHAMN	2006-09-12	2014-12-30	BEIJER ELECTRONICS	2000-06-14	2014-12-30
ABB A	1997-01-03	1999-07-16	BERGS TIMBER B	1997-01-03	2014-12-30
ABB B	1997-01-03	1999-07-16	BESQAB	2014-06-13	2014-12-30
ABB LTD N	1999-06-23	2014-12-30	BETSSON B	1997-01-07	2014-12-30
ACADEMEDIA B	1998-06-22	2010-05-10	BENIMA FERATOR ENGR.	1997-01-03	1998-11-12
ACANDO B	1997-01-03	2014-12-30	BIACORE INTL.	1997-01-08	2006-05-19
ACAP INVEST A	2002-08-20	2014-09-08	BILIA A	1997-01-03	2014-12-30
ACAP INVEST B	2002-11-06	2014-09-05	BILLERUD KORSNAS	2001-11-21	2014-12-30
ACOM	1999-11-05	2012-11-12	BIOGAIA B	1998-06-02	2014-12-30
ACRIMO B	1997-01-07	1998-05-08	BIOINVENT INTL.	2001-06-13	2014-12-30
ACSC	1998-05-14	2007-12-28	BIOLIN SCIENTIFIC	1999-06-04	2010-12-13
ACTIVE BIOTECH	1997-01-03	2014-12-30	BIOPHAUSIA A	1997-01-03	2011-05-09
ADDNODE B	1999-06-11	2014-12-30	BIORA	1997-02-11	2003-07-04
ADDTECH B	2001-09-04	2014-12-30	BIOTAGE	2000-07-03	2014-12-30
AEROCRINE B	2007-06-18	2014-12-30	BJORN BORG	2007-05-08	2014-12-30
AF B	1997-01-03	2014-12-30	BLACK EARTH FARMING	2009-06-23	2014-12-30
AFFARSSTRATEGERNA B	1998-06-30	2009-11-09	BLACKPEARL RESC.	2012-11-07	2014-12-30
AFRICA OIL	2014-07-02	2014-12-30	BOLIDEN	1999-05-04	2014-12-30
AGA A	1997-01-03	2000-04-20	BOLIDEN SDB	1999-05-04	2001-12-04
AGA B	1997-01-03	2000-04-20	BONG	1997-01-07	2014-12-30
AINAX	2004-12-02	2005-01-18	BORAS WAFVERI B	1997-01-03	2010-08-09
AKZO NOBEL SDB	1997-01-03	2002-10-31	BOSS MEDIA	1999-06-28	2008-01-21
ALCATEL	1997-01-08	2001-01-31	BOSTADS AB DROTT	2004-05-07	2004-07-16
ALFA LAVAL	2002-05-21	2014-12-30	BOULE DIAGNOSTICS	2011-06-27	2014-12-30
ALFASKOP	1997-03-04	2001-09-18	BPA A	1997-01-03	1999-07-09
ALLENEX	2006-12-13	2014-12-30	BPA B	1997-01-03	1999-07-09
ALLGON B	1997-01-03	2003-04-17	BRINOVA FASTIGHETER	2003-11-21	2012-07-06
ALLIANCE OIL SDB	2007-05-24	2013-10-07	BRIO B	1997-01-03	2011-03-07
ALLTELE AB	2009-06-16	2014-12-30	BROSTROM	1998-06-18	2008-11-14
ALTHIN MEDICAL B	1997-01-03	2000-03-21	BT INDUSTRIES	1997-01-03	2000-07-14
ALTIMA	2003-12-17	2004-01-16	BTL BILSPEDITIONEN A	1997-01-03	1999-04-30
ANDERS DIOS B	1997-01-03	2000-12-28	BTL BILSPEDITIONEN B	1997-01-03	1999-04-30
ANOTO GROUP	2000-06-19	2014-12-30	BTS GROUP	2001-06-07	2014-12-30
ARCAM B	2012-06-19	2014-12-30	BUFAB	2014-02-24	2014-12-30
ARCTIC PAPER	2012-12-21	2014-12-30	BULTEN	2011-05-23	2014-12-30
ARETE	1997-12-22	2000-11-14	BULTEN B	1997-01-03	2001-02-16
ARISE	2010-03-25	2014-12-30	BURE EQUITY	1997-01-03	2014-12-30
ARTEMA MEDICAL B	1997-01-03	2001-12-14	BYGGMAX GROUP	2010-06-03	2014-12-30
ARTIMPLANT	1997-11-06	2013-05-13	CAPINORDIC	2001-06-25	2003-04-04
ASG B	1997-01-03	1999-12-28	CAPIO	2000-10-17	2006-08-18
ASPIRO	2001-06-07	2014-12-30	CARAN B	1997-01-03	1999-02-18
ASSA ABLOY B	1997-01-03	2014-12-30	CARDO	1997-01-03	2011-02-07
ASSIDOMAN	1997-01-03	2002-01-25	CARL LAMM	2006-10-11	2008-07-18
ASTICUS	1998-04-06	1999-12-29	CARL LAMM HOLDING	2008-06-27	2009-03-20
ASTRA A	1997-01-03	1999-04-23	CARLI GRY	1998-06-25	1999-08-19
ASTRA B	1997-01-03	1999-04-23	CASHGUARD B	2000-05-30	2008-05-16
ASTRAZENECA	1999-04-07	2014-12-30	CASTELLUM	1997-05-26	2014-12-30
ATLANTICA FRB.	1997-01-17	1997-03-21	CATELLA A	1997-01-03	2014-12-30
ATLAS COPCO A	1997-01-03	2014-12-30	CATELLA B	1997-01-03	2014-12-30
ATLAS COPCO B	1997-01-03	2014-12-30	CATENA	2006-04-27	2014-12-30
ATLE	1997-01-03	2001-05-11	CAVOTEC	2011-10-21	2014-12-30
ATRIUM LJUNGBERG B	1997-01-03	2014-12-30	CELL NETWORK	1997-05-20	2000-06-14
AU SYSTEM	2000-06-22	2002-02-19	CELLAVISION	2007-05-29	2014-12-30
AUDIODEV B	2000-09-22	2009-02-18	CELLPOINT SDB	2001-03-16	2003-03-12
AUTOFILL	1998-12-17	2000-07-13	CELSIUS B	1997-01-03	2000-03-17
AUTOLIV	1997-01-03	1997-05-09	CELTICA FASTIGHETS	1997-01-07	2003-07-25
AUTOLIV SDB	1997-05-05	2014-12-30	CISION	1998-09-11	2014-06-09
AVAILO	2000-05-31	2014-04-07	CLAS OHLSON B	1999-10-06	2014-12-30
AVANZA BANK HOLDING	1997-01-03	2014-12-30	CLOETTA B	2009-02-17	2014-12-30
AVEGA GROUP B	2010-12-17	2014-12-30	COASTAL CONTACTS	2009-11-10	2012-12-10
AVESTA SHEFFIELD	1997-01-03	2001-02-23	COLUMNA	1997-04-15	2001-10-12
AVESTAPOLARIT	2001-01-31	2002-12-30	COM HEM HOLDINGS	2014-06-18	2014-12-30
AXFOOD	1997-06-30	2014-12-30	CONCENTRIC	2011-06-17	2014-12-30
AXIS	2000-06-28	2014-12-30	CONCORDIA MARITIME B	1997-01-03	2014-12-30
B&B TOOLS B	1997-01-03	2014-12-30	CONNECTA	2005-05-31	2014-06-09
BACTIGUARD HOLD	2014-06-23	2014-12-30	CONSILIUM B	1997-01-03	2014-12-30
BALDER FASTIGHETS	1998-07-01	2000-04-26	COREM PROPERTY GROUP	2009-06-25	2014-12-30
BALLINGSLOV INTL.	2002-06-20	2008-12-12	CRAD B	2014-12-17	2014-12-30
BAYER SDB	1997-01-08	2000-11-30	CREADES	2013-12-09	2014-12-30
BE GROUP	2006-11-27	2014-12-30	CTT SYSTEMS	1997-11-12	2014-12-30
BEIJER ALMA B	1997-01-03	2014-12-30	CUSTOS A	1997-01-03	2004-07-16
			CUSTOS B	1997-01-03	2000-08-15
			CUSTOS	2000-11-28	2006-09-18
			CYBERCOM GROUP	1999-12-02	2014-12-30

CYNCRONA B	1997-01-08	1997-04-30	GOTIC B	1997-01-03	1997-10-10
D CARNEGIE & CO	2001-06-05	2008-09-22	GOTLAND REDERI A	1997-01-09	2004-02-19
DAGON	2002-07-01	2012-03-12	GOTLAND REDERI B	1997-01-08	2004-02-20
DAHL INTL.	1997-01-03	1999-04-16	GRANGES	2014-10-13	2014-12-30
DEDICARE	2011-05-05	2014-12-30	GRANINGE	2000-01-03	2004-01-16
DGC ONE	2008-06-17	2014-12-30	GUIDE KONSULT B	1998-05-28	2000-02-25
DIAL NXT GROUP	2000-12-07	2002-01-14	GULLSPANGS KRAFT B	1997-01-03	1998-06-16
DIFFCHAMB	1997-01-03	2003-04-01	GUNNEBO	1997-01-03	2014-12-30
DILIGENTIA	1997-01-03	2000-08-15	GUNNEBO INDUSTRIER	2005-06-15	2008-10-01
DIMENSION	2001-02-21	2004-01-16	HALDEX	1997-01-03	2014-12-30
DIN BOSTAD SVERIGE	2000-07-17	2009-10-02	HAVSFRUN INVESTMENT B	1997-01-15	2014-12-30
DIOS FASTIGHETER	2006-05-23	2014-12-30	HEBA B	1997-01-03	2014-12-30
DORO	1997-01-03	2014-12-30	HEMFOSA FASTIGHETER	2014-03-24	2014-12-30
DUNI	2007-11-15	2014-12-30	HEMSTADEN BOSTADS	1997-01-20	1997-01-20
DUROC B	1997-01-03	2014-12-30	HEMTEX	2005-10-07	2014-12-30
EAST CAPITAL EXPLORER	2007-11-12	2014-12-30	HENNES & MAURITZ B	1997-01-03	2014-12-30
ELANDERS B	1997-01-03	2014-12-30	HEXAGON B	1997-01-03	2014-12-30
ELDON B	1997-01-03	1999-10-11	HEXPOL B	2008-06-10	2014-12-30
ELECTRA GRUPPEN	2009-06-02	2014-12-30	HIFAB GROUP	2000-07-07	2014-12-30
ELECTROLUX A	1997-01-16	2014-12-30	HIQ INTERNATIONAL	1999-04-13	2014-12-30
ELECTROLUX B	1997-01-03	2014-12-30	HL DISPLAY B	1997-01-03	2010-07-12
ELEKTA B	1997-01-03	2014-12-30	HMS NETWORKS	2007-10-22	2014-12-30
ELEKTRONIKGRUPPE	1997-01-03	2011-07-11	HOGANAS B	1997-01-03	2013-08-12
ELOS B	1997-01-03	2014-12-30	HOIST INTL. B	1997-01-07	2004-06-18
EMPIRE B	2000-07-13	2003-10-23	HOLMEN A	1997-01-03	2014-12-30
ENATOR B	1997-01-03	1999-07-30	HOLMEN B	1997-01-03	2014-12-30
ENDOMINES	2012-11-08	2014-12-30	HOME PROPERTIES	1999-03-16	2009-01-20
ENEA	1997-01-03	2014-12-30	HQ	2000-07-04	2014-12-30
ENIRO	2000-10-11	2014-12-30	HQ FONDER	2002-07-01	2005-06-17
ENQUEST	2010-04-07	2014-12-30	HUFVUDSTADEN A	1997-01-03	2014-12-30
ENTRA DATA	1997-02-17	2000-09-15	HUFVUDSTADEN C	1998-07-22	2014-12-23
ENTRACTION HOLDING B	2007-06-04	2011-05-09	HUFVUDSTADEN INTL.	1997-09-01	1997-12-22
EPISURF MEDICAL	2013-06-12	2014-12-30	HUMAN CARE H C	2000-07-13	2008-07-09
EPSILON B	2001-06-13	2003-04-17	HUMLEGARDEN A	1997-06-12	1999-12-29
ERICSSON A	1997-01-03	2014-12-30	HUMLEGARDEN B	1997-01-07	1999-12-29
ERICSSON B	1997-01-03	2014-12-30	HUSQVARNA A	2006-06-14	2014-12-30
ESSELTE A	1997-01-07	2002-07-08	HUSQVARNA B	2006-06-14	2014-12-30
ESSELTE B	1997-01-03	2002-07-31	I A R SYSTEMS GROUP	1999-01-05	2014-12-30
ETRION	2010-11-15	2014-12-30	IBS B	1997-01-03	2009-05-08
EUROPOLIT. VODAFONE	1997-01-03	2003-10-22	ICA GRUPPEN	2005-12-09	2014-12-30
EVIDENTIA A	1997-01-03	2000-05-26	IMAGE SYSTEMS	1999-04-29	2014-12-29
EVIDENTIA B	1997-01-03	2000-05-26	IMG INDE.MEDIA GP. B	1997-10-16	2001-05-03
EWORX SCANDINAVIA	2010-02-22	2014-12-30	IMMUNE PHARMA.	2006-01-12	2014-12-30
FABEGE	1997-01-03	2014-12-30	IMS INTEL.MICRO SYS.	1997-01-03	2002-05-31
FABEGE B	1997-01-03	1997-12-02	INDL.& FINL.SYS.A	1998-06-22	2014-12-30
FABEGE B	1998-09-25	2004-10-15	INDL.& FINL.SYS.B	1997-07-01	2014-12-30
FAGERHULT	1997-05-14	2014-12-30	INDUSTRIVARDEN A	1997-01-03	2014-12-30
FAGERLID INDUSTRIER	1997-01-03	1999-12-03	INDUSTRIVARDEN C	1997-01-03	2014-12-30
FAST PARTNER	1997-01-03	2014-12-30	INDUTRADE	2005-10-06	2014-12-30
FASTIGHETS BALDER B	1999-10-13	2014-12-30	INTELLECTA B	1997-01-03	2014-12-30
FAZER KONFEKTYR	1997-01-03	2008-10-17	INTENTIA INTL.B	1997-01-08	2006-02-22
FB INDUSTRI B	1997-12-23	2001-05-23	INTRUM JUSTITIA	2002-06-10	2014-12-30
FEELGOOD SVENSKA	1997-05-13	2014-12-30	INVESTOR A	1997-01-03	2014-12-30
FENIX OUTDOOR B	1997-01-03	2014-04-07	INVESTOR B	1997-01-03	2014-12-30
FENIX OUTDOOR INTL	2014-06-27	2014-12-30	INWIDO	2014-09-29	2014-12-30
FINGERPRINT CARDS B	2000-04-20	2014-12-30	INVIK & CO B	2005-09-01	2007-05-18
FINNVEDEN B	1997-01-03	2004-11-19	IPC	1997-01-03	1998-01-21
FME EU.AKTIEBOLAG B	1997-01-03	2007-03-01	IRO	1997-01-03	2000-11-09
FOLKEBOLAGEN B	1997-01-03	2000-06-27	ITAB SHOP CONCEPT B	2008-07-10	2014-12-30
FORCENERGY B	1997-01-03	1998-03-30	J&W	1997-01-03	2001-07-04
FORENINGS BKN. A	1997-01-03	1997-06-11	JAAKKO POYRY GP.	1997-12-03	2000-05-31
FORENINGS BKN.B	1997-01-03	1997-06-11	JC	2000-04-20	2006-05-19
FORMPIPE SOFTWARE	2010-01-20	2014-12-30	JEEVES INFO.SYSTEMS	1999-04-22	2012-04-05
FRANGO B	1999-04-26	2004-07-16	JLT MOBILE COMPUTERS	1997-12-19	2003-05-02
FRILUFTSBOLAGET E&S	2000-10-12	2001-11-09	JM	1997-01-03	2014-12-30
FRONTLINE	1997-01-03	1997-07-04	JOBLINE INTERNATIONAL	2000-09-18	2001-08-10
G5 ENTERTAINMENT	2014-06-11	2014-12-30	JOHNSON PUMP INTL.	1997-06-23	2002-03-26
GAMBRO A	1997-01-03	2006-05-17	JP BANK A	1997-01-03	1999-06-10
GAMBRO B	1997-01-03	2006-05-17	JP BANK B	1997-01-03	1999-06-11
GANT COMPANY	2006-03-29	2008-01-21	JP NORDISKA	1997-01-03	2003-03-14
GETINGE	1997-01-03	2014-12-30	KABE HUSVAGNAR B	1997-01-03	2014-12-30
GEVEKO B	1997-01-07	2014-12-30	KALMAR INDUSTRIES	1997-01-03	2000-11-09
GIBECK B	1997-12-15	1999-09-15	KANTHAL B	1997-01-08	1997-08-22
GLOBAL HEALTH PARTN.	2008-10-06	2014-12-30	KAPPAHL	2006-02-24	2014-12-30
GLOCALNET	2000-06-06	2006-01-17	KARLSHAMNS	1997-06-06	2005-06-17
GORTON LINES	1997-06-10	2004-12-21	KARO BIO	1998-04-06	2014-12-30
GOTIC A	1997-01-03	1997-09-03	KAROLIN MACHINE TOOL	1998-04-06	2007-10-19

KAROLINSKA DEVELOP.	2011-04-18	2014-12-30	MULTIQ INTERNATIONAL	1998-02-16	2014-12-30
KAUPTHING BANK	2002-12-23	2008-09-22	MUNKSJÖ	2014-12-09	2014-12-30
KINNEVIK A	1997-01-03	2014-12-30	MUNKSJÖ	1997-01-03	2002-04-25
KINNEVIK B	1997-01-03	2014-12-30	MUNTERS	1997-10-22	2010-10-11
KINNEVIK IND. A	1997-01-03	2004-07-23	MYCRONIC	2000-03-10	2014-12-30
KINNEVIK IND. B	1997-01-03	2004-07-23	N & T ARGONAUT A	1997-01-03	2000-02-14
KIPLING HOLDING	2000-05-22	2002-02-22	N & T ARGONAUT B	1997-01-03	2000-02-14
KJESSLER & MANNERST.	1997-01-03	2000-09-05	NACKEBRO	1997-01-03	1998-11-02
KLIPPAN	1997-01-03	2006-01-17	NAN RESOURCES	1997-06-25	2005-01-18
KLOVERN A	2002-08-09	2014-12-30	NARKES ELECTRISKA	1997-01-08	2006-07-14
KLOVERN A	1997-01-21	1997-04-28	NATURKOMPA NIET	1999-04-22	2000-05-23
KLOVERN B	2014-12-10	2014-12-30	NCC A	1997-01-03	2014-12-30
KLOVERN B	1997-01-03	1998-02-09	NCC B	1997-01-03	2014-12-30
KNOW IT	1997-11-11	2014-12-30	NEDERMAN HOLDING	2007-05-18	2014-12-30
KUNGSLEDEN	1999-04-15	2014-12-30	NEFAB B	1997-01-03	2002-08-17
KVAERNER SDB A	1997-03-17	1999-05-05	NEONET	2000-10-24	2010-03-08
LABS2GROUP	1997-12-10	2004-03-12	NET ENTERTAINMENT B	2009-01-15	2014-12-30
LAGERCANTZ GROUP B	2001-09-06	2014-12-30	NET INSIGHT B	1999-06-08	2014-12-30
LAMMHULTS DESIGN GRP.	1997-06-26	2014-12-30	NETONNET	2004-05-26	2011-01-10
LATOUR INVESTMENT B	1997-01-03	2014-12-30	NETWISE B	2000-09-29	2003-04-17
LAWSON SOFTWARE	2006-05-03	2009-05-29	NEUROVIVE PHARMA.	2013-04-11	2014-12-30
LB ICON	1998-06-23	2006-06-16	NEW WAVE GROUP B	1997-12-12	2014-12-30
LBI INTERNATIONAL	1999-06-24	2010-05-10	NGEX RESOURCES	2014-06-23	2014-12-30
LEDSTIERNAN B	1997-01-07	2010-03-08	NIBE INDUSTRIER B	1997-06-18	2014-12-30
LGP ALLGON HOLDING	1997-06-06	2004-03-19	NILO RNRUPPEN B	1998-04-08	2009-03-20
LIFCO B	2014-11-24	2014-12-30	NISCAYAH GROUP B	2006-10-02	2011-07-11
LIFCO B	1998-05-19	2000-10-05	NK CITY FASTIGHETS	1997-03-24	1998-06-26
LILJEHOLMEN A	1997-10-09	1999-06-02	NOBEL BIO CARE	1997-01-03	2008-01-21
LILJEHOLMEN B	1997-10-06	1999-06-23	NOBEL BIO CARE	1997-01-03	2002-07-18
LINDAB B	1997-01-03	2001-08-02	NOBIA	2002-06-20	2014-12-30
LINDAB INTERNATIONAL	2006-12-04	2014-12-30	NOKIA	2007-06-05	2014-12-30
LINDEX	1997-01-03	2007-12-17	NOKIA SDB	1997-01-03	2007-02-21
LINJEBUSS A	1997-01-03	1998-04-14	NOLATO B	1997-01-03	2014-12-30
LODET FASTIGHETS B	1997-01-07	1997-02-03	NORDBANKEN	1997-01-03	1997-12-05
LOGICA	2006-10-17	2008-06-30	NORDEA BANK	1997-01-03	2014-12-30
LOOMIS B	2008-12-10	2014-12-30	NORDIC ACS. BUYOUT	2010-06-08	2014-12-30
LUCARA DIAMOND	2014-05-26	2014-12-30	NORDIC MINES	2008-07-21	2014-12-30
LUNDBERGFORETAGEN B	1997-01-03	2014-12-30	NORDIC SER.PTNS.HDG.B	2008-01-16	2014-12-30
LUNDGRENS B	1997-01-03	2000-02-10	NORDIFAGRUPPEN A	1997-01-15	2000-12-28
LUNDIN GOLD	2014-12-23	2014-12-30	NORDIFAGRUPPEN B	1997-01-03	2001-10-26
LUNDIN MINING SDB	2004-12-06	2014-12-30	NORDNET B	2000-04-20	2014-12-30
LUNDIN OIL B	1997-01-03	2001-10-05	NORDSM.& THULIN B	1997-01-03	1998-03-31
LUNDIN PETROLEUM	2003-10-03	2014-12-30	NORRPORTEN	1997-01-03	2000-12-01
LUXONEN SDB	1997-01-03	2013-07-05	NORSK HYDRO SDB	1997-01-07	2004-03-24
M2 FASTIGHETER	1997-01-03	1997-04-18	NOTE	2004-06-24	2014-12-30
M2S SVERIGE B	1999-12-07	2001-10-25	NOVACAST TECHS.B	2007-04-12	2010-12-13
MALDATA B	1997-01-03	2000-04-04	NOVESTRA	2000-06-22	2014-12-30
MALMBERGS ELEKTR. B	1999-03-15	2014-12-30	NOVOTEK B	1999-07-01	2014-12-30
MANDAMUS	1998-06-16	2003-11-19	NP3 FASTIGHETER	2014-12-05	2014-12-30
MANDATOR	1997-01-07	2007-12-21	OASMA PHARMA.	2010-06-28	2014-12-30
MARIEBERG TID.A	1997-01-03	1998-07-07	ODD MOLLY INTL.	2010-07-22	2014-12-30
MATTEUS	1997-01-03	2001-08-30	OEM INTERNATIONAL B	1997-01-08	2014-12-30
MAXIM PHARMS	1997-10-27	2005-09-19	OMI CORPORATION SDB	1997-01-17	1998-04-24
MEDA A	1997-01-03	2014-12-30	OMX	1997-01-03	2008-01-21
MEDICOVER HOLDING	1997-07-02	2006-08-18	OPCON	1999-01-04	2014-12-30
MEDIVIR B	1997-01-03	2014-12-30	OPTIMA BATTERIES B	1997-01-17	2000-11-10
MEKONOMEN	2000-05-30	2014-12-30	OPTIMAIL A	1998-07-06	2005-10-14
MELKER SCHORLING	2006-12-07	2014-12-30	OPUS GROUP	2013-07-03	2014-12-30
MERTIVA	1997-01-16	2014-12-30	ORC GROUP	2000-10-20	2012-03-09
METO	1999-06-18	2000-02-10	ORESUND INVESTMENT	1997-01-03	2014-12-30
METRO INTL.SDB A	2000-08-21	2012-03-12	OREXO	2005-11-10	2014-12-30
METRO INTL.SDB B	2000-08-21	2012-03-12	ORIFLAME COSMETICS	2004-03-25	2014-12-30
MICRO SYSTEMATION B	2011-12-28	2014-12-30	ORTIVUS A	1997-01-03	2014-12-30
MIDSONA A	1999-06-16	2014-12-30	ORTIVUS B	1997-01-03	2014-12-30
MIDSONA B	1999-06-16	2014-12-30	OSCAR PROPERTIES	2014-02-18	2014-12-30
MIDWAY HOLDINGS A	1997-01-08	2014-12-30	OSTGOTA ENSK. BANKEN	1997-01-03	1997-06-19
MIDWAY HOLDINGS B	1997-01-03	2014-12-30	OXIGENE	1997-01-03	2010-04-12
MILLICOM INTL.CELU.SDR	2004-03-31	2014-12-30	PA RESOURCES B	2006-06-20	2014-12-30
MIND	2000-06-14	2002-06-28	PANDOX	1997-06-24	2004-01-16
MOBERG PHARMA	2011-05-27	2014-12-30	PARTNERTECH	1997-06-13	2014-12-30
MODERN TIMES GP.MTG A	1997-09-19	2014-12-30	PEAB B	1997-01-03	2014-12-30
MODERN TIMES GP.MTG B	1997-09-19	2014-12-30	PEAB INDUSTRI B	2007-10-02	2008-10-17
MODUL DATA	1997-01-03	2010-12-13	PEAK PERFORMANCE B	1997-01-03	1998-08-06
MOGUL	2000-09-12	2003-10-14	PERBIO SCIENCE	1999-10-19	2003-09-24
MONARK STIGA	1997-01-03	1999-12-27	PERGO	2001-06-20	2006-12-19
MQ HOLDING	2010-06-21	2014-12-30	PERSTORP B	1997-01-03	2001-07-20
MSC KONSULT B	1998-05-22	2014-12-30	PHARMACIA SDB	1997-01-03	2003-04-11

PIREN B	1997-01-03	2000-09-28	SKANDIA FORSAKRINGS	1997-01-03	2006-03-17
PLATZER FASTIGHETER	2013-12-02	2014-12-30	SKANDITEK INDRI.FRV.	1997-01-03	2009-11-09
PLATZER FTGH. B	1997-01-03	2001-08-03	SKANSKA B	1997-01-03	2014-12-30
PLM	1997-01-03	1999-03-05	SKF A	1997-01-03	2014-12-30
POOLIA B	1999-06-24	2014-12-30	SKF B	1997-01-03	2014-12-30
POWERWAVE TECH.	2004-06-07	2006-05-19	SKISTAR B	1997-01-03	2014-12-30
PRECISE BIOMETRICS	1999-12-14	2014-12-30	SKOOGS B	1997-01-03	1997-10-22
PREVAS B	1998-06-02	2014-12-30	SOCIETE EURO A SDB	1998-10-14	2000-11-03
PRICER B	1997-01-03	2014-12-30	SOCIETE EURO B SDB	1998-10-14	2000-11-03
PRIFAST	1997-01-03	1999-05-07	SOFRONIC B	1998-12-04	2014-12-30
PROACT IT GROUP	1997-10-17	2014-12-30	SOLITAIR KAPITAL	1997-01-03	1998-10-30
PROBI	1998-12-17	2014-12-30	SONG NETWORKS HLDG.	2000-03-17	2004-09-20
PROFFICE B	1999-10-12	2014-12-30	SORB INDUSTRI	1999-05-12	1999-08-20
PROFILGRUPPEN B	1997-06-23	2014-12-30	SPCS SCANDINVN. PC SYST.	1997-06-10	1999-06-24
PRONYX	1997-04-15	2002-10-15	SPCSGRUPPEN	1999-06-29	2001-07-26
PROSOLVIA B	1997-06-19	1999-01-13	SPECTRAPHYSICS A	1997-01-03	1999-04-23
PROTECT DATA	1997-06-19	2006-10-20	SPENDRUPS B	1997-01-03	2001-08-21
PROVOBIS B	1997-01-03	2000-06-26	SPIRA	1997-01-03	1997-12-30
PSI GROUP	2008-08-27	2012-01-09	SSAB A	1997-01-03	2014-12-30
QLIRO GROUP	2010-12-16	2014-12-30	SSAB B	1997-01-03	2014-12-30
QMED	1999-12-07	2011-01-10	STADSHYPOTEK A	1997-01-03	1997-06-30
RATOS A	1997-01-10	2014-12-30	STENA LINE B	1997-01-03	2001-02-20
RATOS B	1997-01-03	2014-12-30	STOCKWIK FORVALTNING	1997-01-03	2014-03-26
RAYSEARCH LABS.B	1997-01-03	2014-12-30	STORA A	1997-01-03	1998-12-15
READSOFT B	1999-06-23	2014-07-14	STORA B	1997-01-03	1998-12-15
REALIA A	1997-01-21	2002-05-28	STORA ENSO A	1998-12-30	2014-12-30
REALIA B	1997-01-03	2002-06-26	STORA ENSO R	1998-12-30	2014-12-30
RECIPHARM AB	2014-04-04	2014-12-30	STORHEDEN B	1997-01-03	1998-08-14
REDERI AB TNSAT.B	1997-01-03	2014-12-30	STRALFORS B	1997-01-07	2006-03-17
REJLERS B	2006-12-19	2014-12-30	STUDSVIK	2001-05-07	2014-12-30
RESCO B	1997-01-03	2006-01-17	SWECO A	1998-10-02	2014-12-29
REZIDOR HOTEL GROUP	2006-11-29	2014-12-30	SWECO B	1998-09-23	2014-12-30
RIDDARHYTTAN RES.	1997-06-05	2005-08-19	SVEDALA INDUSTRIER	1997-01-03	2001-09-27
RKS B	1999-05-18	2004-07-15	SWEDBANK A	1997-01-03	2014-12-30
RNB RETAIL AND BRANDS	2001-06-27	2014-12-30	SVEDBERGS I DALSTORP B	1997-10-06	2014-12-30
RORVIK TIMBER	1997-06-26	2014-10-13	SWEDISH MATCH	1997-01-03	2014-12-30
RORVIKS GRUPPEN B	1997-01-03	1997-06-24	SW. ORPHAN BIOVITRUM	2006-09-18	2014-12-30
ROTTNEROS	1997-01-03	2014-12-30	SWEDOL B	2008-06-13	2014-12-30
SAAB B	1998-06-22	2014-12-30	SVENSKA HANDBKN.A	1997-01-03	2014-12-30
SAGAX	2007-10-10	2014-12-30	SVENSKA HANDBKN.B	1997-01-03	2014-12-30
SAGAX B	2013-04-09	2014-12-30	SVENSKA ORIENT B	1997-10-30	2003-06-06
SAINT GOBAIN SDB	1997-01-10	2001-02-28	SVITHOID TANKERS B	2006-07-14	2008-07-18
SAK I	1997-05-14	2011-04-11	SVOLDER B	1997-01-03	2014-12-30
SALUS ANSVAR B	1997-01-07	2007-12-14	SYDKRAFT A	1997-01-03	2001-09-28
SANDBLOM & STOHNE B	1997-01-03	1998-02-06	SYDKRAFT C	1997-01-03	2001-09-28
SANDVIK	1997-01-03	2014-12-30	SYNGENTA	2000-11-28	2003-12-29
SAPA	1997-05-22	2005-03-18	SYSTEMAIR	2007-10-15	2014-12-30
SARDUS	1997-04-08	2007-01-16	TANGANYIKA OIL SDB	2007-02-15	2008-09-22
SAS	1997-01-03	2014-12-30	TECHNOLOGY NEXUS	1998-06-03	2009-06-18
SCA A	1997-01-03	2014-12-30	TELE2 A	1997-01-03	2014-12-30
SCA B	1997-01-03	2014-12-30	TELE2 B	1997-01-03	2014-12-30
SCAN MINING	1997-01-07	2007-08-17	TELECA B	1997-02-24	2008-11-14
SCANCEM A	1997-01-03	1999-12-21	TELELOGIC	1999-03-09	2008-01-21
SCANCEM B	1997-01-07	1999-12-20	TELIASONERA	2000-06-14	2014-12-30
SCANDI STANDARD	2014-06-30	2014-12-30	TELIGENT	1999-04-13	2008-10-29
SCANDIACONSULT	1997-01-03	2003-05-08	TERRA MINING	1997-01-07	1997-01-09
SCANDIC HOTELS	1997-01-08	2001-07-06	TETHYS OIL	2013-05-03	2014-12-30
SCANDINAVIA ONLINE	2000-06-08	2002-01-11	THULE GROUP	2014-11-27	2014-12-30
SCANIA B	1997-01-03	2014-03-10	TICKET TRAVEL	1997-04-28	2010-01-11
SEAMLESS DISTRIBUTION	2012-06-14	2014-12-30	TIETO CORPORATION	1999-07-12	2014-12-30
SEB A	1997-01-03	2014-12-30	TILGIN	2006-12-18	2010-12-15
SEB C	1997-01-03	2014-12-30	TIVOX B	1997-01-03	2005-05-20
SECO TOOLS B	1997-01-03	2011-12-12	TORNET FASTIGHETS B	1997-01-03	2004-10-29
SECTRA B	1999-03-04	2014-12-30	TRACTION B	1997-07-04	2014-12-30
SECURITAS B	1997-01-03	2014-12-30	TRADEDOUBLER	2005-11-09	2014-12-30
SECURITAS DIRECT	2006-10-02	2008-05-16	TRANSCOM WW	2014-12-01	2014-12-30
SEGERSTROM & SVENS.B	1997-01-03	2001-03-26	TRANSMODE	2011-05-30	2014-12-30
SEMAFO	2011-10-21	2014-12-30	TRELLEBORG B	1997-01-03	2014-12-30
SEMCON	1997-05-27	2014-12-30	TRIBONA	2013-05-22	2014-12-30
SENEA	1997-01-03	2006-09-18	TRICORONA	1997-01-03	2010-06-07
SENSYS TRAFFIC	2001-02-01	2014-12-30	TRIGON AGRI	2010-12-09	2014-12-30
SHELTON PETROLEUM	2012-11-20	2014-12-30	TRIO INFO.SYSTEMS	1997-01-03	2006-06-16
SIAB A	1997-01-03	1997-06-30	TRUSTOR B	1997-01-03	2000-10-05
SIAB B	1997-01-03	1997-06-30	TRYCKINVEST I NORDEN	1998-06-09	1998-08-21
SIFAB	1997-01-03	1998-06-17	TRYGGHANSA B	1997-01-03	1998-02-06
SIGMA B	2001-10-01	2013-03-11	TURNIT B	1997-01-03	2005-02-16
SINTERCAST	1997-01-03	2014-12-30	TV4 A	1997-01-03	2005-07-22

UNIBET GROUP SDB	2004-06-09	2014-12-30	VISION PARK	1997-09-25	2001-11-14
UNIFLEX B	2004-11-22	2014-12-30	VITEC SOFTWARE GRP. B	2011-07-05	2014-12-30
UNITED TANKERS	1997-01-07	1997-09-01	VITROLIFE	2001-06-27	2014-12-30
UTFORS	2000-12-12	2003-04-04	VLT B	1997-01-07	2006-08-25
WALLENSTAM B	1997-01-03	2014-12-30	WMDATA B	1997-01-03	2006-08-18
VBB A	1997-01-07	1997-08-22	VOLVO A	1997-01-03	2014-12-30
VBB B	1997-01-03	1997-09-11	VOLVO B	1997-01-03	2014-12-30
VBG GROUP	1997-01-03	2014-12-30	VOSTOK GAS SDB	1997-03-07	2008-10-17
VENCAP INDUSTRIES ED	1997-01-03	1997-05-22	VOSTOK NAFTA INV.SDR	2007-07-05	2014-12-30
VENUE RETAIL GROUP B	1997-07-02	2014-12-30	XANO INDUSTRIES B	1997-01-03	2014-12-30
VERIMATION	1997-01-08	1998-09-23	XPONCARD	1997-01-03	2008-06-09
VICTORIA PARK	2013-12-10	2014-12-30	ZETECO B	1997-01-03	2000-12-21
VICTORIA PARK B	2014-05-20	2014-12-30	ZODIAK TELEVISION B	1997-04-15	2008-08-14
WIHLBORGS FASTIGHETER	2005-05-24	2014-12-30			