The MAX Effect and Investor Sentiment in Sweden

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May 27, 2021

Abstract

Motivated by existing literature about the effect of maximum daily returns (MAX) on subsequent stock returns and the link between this effect and market sentiment, we investigate the possible effect of MAX on stock performance in Sweden and its relation with market sentiment. Portfolio-level analyses show evidence of MAX negatively affecting returns of stocks listed in Sweden, while firm-level cross-sectional regressions show that MAX has little or no effect on individual stocks' returns. Research also indicates that the magnitude of the MAX effect is higher when the sentiment of the Swedish stock market is low during the previous month. Moreover, the results indicate that high MAX stocks are likely to retain their high MAX in future months. Finally, all results are robust against changing the portfolio sorting approach and the MAX definition.

Tutor: Magnus Dahlquist

Keywords: MAX Effect, Extreme Returns, Investor Sentiment, Lottery-type Stocks, Stock Return Predictability

Acknowledgements: We would like to thank Magnus Dahlquist for the guidance and support during the process of writing this thesis.

Master Thesis

Stockholm School of Economics

Department of Finance

Contents

1 Introduction

The MAX effect has been studied well by economists during the last decade. It has been tested in a number of countries and regions. In most of them, MAX was found to have a substantial effect on the pricing of stocks. The possible tendency of investors to prioritize lottery like-stocks gave a pathway to several pieces of research. However, it has not yet been studied in the Nordic or, namely, in the Swedish stock market. Moreover, despite the fact that the link between sentiment and the MAX effect has been found in a number of countries, no such testing has been done in Sweden.

The MAX effect itself is the term used to describe the way maximum one-day returns during a month (MAX) affect the pricing of a stock and its future returns. As the MAX effect can vary from region to region, in this paper, we would like to analyse this effect in Sweden. The main question that we bring up in this paper is:

Is there a negative relationship between maximum daily return (MAX) and future stock returns in the Swedish stock market?

In order to find the answer, we gather Swedish stock market data and form decile portfolios every month based on MAX and perform a comparative analysis of them. After that, we run stock-level Fama-Macbeth regressions to inspect the effect of the previous month's MAX on the current month's MAX and return.

After finding an answer to that question, we construct a sentiment level index based on Swedish macroeconomic and stock-market level data to inspect the influence of sentiment level on the MAX effect and the difference between the monthly decile portfolios' return sorted by MAX and the sentiment level. Therefore, our additional research questions are:

The stocks that exhibit a high MAX in a month, are more likely to exhibit a high MAX in the next month.

Following the month with a high sentiment level, the difference between Fama-French-Carhart four factor model alphas of high and low MAX portfolios is greater.

We answer the first question by running the regression of MAX of the current month on the previous month's MAX and a set of regressors to see if MAX of the previous month can predict the current one. We also construct a probability matrix to illustrate the chances of stocks changing their MAX decile in the future.

To answer the second question, we create a sentiment level index using principal component analysis (PCA). It enables us to analyse the MAX effect in different sentiment states.

The first benefit of this research is finding the link between the MAX effect and return on the Swedish stock market. It offers a deeper understanding of price anomalies and provides possible implications for predicting further returns of stocks as well as information on whether these stocks are overpriced. The other significant benefit is to create the sentiment level index and finding the relationship between the MAX effect and investors' sentiment. It would help to get a better understanding of the behavior of investors on the stock market. Overall, this research represents tendencies and patterns of investor behavior and stock pricing on the Swedish stock market.

As a result, we find the MAX effect is present in the Swedish stock market on portfolio level and no significant MAX on individual stock level. Our evidence shows that returns of stocks are dependent on the maximum daily return of the previous month for equal-weighted portfolios. Moreover, we find that stocks, which exhibit high MAX tend to keep it.

Moreover, we observed that accounting for the sentiment level index, in a low sentiment state, there is a higher difference in portfolios' excess returns. For the high sentiment state, the returns differ less as well as unexplained returns.

Overall, we find several interesting and unique characteristics and features of the Swedish stock market, such as the MAX effect, the tendency of stocks to keep the MAX and dependence of MAX volume on the sentiment state, which can be examined and tested further as a development of this paper.

Our results contribute to the existing literature of stock price anomalies. First of all, our results go along with the outcome Bali et al. (2011) achieved: the negative effect of MAX on return and high dependence of Max on the previous month's MAX. Moreover, we find that Swedish stock market expresses some of the same characteristics that US stock market does, while showing several interesting and different ones: the MAX effect has higher influence on portfolios than on individual stocks and is has small effect on value-weighted portfolios.

We also perform the analysis of both sentiment and its link to MAX, following Baker and Wurgler (2006) approach which, to the best of our knowledge, has not been done extensively before and find that in Sweden, the difference between returns of portfolios increases in low sentiment states.

2 Literature Review

The role of extreme positive returns in the cross-sectional pricing of stocks and the term "MAX effect" has first been brought up by Bali et al. (2011). They describe the MAX effect as a relation between maximum daily return of a stock during a month (MAX) and lower future returns of the same stock. In their paper they describe two evidence points for the MAX effect to exist: the first one being lack of diversification of investor portfolios and the second one is preference to lottery-like stocks, which are low-priced stocks with high idiosyncratic volatility and high idiosyncratic skewness (Kumar (2009)). Taking into account the two above-mentioned points, Bali et al. (2011) found out that investors are more likely to pay a higher price for a stock if it demonstrates high extreme positive returns. As a result, such stocks show lower returns in the future. They also find that stocks with extreme negative one-day returns show the opposite behavior: they show higher future returns as investors undervalue such stocks. This conclusion is consistent with cumulative prospect theory (Tversky and Kahneman (1992)) and the optimal beliefs framework of Brunnermeier et al. (2007).

Further research on this topic strengthened the support for the persistence of the MAX effect in many regions and expanded the area of research geographically. In Fong and Toh (2014), authors show that a MAX strategy that longs a value-weighted portfolio of high MAX stocks and shorts a value-weighted portfolio of low MAX stocks produces an average return of 1% per month and an even more negative alpha based on the four-factor model (FF4F) of Fama and French (1992) and Carhart (1997).

Baker and Wurgler (2006) developed the concept of sentiment level index. By sentiment, the authors mean a belief about future cash flows and investment risks that are not justified by the facts at hand. Authors also assume that it is costly to bet against the sentiment, so rational investors, or so-called arbitrageurs are not as aggressive in forcing prices to fundamentals as the standard models would suggest. Therefore, the authors suggest that there are no limits to arbitrage. Moreover, the authors also link the MAX effect to the sentiment level of the financial market.

Baker and Wurgler (2006) come up with a way of constructing an index that would measure the sentiment using a macroeconomic approach. They describe possible components and proxies of this index, such as trading volume, investor surveys and dividend premium. The authors also state that there is no single way to estimate the sentiment level, but rather it can be done using various proxies. The main criteria of choosing the proxies are data availability and the fact that proxies relate to as many market areas as possible (e.g. households, funds, the stock market as a whole.)

Cheema et al. (2020) and Han and Li (2017) further developed the explained concept in Baker and Wurgler (2006) and created a sentiment level index by estimating the first principal component from the residuals of three individual sentiment proxies, namely, the price-to-earnings ratio (PE), turnover ratio (TO), and the number of newly opened individual investor accounts (IIA). Baker and Wurgler (2006) stated that residuals of the orthogonalization procedure can serve as the proxies for the irrational part of investor sentiment and thus, the PCA and residuals method can determine sentiment level index accurately.

Further expanding the geographic reach of Bali et al. (2011) article, Walkshäusl (2014) and Aboulamer and Kryzanowski (2016) conducted a research on the MAX effect research in EU countries and Canada respectively. The conclusion of the papers, however, was different. While according to Walkshäusl (2014) the MAX effect is present in the EU stock market, in Canada there is no such effect and therefore investors do not prefer stocks with high maximum daily returns, as stated in Aboulamer and Kryzanowski (2016).

Despite the extensive research on the MAX effect in several geographical points, it has not yet been researched in the Swedish market. Furthermore, the direction and presence of the MAX effect can differ depending on the country's market characteristics. Therefore, it is worth seeing whether this effect exists in Sweden.

Moreover, the relationship between sentiment and the MAX effect has not been thoroughly studied. Therefore, we decided to research this link since it has only been studied in a few countries, not including Sweden.

In this paper we aim to find out whether the Max effect is present in Swedish market and if it is linked to the sentiment level index, which we also construct.

3 Data

In our research, we use a list of stocks of Swedish companies for the period from February 1993 to December 2020. The stock data are acquired from the FinBas database. We use daily stock data on the last price of stocks to calculate the returns and maximum daily returns of each stock. The last monthly stock price data are used to calculate the monthly return of stocks as well as other characteristics such as illiquidity, size, idiosyncratic volatility, momentum, skewness, book-to-market ratio and others, described in the Methodology part. We use market values, book values, and trading volume to calculate the above-mentioned ratios, which we also get from the FinBas database. The figures that are in different currencies are exchanged to Swedish Krona using Riksbank exchange ratios.

The data were cleaned by considering only stock data, which has 10 or more observations per month. After that we filter out the stocks that are present on the stock market for less than two years, as if we include them, this will cause problems with Fama-Macbeth regressions further on as there will not be enough data points for the regression to be appropriately representative. Moreover, several stocks' data were incorrect in the database due to typing errors. For example, one stock increased precisely a hundred times in one day and the next day, it dropped by precisely a hundred times. We cannot imagine any real-life circumstances under which this could be possible, so we changed this value to be in line with other observations for this stock. After cleaning the data and calculating the ratio, it was sufficient to check our first hypothesis.

In order to check the additional hypothesis, we had to create a sentiment level index. For this purpose, we acquired a price to equity ratio of all Swedish companies from Data Stream. We then transform these ratios into Swedish market price to equity ratio by value-weighting them. We further checked that our data were correct by getting the price to equity ratios data from Morningstar Direct. The results were very similar, which assured us of doing the calculations correctly, so we decided to use the Data Stream dataset for our analysis. Then, we gathered data for the Swedish mutual fund's net cash flows using Morningstar Direct. Finally, turnover data were taken from FinBas and was the same as when checking hypothesis 1. However, the turnover index for the Swedish stock market was created by value-weighting the data.

Further on, we gathered some macroeconomic data to create a sentiment level index. Namely: growth of M3 from Statistics Sweden's website, repo rate and exchange rate of Euro to Swedish Krona from Riksbank's website, growth of industrial production in Sweden from Eurostat's database, and consumer confidence index from The Organisation for Economic Co-operation and Development (OECD) database.

As a result, after cleaning and sorting the data, we gathered a continuous series of data from January 2001 until December 2020. These data are sufficient to test our hypotheses.

4 Methodology

4.1 The MAX effect and Cross-section of Stock Return

4.1.1 Data Creation

As mentioned earlier, we gather stocks' monthly and daily data from the FinBas dataset. We use the time range from January 1994 to December 2019 because some of our variables, such as turnover, are not available before this period and December 2019 is the last available date in the dataset. We believe that the length of the time range is enough to construct representative econometric models to check our hypothesis.

Unfortunately, the dataset provides only price data of stocks but not the stock returns. Therefore, we acquired the last price data (instrument LAST on the FinBas dataset), which is defined as the stock's last traded price at the end of the trading day. The LAST price is adjusted for corporate actions making the prices in a time series comparable over time. The last price is chosen because it allows us to capture all price changes during a specified time period.

Moreover, only stocks traded on the Stockholm Stock Exchange in SEK were included in the dataset. Therefore, we assume that this sample accurately represents the behavior of publicly traded Swedish companies.

After loading the data and converting them to the same format, we calculated returns for all chosen stocks by applying the following return formula:

$$R_{i,t} = \frac{LAST_{i,t} - LAST_{i,t-1}}{LAST_{i,t-1}} \tag{1}$$

Where $\mathrm{R}_{\mathrm{i,t}}$ is the return of the stock i in time period t and $\mathrm{LAST}_{\mathrm{i,t}}$ is the last traded price of the stock i in time period t.

After performing this procedure twice, for monthly data and daily data, we find the maximum daily return of every stock for every month and merge this variable with the monthly data as the MAX effect indicator.

4.1.2 Variable Definition

Short-term Reversal, based on Jegadeesh (1990) and Lehmann (1990), is defined as the price return of each stock over the previous month.

Momentum, based on Jegadeesh and Titman (1993), is the cumulative return of each stock in the previous 11 months starting from month $t-12$ to $t-4$.

Illiquidity of each stock in month t, based on Amihud (2002), is the ratio of the absolute monthly return to its trading volume in Swedish Krona. It is calculated as:

$$ILLIQ_{im} = 1/D_{im} \sum_{t=1}^{D_{im}} \frac{|R_{it}|}{VOLD_{it}} \tag{2}$$

Where $R_{\mathrm{i,t}}$ is the return on stock i in day t, $D_{i,m}$ is the number of the trading days for stock i in month m, and $VOLD_{\mathrm{i,t}}$ is the trading volume in day t in Swedish Krona (SEK).

Size of a firm, following Bali et al. (2011), is considered as the natural logarithm of the market value of equity which is computed as the stock's price times the number of shares outstanding in SEK millions. In case that a firm's market value was not reported in Swedish Krona, we converted it using the Riskbank's monthly exchange rate data.

Book-to-market Ratio (B/M) is the ratio of each company's book value to its market capitalization. We computed it using the monthly market capitalization data and yearly book value data from the FinBas database, which they collected from companies' annual reports.

Beta, following Bali et al. (2011), is estimated via assuming a single factor return generating process:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \epsilon_{i,d} \tag{3}$$

where $R_{\mathrm{i,d}}$ is the return on stock i on day d and, $R_{\mathrm{m,d}}$ is the market return on day d, $r_{\mathrm{f,d}}$ is the risk-free rate on day d, and $\epsilon_{\mathrm{i,d}}$ is the idiosyncratic return (daily residual) on day d. Over the period of a month, we regress the daily excess return of each stock over the market excess return. So, the coefficient β_{i} will be the stock's beta in that month.

Idiosyncratic Volatility (IVOL) of stock i in month t , following Bali et al. (2011) is calculated as the standard deviation of daily residuals in month t:

$$IVOL_{i,t} = \sqrt{var(\epsilon_{i,d})} \tag{4}$$

4.1.3 Descriptive Statistics

Figure 1 depicts the number of stocks that were used in forming the decile portfolios from January 1994 to December 2019. As expected, due to a higher number of new listings than delistings every year, there is an upward trend in the number of stocks. There were 90 stocks in the beginning and 321 stocks at the end. The average number of stocks is 257 during the whole period. For more reliable results, we removed the stocks that were traded for less than 24 months. This is the reason for the drop in the last two years.

Value-weighted MAX portfolios are formed every month from January 1994 to December 2019 by sorting stocks on Stockholm Stock Exchange by their maximum daily return in the previous month (MAX). Thus, decile 1 (D1) is the portfolio of stocks with the lowest MAX in the previous month, while decile 10 (D10) is the portfolio with the highest MAX over the previous month.

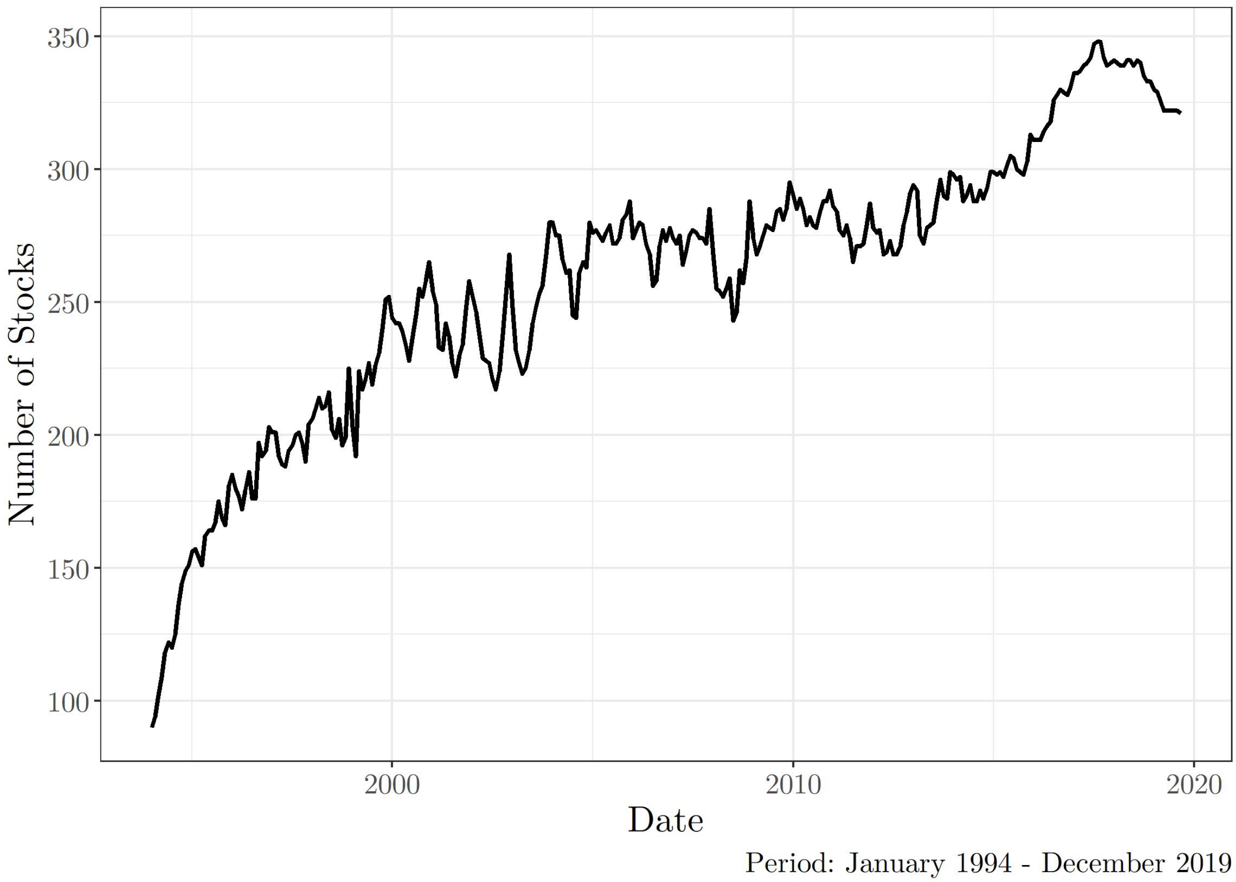

Figure 1: Number of Stocks in the Sample

Table 1 represents the summary statistics of the analyzed sample of Swedish stocks. As stated in Panel A, on average, there are 25-26 firms in each decile at every point in time. Market share of the portfolios shows that the closer to D1, the larger is the market share. Portfolios D1-D3 (Lower MAX) represent more than 48% of the market capitalization on average, while portfolios D8-D10 (High MAX) represent almost 12%.

Panel B shows several general attributes of the firms in every decile portfolio. Every attribute is the average (across one decile over the whole period) of median (across deciles and months) values of that attribute. The process of creation of these variables was discussed in detail in subsection 4.1.2. For example, the average spread of MAX returns between decile portfolios 10 and 1 is 4.43%.

It can also be noted that the average company capitalization and average stock price have a steep declining trend from D1 to D10. The average median share price and capitalization in D1 are 47.4 SEK and 7.82 SEK billions, respectively, while for D10, these figures are 21.0 SEK and 0.51 SEK billions, respectively.

Beta in Panel B represents the market beta of every decile portfolio. Beta is lower for the D1 (0.50) and grows until D4, but across D4 to D10, it is similar and remains on the same level of

Table 1: Descriptive statistics of MAX portfolios

MAX deciles	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Panel A. Portfolio size										
No. of firms	26	26	26	26	26	25	25	25	25	25
% of Overall market value	16.7	16.3	15.3	12.3	10.7	9.5	7.2	6.0	4.0	2.1
Panel B. Firm characteristics										
MAX (Percent)	3.31	3.65	3.88	4.09	4.33	4.72	5.10	5.45	6.09	7.74
Size (SEK Billions)	7.82	7.83	6.19	4.44	3.64	2.67	1.89	1.69	1.07	0.51
Price	47.4	45.5	41.3	38.8	35.8	36.8	33.0	31.7	27.0	21.0
Beta	0.50	0.62	0.64	0.65	0.65	0.67	0.67	0.67	0.65	0.67
BM ratio	0.60	0.57	0.54	0.53	0.53	0.51	0.51	0.50	0.52	0.49
Illiq (10^{-8})	0.80	0.47	0.56	0.69	1.05	1.39	2.36	3.96	6.69	17.51
IVOL (Percent)	1.36	1.47	1.58	1.68	1.82	1.94	2.13	2.29	2.59	3.31

The portfolios are created every month from January 1994 to December 2019 by sorting stocks on Stockholm Stock Exchange by their maximum daily return in the prior month. Decile portfolio 1 (D1) includes stocks with the lowest MAX, while decile portfolio 10 includes the highest-MAX stocks. Panel A shows the average number of stocks per decile and average percent of stocks' market capitalization in the corresponding decile. Panel B reports the average (across one decile over the whole period) of median (across deciles and months) values of stock attributes for every decile portfolio. These attributes are maximum daily return over a month in percent (MAX), market capitalization (size) in SEK billion, stock price in SEK(price), market beta (beta), book-to-market ratio (BM ratio), illiquidity (Illiq) (Amihud (2002)) and idiosyncratic volatility in percent (IVOL)

around 0.65-0.67. The average book-to-market ratio, which can be seen as a firm distress factor Fama and French (1992), tends to decrease as we move from D1 to D10: from 0.6 to 0.5.

Illiquidity is measured using the formula developed by Amihud (2002). The clear pattern that can be seen among deciles, is thet the illiquidity grows as we move to D10. For D10, average liquidity is 17.51×10^{-8} and for D1 it is 0.80×10^{-8}.

Finally, average idiosyncratic volatility (IVOL), calculated using the Bali et al. (2011) formula. Consistent with Kumar (2009), average idiosyncratic volatility tends to increase from the first decile portfolio to the tenth. For D1, this IVOL is 1.36%, and for D10, it is 3.31%.

4.2 Sentiment Level Index Creation

In order to develop the sentiment index, we mainly applied the method used by Baker and Wurgler (2006) , and also used Han and Li (2017) and Fong and Toh (2014) as complementary guidance.

To measure the sentiment level, we first find several proxies for the sentiment. They are market turnover ratio (TURN), Dividend Premium (DIV) and net aggregate flow to mutual funds (FMF).

As stated in Han and Li (2017), there are no definitive or indisputable market sentiment measures. The sentiment proxies are highly country-specific and are also subject to the availability of data. Now, we discuss each of the sentiment proxies that we used to create the index.

Market Turnover Ratio (TURN): The basic idea of Baker and Stein (2004) is that market liquidity can be a sentiment indicator so that high liquidity is a sign of irrational investors' positive sentiment. Accordingly, the market turnover ratio can be used as a proxy for market liquidity.

Dividend Premium (DIV): Following the Catering Theory of Dividends, proposed in Baker and Stein (2004), the decision to pay dividends is driven by prevailing investors' demand for dividend payers. Baker and Wurgler (2007) posit that there may be an inverse relationship between the premium for dividend-paying stocks and investors' sentiment. Following Baker and Stein (2004), the dividend premium is calculated as the log difference between the average market-to-book ratios of dividend payers and nonpayers.

Dividend data are taken from FinBas. First, the companies are sorted into two groups every month based on whether they pay dividends this month. After that, the value-weighted market-to-book value ratio is calculated every month for payers and non-payers separately using the following formula:

$$MB_t = \frac{(1/BM_{it}) * MV_{it}}{\sum_{i=1}^{n} MV_{it}} \tag{5}$$

Where MB_t is value weighted market-to-book ratio of dividend payers or non-payers in month t, BM_{it} is book-to-market ratio of company i in time t and MV_{it} is market value of company i in time t with n companies in t in chosen subset (payers or non-payers). After that, dividend premium is calculated using the formula:

$$DIV_t = \ln(MB_t^p) - \ln(MB_t^{np}) \tag{6}$$

Where Div_t is dividend premium in month t, and MB_t^p is market-to-book ratio of dividend payers and MB_t^{np} is the same ratio for non-payers.

Flow to Mutual Funds: The inclusion of net aggregate flow to mutual funds (FMF) is based on Indro (2004)). In that paper, he finds that flow to mutual funds is higher when individual investors become more bullish in the previous and current period. Baker and Wurgler (2006) use Close-end fund discount as a proxy, but due to the low number of CE funds in Sweden, we decided to replace it with the flow to mutual funds.

Following Brown et al. (2003), we compute net flow to mutual fund i in during month t by:

$$F_{i,t} = NAV_{i,t} - NAV_{i,t-1} \times (1 + r_{i,t-1}) \tag{7}$$

Where $NAV_{i,t}$ is net assets under management value for fund i in month t and r_t is the return of fund i in month t.

Then we calculate the net aggregate flow to all mutual funds in each month by adding together the net flows to all mutual funds. In general, the three described indices are worthy components for creating an investor sentiment index as they tend to change depending on the state of the market and can accurately reflect the mood on the Swedish stock market. Moreover, all these variables are available during the research period and have no missing or artificial values and breaks.

To correctly create a local sentiment level index for the Swedish stock market, we perform several steps described below.

First of all, we check all the sentiment proxies for the presence of a trend that is not associated with the market sentiment, following Baker and Wurgler (2007). It turns out that there is a deterministic trend in turnover ratio and net aggregate flow to mutual funds that is upward. It is related to the Swedish stock market's overall growth over the sample period and has no link with market sentiment. We divide the variables by their last five-month moving averages to eliminate that trend and have valid and representative sentiment level proxies. That approach of dealing with trends was developed by Baker and Wurgler (2007) and Chen et al. (2014). The procedure also assists in ensuring that all proxies are stationary across the sample period.

As a result of the detrending procedure, we achieve the following variables as proxies for sentiment:

$$DIV_t = \frac{DIV_t^{un}}{DIV5_t} \tag{8}$$

Where DIV_t^{un} is the dividend premium in time, t and $DIV5_t$ is the dividend premium during the previous five months. And:

$$TURN_t = \frac{TURN_t^{un}}{TURN5_t} \tag{9}$$

Where $TURN_t^{un}$ is the market turnover ratio in time t and $TURN5_t$ is the average turnover ratio during the previous five months. And:

$$FMF_t = \frac{FMF_t^{un}}{FMF5_t} \tag{10}$$

Where FMF_t^{un} is the net aggregate flow to mutual funds in time t and $FMF5_t$ is the average net aggregate flow to mutual funds during the previous five months.

As mentioned in Baker and Wurgler (2006), a problem in forming the index is finding out the relative timing of the variables. In other words, some variables may reflect the sentiment earlier or later than other variables. Therefore, following Baker and Wurgler (2006), we estimate the first principal component (PCA) of six proxies, including $TURN_t$, DIV_t, FMF_t, and their lags (1-month lag), $TURN_{t-1}$, DIV_{t-1}, FMF_{t-1}. Then, we look at the correlations between the created index and these six variables. Using Table 2, which contains these correlations, we select $TURN_t$, DIV_{t-1} and FMF_{t-1} to include in our PCA because they have a higher correlation with the first-stage index than their peer.

Then, as was noted in Baker and Wurgler (2007), sentiment proxies have an irrational component and a rational one. The rational component comes from the macroeconomic background and the current state of the economy. Investors receive information about it, and it affects their sentiment. In order to minimize and try to whither off the rational component, we use the approach

Variables	Correlation with the first-stage index
$TURN_t$	-0.23
$TURN_{t-1}$	-0.05
DIV_t	-0.82
DIV_{t-1}	-0.83
FMF_t	-0.18
FMF_{t-1}	-0.29

Table 2: The correlations between proxy variables and the first-stage index

suggested by Baker and Wurgler (2006) and Verma and Soydemir (2009). The approach involves regressing every proxy on a chosen set of macroeconomic variables and then using the residuals of these three regressions to create a sentiment level index as these residuals are implied to be the irrational part of the variables used as proxies.

The variables used to regress the proxies are the change in money supply M3, the change in orders in Sweden's industry, Euro-to-SEK exchange rate and Swedish repo rate. These are the primary macroeconomic factors available during the sample's whole time period without missing values or breaks and capturing as many macroeconomic factors as possible. Moreover, the data sample of these variables has the same frequency as the three sentiment proxies. Therefore, we concluded that these regressors would allow us to shape a sufficient and accurate representation of macroeconomic factors' effect on sentiment level and its proxies.

After that, we perform principal component analysis to DIV, TURN, and FMF residuals and extract the first principal component from the analysis as the local Swedish sentiment level index. The first component of principal analysis should accurately capture individual proxies' variation and accurately represent the Swedish local sentiment level index.

The resulting PCA is:

$$S_t = +0.65TURN_t + 0.74DIV_{t-1} + 0.18FMF_{t-1} \tag{11}$$

Panel A in Table 3 shows the summary statistics for the factors used to construct the sentiment level index and the index itself. Arithmetic mean and standard deviation for the three components used for creating sentiment level index are 0 and 1 correspondingly as they were scaled before index creation for comparability and possible use in PCA analysis. The same applies to the sentiment index: it was scaled as well. The mean monthly market excess return is 0.79%, and the standard deviation is 5.20%. This results in a Sharpe ratio of 0.15. This indicates that the price of risk is low in the Swedish stock market. This price of risk also undermines the risk aversion of investors on the market. Therefore, it can be noted that Swedish investors are risk-averse compared to other countries.

Panel B in Table 3 represents the correlation matrix of the variables from panel A of Table 3. As can be seen from the table, the correlation of sentiment index with residuals of three proxies

Table 3: Descriptive statistics of PCA model

Variable	Obs.	Mean	St. dev.	Median	Min	Max
Panel A. Summary statistics						
Ret	215	0.01	0.05	0.01	-0.18	0.22
S_t^{PCA}	215	0.00	1.00	-0.14	-2.25	4.05
$TURN$	215	0.00	1.00	-0.03	-3.31	3.11
DIV	215	0.00	1.00	-0.04	-4.56	4.33
FMF	215	0.00	1.00	0.01	-6.92	8.49
Panel B. Correlation Matrix						
	Ret	S_t^{PCA}	$TURN$	DIV	FMF	
Ret	1	0.09	0.18	0.01	-0.02	
S_t^{PCA}	0.09	1	0.70	0.74	0.20	
$TURN$	0.18	0.70	1	0.17	-0.10	
DIV	0.01	0.74	0.17	1	0.10	
FMF	-0.02	0.20	-0.10	0.10	1	

This table shows summary statistics for the monthly excess return of market portfolio (Ret), sentiment level index (S_t^{PCA}), constructed using Baker and Wurgler (2007) method, market turnover ratio ($TURN$), dividend premium (DIV) and net aggregate flow to mutual funds (FMF). $TURN$, DIV and FMF are detrended and standardized. S_t^{PCA} is standardized. Panel A reports the number of observations, arithmetic mean, standard deviation, median, minimum and maximum of the variables, while panel B shows the correlation matrix of these variables. The PCA variables in Panel A are standardized as means are 0 and standard deviations are 1.

(FMF, TURN and DIV) is relatively high, which is why the sentiment level index was created. Moreover, there is no high correlation between the variables in the table, which means they are independent and are valid proxies for creating a sentiment level index with the chosen approach.

5 Empirical Results

5.1 Future Returns and MAX

Table 4 reports the coefficients of regression of return in the current month on the subset of stock characteristics of the previous month. In other words, we went through Fama-Macbeth tests to see the cross-sectional relation between MAX and the other variables in the previous month with the return in the next month.

The monthly cross-sectional regressions are run as below:

$$\begin{aligned} R_{i,t+1} = \delta_{0,t} + \delta_{1,t} MAX_{i,t} + \delta_{2,t} BETAi,t + \delta_{3,t} SIZE_{i,t} + \delta_{4,t} BM_{i,t} \\ + \delta_{5,t} MOM_{i,t} + \delta_{6,t} REV_{i,t} + \delta_{7,t} ILLIQ_{i,t} \end{aligned} \tag{12}$$

where $R_{i,t+1}$ is the return on stock i in month $t + 1$. We defined the other variables in section 4.1.2. Table 4 reports the time-series averages of the coefficients $\delta 1$ to $\delta 7$ over the 312 months. The Newey-West t-statistics are provided in parentheses below each coefficient. The average of $\delta 1$, is obtained from regressing next months' returns on only MAX is -0.0225 with a t-statistic of -1.67. This value is -.0219 with the t-statistic of -0.96 when we regress next month's return on MAX with the presence of other variables in the regression.

The coefficients on the individual control variables are worth mentioning. The size effect is small and statistically significant. The value effect, which is represented by δ_7, is very small, negative and significant. The stocks exhibit medium-term momentum as the coefficient is positive and significant. But there is no significant relationship between short-term reversal and illiquidity with the stocks' future returns. The slope on Beta is close to zero, which contradicts the CAPM model. The last line of the Table 4, provides the full-specification with MAX and six other variables. The coefficient of MAX in this setting is -0.0219 and statistically insignificant. This is similar to Bali et al. (2011) result in terms of the relationship direction.

Even though most of the variables are not significant at the 5% level ($|t\text{-statistics}| < 2$), several conclusions can be made from Table 4. First of all, the MAX coefficient insignificance, both on its own and as a part of regression with other variables, tells that the MAX effect is not strong in the Swedish stock market on individual stock level, and if it is present, the direction of the effect is the same as described in Bali et al. (2011). They found a negative relationship between MAX and returns, and in Table 4, the coefficient is -0.0225 when regressing next month's return only on MAX and -0.0219 when adding other variables. Thus, despite the inability to be sure that MAX has a negative effect on future returns, we suppose there is still the possibility that such an effect exists.

Interestingly, the only two variables in our regression that are significant at the 5% confidence level are momentum and reversal, which means that future returns highly depend on the returns over the previous 12 months in the Swedish stock market. Moreover, higher returns in previous months, on average, increase the returns in the current month. Therefore, a 1% increase in the stock return in the previous month, on average, controlling for other variables, increases the stock return in the current month by 0.0069%.

The variables that are also worth mentioning are book-to-market ratio and size. Higher book-to-market tend to lower next month's return, while larger companies by market capitalization tend to have higher returns on their stock. The coefficients of these variables are significant on their own. However, they are not significant when other variables are included in the regression. It means that these factors' effect most likely depends on other variables included in the regression.

Despite the MAX coefficient is negative, we cannot confidently claim that MAX affects the returns of individual stocks as the t-statistics of the coefficient are too low. Therefore, we can state that after performing the analysis and constructing the Fama-Macbeth regression of return of the current month on the MAX of the previous month, we cannot state that there is a significant negative dependence of return of stock from its maximum daily return in the previous month in Swedish stock market on individual stock level.

Table 4: Firm-level Cross-sectional Return Regression

MAX	BETA	SIZE	BM	MOM	REV	ILLIQ
-0.0225						
(-1.67)						
	-0.0005					
	(-0.56)					
		0.0006				
		(2.96)				
			-0.0030			
			(-2.14)			
				0.0075		
				(5.69)		
					0.0110	
					(1.85)	
						-186.913
						(-0.50)
-0.0219	-0.0013	0.0003	-0.0013	0.0069	0.0118	-823.852
(-0.96)	(-1.02)	(1.03)	(-0.81)	(4.27)	(1.80)	(-1.05)

We created this table following Bali et al. (2011). Every month from January 1994 to December 2019, we run a firm-level regression of the return on subsets of lagged predictor variables including MAX in the previous month an other seven variables that are defined in the Appendix. The table reports the time-series averages of the cross-sectional regression coefficients and their associated t-statistics.

5.2 Future MAX and MAX

Table 5 depicts the results of the regression of max of current MAX on the MAX of previous max and the set of one-month lagged variables: market beta, company size, book-to-market ratio, momentum, reversal and illiquidity. The formula of the regression is:

$$\begin{aligned} MAX_{i,t+1} = \eta_{0,t} + \eta_{1,t} MAX_{i,t} + \eta_{2,t} BETA_{i,t} + \eta_{3,t} SIZE_{i,t} + \eta_{4,t} BM_{i,t} \\ + \eta_{5,t} MOM_{i,t} + \eta_{6,t} REV_{i,t} + \eta_{7,t} ILLIQ_{i,t} \end{aligned} \tag{13}$$

where $MAX_{i,t+1}$ is the return on stock i in month $t+1$. We defined the other variables in subsection 4.1.2. After calculating this regression for every month, we find the time-series arithmetic mean for each coefficient. We report the time-series average coefficients in Table 5. The Newey-West t-statistics are provided in parentheses below each coefficient.

As can be seen from Table 5, the MAX of the previous month is significant both on its own and together with other variables (t-stats of 20.0 and 8.30 respectively). The same applies to the size of the company (t-stats of -43.75 and -35.10, respectively). Book-to-market is not significant on its own with t-stat 1.90, but in the regression with other variables, it has a t-stat of -6.74. High coefficients for illiquidity are explained by the fact that the illiquidity variable itself is very small compared to other variables.

In Table 5, however, most of the variables have a significant influence on the next month's MAX. The most remarkable is the MAX of the previous month. The coefficient is positive and significant on a 5% confidence level. Therefore, a 1% increase in the previous month's MAX, on average, increases the MAX of the current month by 0.1065% while controlling for other variables. This result supports the theory that high MAX stocks tend to retain their MAX.

Another supporting argument regarding this claim is presented in Table 6. There, it can be seen that stocks with all MAX levels tend to remain in the same decile or move one decile up or down. However, while stocks in all MAX deciles have probabilities of staying in the same decile of 12% to 18%, the D10 stocks, which is the highest MAX decile, have twice the chance (30%) to remain there. Thus, it can be seen that for most stocks, their highest probability value is remaining in the same decile. However, the fact that the highest MAX decile has a far higher value strongly supports the claim that if the stock showed high MAX in the past, it is likely to do so in the future.

Regarding other coefficients in Table 5, it is worth noting that the size determines the MAX effect of the following month greatly. The coefficient is highly significant and negative, which means that companies with higher market capitalization show lower one-day maximum returns. This is in line with summary statistics in Table 1, where the trend of smaller companies to be in higher MAX decile is very clear. This is also reasonable as big companies, on average, have lower price volatility and rarely happen to express price spikes, so less likely to exhibit high MAX.

Based on the model results and the results of the probability table (Table 6), we find a significant positive relationship between MAX of the previous month and MAX of the current month. Therefore, we agree with the hypothesis that stocks exhibiting a high MAX in a month are more

Table 5: Cross-sectional Predictability of MAX

MAX	BETA	SIZE	BM	MOM	REV	ILLIQ
0.2123						
(20.00)						
	-0.0011					
	(-1.49)					
		-0.0069				
		(-43.75)				
			-0.0013			
			(-1.90)			
				-0.0044		
				(-4.53)		
					-0.0144	
					(-3.74)	
						1281.369
						(2.95)
0.1065	0.0010	-0.0060	-0.0047	0.0001	-0.0047	107.18
(8.30)	(1.41)	(-35.10)	(-6.74)	(0.14)	(-1.30)	(0.27)

We created this table following Bali et al. (2011). Every month from January 1994 to December 2019, we run a firm-level regression of next month's MAX on subsets of lagged predictor variables including MAX in the previous month an other seven variables that are defined in the Appendix. The table reports the time-series averages of the cross-sectional regression coefficients and their associated t-statistics.

likely to exhibit a high MAX in the next month.

5.3 Sentiment Level Index

After conducting the PCA using the pattern from subsection 4.2, we calculate the index for every month using equation 11. Then, we input the corresponding proxies' residuals every month. After doing that, we find the median of the resulting calculation(which is: -0.1524) and subtract it from the PCA equation calculation every month. The resulting difference is presented in Figure 2.

It is important to notice that the value of the sentiment level itself does not depict the market's sentiment; the level being above or below the median represents the sentiment level index of the stock market. Therefore, we create a binary variable equal to 1 if the sentiment in the current month is higher than the median and 0 otherwise. As a result, we get 120 months with high sentiment and 120 with low sentiment.

Further, in our research, we use this index to divide the sample into groups based on the value of this binary variable. We take the sentiment level index of the previous month. If it is 1, we

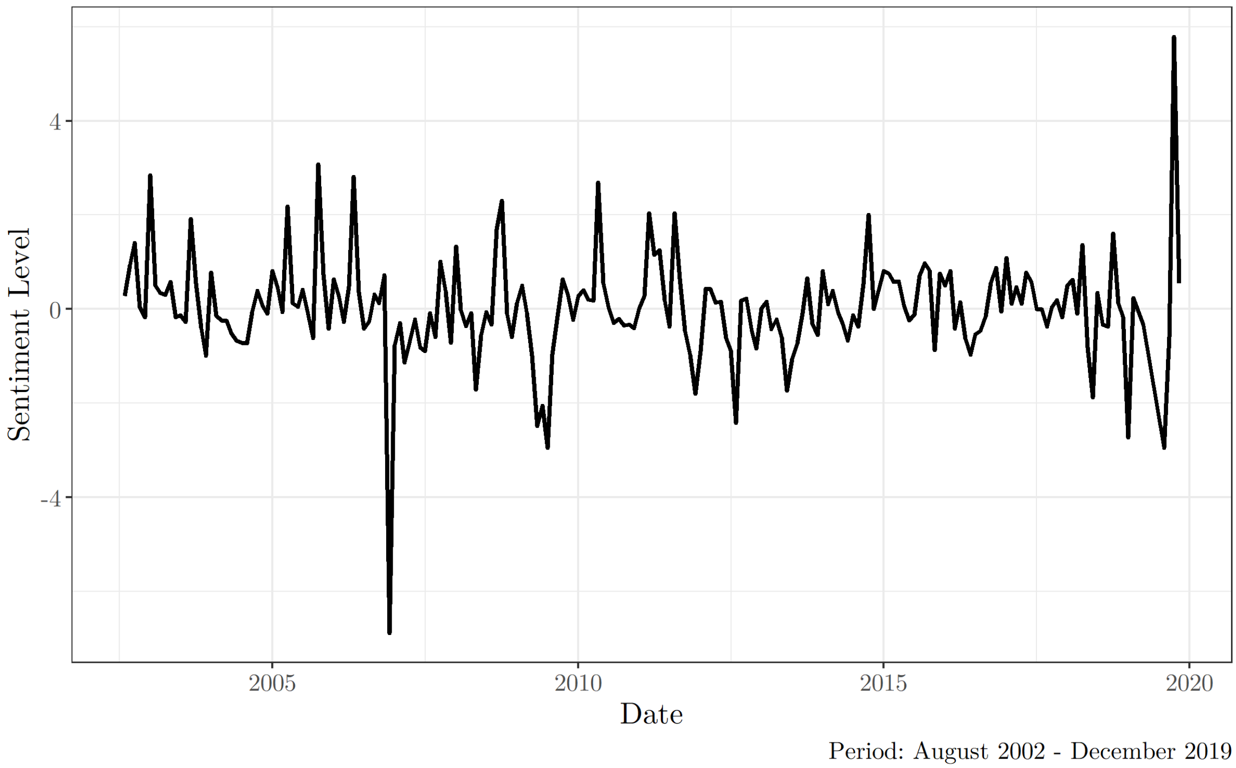

Figure 2: Sentiment Level

assign the observation data to the first group, if 0, to the second. We use the sentiment as an instrument to check our supporting hypothesis. This approach is used to see the sentiment's effect on Max, if there is any. It turns out that depending on sentiment, the MAX effect can be very strong or barely noticeable, which will be described in detail further in the text.

Figure 2 depicts the resulting sentiment level. The illustration is provided to form an understanding of the outcome of PCA analysis visually. However, the numbers alone on Y-axis, which are deviations from the mean, cannot be interpreted as the relative sentiment level indicator.

Moreover, as the sentiment level index does not have a set definition or a construction approach, the adopted approach may not match one's ideas of the sentiment level index. It is also possible that one disagrees with the estimated sentiment index on a specific date. However, sentiment is a behavioral concept, and one's perception of the index on a specific date may be different from other individuals.

In our analysis of sentiment level index creation, we carefully gathered the data from various areas of the Swedish financial market and macroeconomics to achieve a sentiment level index as highly representative as possible with the data at hand. In addition, we also thoroughly followed Baker and Wurgler (2006) to capture all the details of the sentiment level index.

5.4 Deciles Returns

Table 6 reports the probabilities of stocks moving from one decile sorted by previous month's MAX to the other. The rows represent the initial decile, and columns are the deciles to which stocks move to. These probabilities were calculated by dividing the number of times the stock from the current decile has moved to chosen decile by the total number of times this stock has been in this decile.

As stated in the table, stocks tend to remain in the same decile over time or move to neighbor deciles. The decile that stands out is the 10th decile, which is the highest MAX decile. Stocks from this decile have a 30.4% chance to remain there, compared to 11-15% for other stocks, which means that high MAX stocks tend to show high MAX in future months. This is consistent with the outcome of regression from Table 5, which also shows the same result.

Table 6: Probability of Stocks decile change (%)

	Low MAX	2	3	4	5	6	7	8	9	High Max
Low MAX	18.8	13.0	10.9	10.6	9.3	8.9	8.2	7.7	7.2	5.4
2	16.3	15.4	14.0	12.2	10.2	8.9	7.6	6.7	5.2	3.6
3	13.0	14.0	13.3	12.1	11.5	9.6	8.4	7.4	5.7	5.0
4	11.0	12.7	12.2	11.9	11.0	10.6	10.0	8.4	7.3	4.9
5	9.2	11.0	11.6	11.4	11.4	11.0	10.5	9.2	8.2	6.6
6	6.9	9.4	10.2	10.5	11.2	11.6	11.6	11.2	9.9	7.6
7	6.4	7.3	9.2	10.2	11.1	11.3	11.9	11.6	11.7	9.2
8	5.1	6.5	8.1	8.8	9.9	11.5	12.2	12.8	13.6	11.4
9	4.1	5.1	6.4	7.5	9.2	10.3	11.6	13.9	15.3	16.5
High Max	3.1	3.6	3.9	4.7	6.2	7.7	9.5	13.1	17.9	30.4

Decile portfolios are formed every month from January 2001 to December 2019 based on stock's maximum daily return (MAX) in previous month. The table reports transition matrices for the stocks in these portfolios, i.e., the probability (in percent) that a stock in decile i (as given by the rows of the matrix) in one month will be in decile j (as given by the columns of the matrix) in the subsequent month.

Figure 3 enables us to compare the cumulative return of the High and Low MAX portfolios with each other and with the market portfolio. It is discernible that by investing $1 in the High MAX portfolio in January 1994, an investor could have $92.1 in December 2019. This number is $60.6 and $67.3 for the Low MAX and the market portfolio, respectively.

Table 7 states that higher MAX deciles tend to produce higher excess returns without taking sentiment into account. This trend seems not to go along with the results we achieved from the regression in Table 4. However, it is explainable. First of all, the observations in regression 12 all have the same weight, so this regression equally weights the stocks. Moreover, in tables 7-8, we do not look at individual stocks but rather at portfolios of these stocks, whereas in tables 4 and 5, we inspect results at the firm level. Finally, the models in tables 4 and 7 are different by construction. In regression 12, we account for all Fama-French-Carhart model factors, while in Table 7, only the excess returns are presented.

It is worth mentioning that the standard deviation of the portfolio returns grows together with its excess returns. It results in a higher price of the risk and a lower Sharpe ratio, as a result, for higher MAX portfolios.

In all portfolios, the alphas are insignificant at a 5% confidence level, which was mentioned earlier, while the betas for the same decile portfolios are certainly significant (a t-stat around 20 for all of the portfolios). It means that using the FF4F model can efficiently describe portfolio returns on itself.

Noticeably, the market betas in Table 7 tend to increase as we go from low to high MAX. It means that stocks in the higher MAX deciles are much more dependent on the market conditions than those in lower deciles. This can be linked to the fact that according to Table 1, the size of the company decreases when we go from first to the tenth decile. Therefore, higher deciles consist of smaller companies that are more affected by market conditions than the larger companies in the first deciles.

Furthermore, the low alpha significance numbers tell us that there are no unexplained return factors for every portfolio, and all returns can be explained by momentum, book-to-market ratio, market cap and market beta. Therefore, MAX does not affect these portfolios and does not affect the returns.

Regarding the difference between the tenth and first decile portfolios, the latter has lower excess returns on average but almost the same alpha. Also, the alphas are insignificant on themselves, so is their difference, which equals -0.05% with a t-statistics of -0.11. Therefore, we can conclude that despite the difference in excess returns, we did not observe any influence from MAX on decile value-weighted portfolio returns, and the FF4F model well explains their return.

The situation is very different, however, if we look at the equal-weighted decile portfolios. Table 8 presents the same results as Table 7, but within portfolios, every stock has the same weight.

Now, excess returns decrease as we go from D1 to D10 while portfolio return volatility increases. It leads to an apparent trend of Sharpe ratios decreasing. The betas of all portfolios are still significant on a 5% confidence level. Market betas also tend to be higher for higher MAX portfolios, as it was in Table 7.

Nonetheless, now portfolio alphas, or, in other words, abnormal returns, are significant and tend to be lower for higher MAX portfolios. Moreover, the trend of decreasing alphas is robust across deciles. Therefore, the difference between alphas of the tenth and first decile portfolio is -0.99%, with a t-stat of -2.73. At the same time, the difference between excess returns for the same portfolios is -1.09% with a t-stat of -2.43.

These numbers indicate that the FF4F model cannot fully explain the returns of these portfolios,

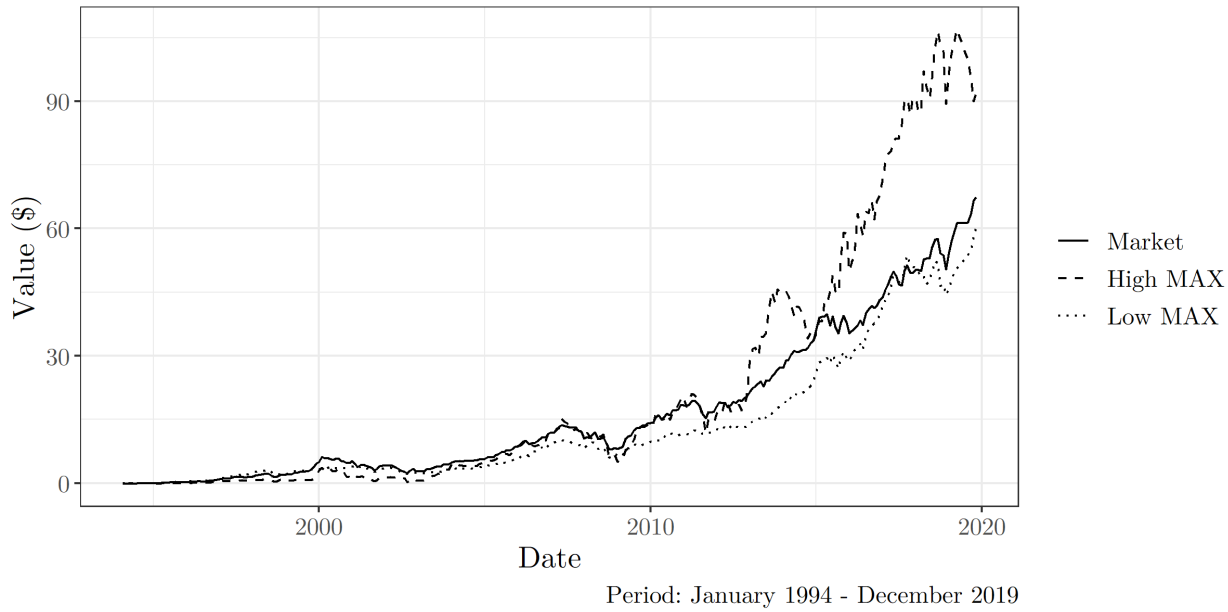

Figure 3: Value of $1 investment in January 1994 throughout the study period

and as such, we believe that the unexplained alpha appeared due to the MAX effect as this is the instrument that we sorted the stocks on and did not control for it in FF4F.

Therefore, we can state that the MAX effect is found in Swedish stock decile equal-weighted portfolios, and the direction of the MAX effect is such that higher MAX portfolios generate lower returns and produce negative alpha.

There is a significant difference between returns of equal-weighted portfolios and value-weighted ones and the direction and magnitude of the MAX effect. While among value-weighted portfolios there is no significant MAX effect and stocks show returns, well predicted by FF4F, the equal-weighted portfolios show the same direction of MAX effect as in Bali et al. (2011) in the US stock market. The portfolios of stocks with higher MAX tend to generate lower returns and lower unexplained returns, not predicted by FF4F. This effect goes along with our regression 12, but its magnitude is higher when accounted for on the portfolio level. We suppose that difference between the trend in the two portfolio designs is explained by taking the size into account. As shown in Table 1, higher MAX companies tend to be smaller in size, so if we construct equal-weighted portfolios, such companies' stocks get a higher share than they normally would. Also, extreme MAX companies, get higher portfolio shares as well. According to regression 12, such companies have a probability of negatively affecting the subsequent returns. In value-weighted portfolios, lower MAX and non-extreme-MAX companies get higher portfolio shares. Therefore, this effect is mitigated, and no difference between unexplained returns is visible.

Table 7: Returns and alphas of MAX portfolios (Value-weighted)

Decile	Excess Return (%)	Std.Dev. (%)	Sharpe Ratio	FF4F Alpha (%)	Alpha t-stats	Beta	Beta t-stats
Low MAX	1.26	4.92	0.26	0.22	(1.05)	0.70	(18.07)
2	1.53	5.09	0.30	0.33	(1.73)	0.79	(22.25)
3	1.03	5.95	0.17	-0.30	(-1.38)	0.92	(22.55)
4	1.30	5.75	0.23	0.02	(0.08)	0.88	(21.44)
5	1.08	6.07	0.18	-0.39	(-1.79)	0.97	(23.84)
6	1.13	6.99	0.16	-0.33	(-1.47)	1.10	(25.73)
7	1.31	8.40	0.16	-0.11	(-0.37)	1.17	(20.12)
8	1.62	9.34	0.17	0.06	(0.17)	1.27	(18.53)
9	1.53	10.06	0.15	-0.08	(-0.19)	1.30	(16.77)
High MAX	1.85	10.83	0.17	0.16	(0.37)	1.37	(16.44)
$10-1$	0.59			-0.05			
	(1.04)			(-0.11)			

The table shows characteristics of decile portfolios sorted by the MAX effect every month. The sample period is from January 2001 to December 2019. The excess return shows the mean return in excess of the risk-free rate (repo rate) and Std.Dev. column is the standard deviation of excess return. The Sharpe Ratio is the excess return divided by its standard deviation. The FF4F Alpha shows Fama-French-Carhart alpha with its t-statistics in column Alpha t-stats. Columns 7 and 8 are market betas of FF4F and its t-statistics. The last row $(10-1)$ shows the average returns and alphas of a portfolio that longs the High MAX decile and shorts the Low MAX decile, as well as t-statistics for the difference. All returns are expressed in percent per month.

5.5 Deciles Returns Relation with Sentiment

Sorting by the sentiment level significantly changes the results that we described in Table 7. Now, panel A of Table 9 represents the high sentiment state of the stock market for value-weighted portfolios. Overall, the trends and directions of effect in this panel match with the ones in Table 7. The excess returns tend to increase from decile 1 to decile 10, along with the standard deviation of the excess return. As a result, the Sharpe ratio also decreases if going from low to high MAX decile. However, the pace at which the Sharpe ratio decreases is not as consistent as in Table 7. It is still lower for higher MAX deciles but then remains around 0.17 and fluctuates around that number.

Regarding alphas and betas of the FF4F model in Table 9 panel A, their patterns are the same as in Table 7. Almost all the alphas are insignificant, except for the second decile, where t-statistics is high enough to consider the alpha borderline significant (t-stat 1.89 with an alpha of 0.56%). The market betas for all the portfolios are still highly significant; however, the substantial increase

Table 8: Returns and alphas of MAX portfolios (equal-weighted)

Decile	Excess Return (%)	Std.Dev. (%)	Sharpe Ratio	FF4F Alpha (%)	Alpha t-stats	Beta	Beta t-stats
Low MAX	1.46	5.17	0.28	0.27	(1.30)	0.74	(18.95)
2	1.35	5.03	0.27	0.10	(0.71)	0.82	(31.12)
3	1.17	5.28	0.22	-0.17	(-1.26)	0.89	(35.47)
4	1.14	5.19	0.22	-0.11	(-0.81)	0.85	(32.25)
5	1.10	6.29	0.18	-0.25	(-1.25)	0.95	(24.99)
6	1.10	6.30	0.17	-0.24	(-1.54)	0.99	(33.54)
7	0.84	7.16	0.12	-0.36	(-1.96)	1.02	(29.60)
8	0.96	7.60	0.13	-0.36	(-1.77)	1.10	(28.68)
9	0.58	8.60	0.07	-0.78	(-2.97)	1.17	(23.79)
High MAX	0.38	9.04	0.04	-0.72	(-2.41)	1.07	(18.97)
$10-1$	-1.09			-0.99			
	(-2.43)			(-2.73)			

The table shows characteristics of decile portfolios sorted by the MAX effect every month. The sample period is from January 2001 to December 2019. The excess return shows the mean return in excess of the risk-free rate (repo rate) and Std.Dev. column is standard deviation of excess return. Sharpe Ratio is excess return divided by its standard deviation. The FF4F Alpha shows Fama-French-Carhart alpha with its t-statistics in column Alpha t-stats. Columns 7 and 8 are market betas of FF4F and its t-statistics. The last row $(10-1)$ shows the average returns and alphas of a portfolio that longs the High MAX decile and shorts the Low MAX decile, as well as t-statistics for the difference. All returns are expressed in percent per month.

in beta from D1 to D10 is not present.

The difference in decile returns is 0.45, while the difference in alphas is -0.05. The same as in Table 7. Again, insignificant alphas and highly significant market betas indicate that FF4F models can accurately explain the returns of portfolios, and there is no abnormal return. Therefore, it can be seen that despite the difference in excess returns, all of it is explained by portfolio characteristics, and MAX does not influence the portfolio returns in a high sentiment state.

Panel B demonstates the perfrmance of value-weighted deciles in the low sentiment state. The difference is that the excess returns are even higher as we go to the tenth decile. There is also no more large decline in Sharpe ratios. They are still higher for the first two decile portfolios, but after that, there is no clear pattern, despite the fact that the volatility of excess returns grows with MAX portfolios.

Betas are still significant and increasing along with decile portfolio numbers. However, alphas are now barely significant for half of the portfolios. Thus, we can no longer state that portfolios do not produce any abnormal returns, and the FF4F model explains everything.

Now, the difference in excess return between portfolio 10 and portfolio 1 is 1.61%. Moreover, the difference between alphas of decile portfolio 10, and decile portfolio 1 is 0.85%. This difference is close to significant, so we can state that this difference is not explained by the FF4F model. We can attribute this difference to the MAX effect as it is the variable that is used to sort the portfolios.

As a result, we can say that the MAX effect is only found in the low sentiment state of the Swedish stock market for value-weighted decile portfolios, and it results in high MAX stocks earning more during the low sentiment on the market.

Again, if we look at Table 10, which is the same in every way as Table 9, several major differences can be spotted. First of all, now, excess returns are lower for high MAX portfolios. The trend exists independent of the sentiment level of the market. Volatility grows toward high MAX portfolios in both panels as well. Therefore, Sharpe ratios steadily decrease for both of them.

All the market betas are significant across both panels, which is the same as in Table 9. However, in Table 10 alphas are lower for higher MAX portfolios. The alphas are again borderline significant, and their significance is more or less the same, independent of the sentiment level of the stock market.

In Table 10, the differences between excess returns of the tenth and first portfolios is -0.77% with a t-statistics of -1.29 for high sentiment state and -0.88% with a t-statistics -1.08 for low sentiment state. At the same time, the difference between alphas of the same portfolios is -0.55% with t-statistics of -1.02 for high sentiment and -0.82% with a t-stat of -1.11 for the low sentiment.

Overall, although the direction of the MAX effect is opposite for both portfolios, which was explained in section 5.4, its magnitude is always higher in low sentiment states. Therefore, we can conclude that the difference between the portfolio alphas is greater in low sentiment states.

5.6 Robustness Tests

In order to check the robustness of our findings, we perform a number of tests for each of our hypotheses.

First of all, to check the robustness of our first and second hypothesis, of whether MAX affects the returns of the next month and whether MAX of the previous month can predict next month's MAX, we decided to change our definition of the MAX from the one-day highest daily return of the month to the arithmetic mean of five days on which the stock showed highest daily return. This method allows us to check if the effect will still appear even if we do not take a single date, which can be an outlier but instead take the mean of several days. As a result, this would allow us to see if the results change because of a definition difference.

We perform the same regression as in sections 5.2 and 5.3. The only difference is that we now use the new definition of MAX instead of the original one. The results are presented in Table 11 and Table 12.

Table 9: Returns of MAX portfolios following different sentiment states(value-weighted)

Decile	Excess Return (%)	Std.Dev. (%)	Sharpe Ratio	FF4F Alpha (%)	Alpha t-stats	Beta	Beta t-stats
Panel A. High sentiment							
Low MAX	1.04	5.02	0.21	0.25	(0.74)	0.82	(11.09)
2	1.57	5.29	0.30	0.56	(1.89)	0.94	(14.26)
3	1.13	5.50	0.21	0.14	(0.43)	1.00	(13.78)
4	0.88	5.73	0.15	-0.27	(-0.87)	1.06	(15.13)
5	1.00	5.59	0.18	0.00	(0.02)	1.03	(15.41)
6	0.91	7.14	0.13	-0.31	(-0.88)	1.22	(15.46)
7	1.22	8.43	0.14	0.08	(0.14)	1.20	(9.37)
8	0.79	7.97	0.10	-0.34	(-0.62)	1.11	(9.04)
9	1.50	10.03	0.15	-0.02	(-0.04)	1.43	(12.45)
High MAX	1.49	9.28	0.16	0.20	(0.27)	1.05	(6.52)
$10-1$	0.45			-0.05			
	(0.52)			(-0.06)			
Panel B. Low sentiment							
Low MAX	1.46	4.62	0.32	0.20	(0.63)	0.75	(11.49)
2	1.74	4.64	0.37	0.44	(1.51)	0.80	(13.64)
3	0.71	5.54	0.13	-1.02	(-3.21)	0.99	(15.61)
4	1.47	5.59	0.26	-0.21	(-0.61)	0.98	(14.47)
5	1.45	5.98	0.24	-0.22	(-0.59)	1.00	(13.68)
6	1.44	6.44	0.22	-0.50	(-1.32)	1.12	(14.78)
7	2.29	8.66	0.26	0.68	(1.36)	1.22	(12.22)
8	2.47	10.92	0.23	0.77	(1.15)	1.38	(10.26)
9	1.65	7.77	0.21	-0.06	(-0.09)	0.96	(6.88)
High MAX	3.07	11.69	0.26	1.05	(1.35)	1.38	(8.83)
$10-1$	1.61			0.85			
	(1.62)			(1.00)			

The table shows characteristics of decile portfolios sorted by the MAX effect every month. The table is sorted in two panels based on the sentiment level of the market. Panel A includes observations with high sentiment in the previous month and Panel B includes low sentiment observations. The sample period is from January 2001 to December 2019. The excess return shows the mean return in excess of the risk-free rate (repo rate) and Std.Dev. column is standard deviation of excess return. Sharpe Ratio is excess return divided by its standard deviation. The FF4F Alpha shows Fama-French-Carhart alpha with its t-statistics in column Alpha t-stats. Columns 7 and 8 are market betas of FF4F and its t-statistics. The last row $(10-1)$ of each panel shows the average returns and alphas of a portfolio that longs the High MAX decile and shorts the Low MAX decile, as well as t-statistics for the difference. All returns are expressed in percent per month.

Table 10: Returns of MAX portfolios following different sentiment states (equal-weighted)

Decile	Excess Return (%)	Std.Dev. (%)	Sharpe Ratio	FF4F Alpha (%)	Alpha t-stats	Beta	Beta t-stats
Panel A. High sentiment							
Low MAX	1.10	4.78	0.23	0.23	(1.08)	0.76	(16.19)
2	1.42	5.16	0.28	0.46	(2.50)	0.94	(23.16)
3	1.15	5.46	0.21	0.08	(0.35)	1.00	(21.03)
4	1.17	5.52	0.21	0.20	(0.97)	0.96	(20.66)
5	1.05	6.84	0.15	-0.01	(-0.01)	1.03	(10.86)
6	0.99	6.64	0.15	-0.11	(-0.47)	1.14	(22.11)
7	0.89	6.89	0.13	-0.15	(-0.51)	1.11	(17.38)
8	0.84	6.93	0.12	-0.12	(-0.40)	1.13	(16.63)
9	0.65	8.18	0.08	-0.09	(-0.20)	1.05	(10.69)
High MAX	0.34	8.12	0.04	0.32	(-0.65)	0.93	(8.38)
$10-1$	-0.77			-0.55			
	(-1.29)			(-1.02)			
Panel B. Low sentiment							
Low MAX	2.11	6.13	0.34	0.48	(0.93)	0.77	(7.38)
2	1.69	5.13	0.33	0.08	(0.35)	0.86	(18.26)
3	1.43	5.35	0.27	-0.27	(-1.27)	0.94	(21.67)
4	1.43	5.26	0.27	-0.25	(-1.08)	0.89	(19.43)
5	1.57	6.40	0.25	-0.35	(-1.18)	1.03	(17.20)
6	1.78	6.66	0.27	-0.10	(-0.39)	1.07	(20.11)
7	1.47	7.16	0.20	-0.31	(-1.16)	1.10	(20.67)
8	1.38	8.00	0.17	-0.34	(-1.14)	1.16	(19.12)
9	0.90	7.60	0.12	-0.90	(-2.54)	1.15	(16.14)
High MAX	1.24	9.13	0.14	-0.34	(-0.64)	1.09	(10.35)
$10-1$	-0.88			-0.82			
	(-1.08)			(-1.11)			

The table shows characteristics of decile portfolios sorted by the MAX effect every month. The table is sorted in two panels based on the sentiment level of the market. Panel A includes observations with high sentiment in the previous month and Panel B includes low sentiment observations. The sample period is from January 2001 to December 2019. The excess return shows the mean return in excess of the risk-free rate (repo rate) and Std.Dev. column is standard deviation of excess return. Sharpe Ratio is excess return divided by its standard deviation. The FF4F Alpha shows Fama-French-Carhart alpha with its t-statistics in column Alpha t-stats. Columns 7 and 8 are market betas of FF4F and its t-statistics. The last row $(10-1)$ of each panel shows the average returns and alphas of a portfolio that longs the High MAX decile and shorts the Low MAX decile, as well as t-statistics for the difference. All returns are expressed in percent per month.

The MAX coefficient in Table 4 is -0.0225 with a t-stat of -1.67 when regressing the return of the following month only on max and -0.0219 with t-stat -0.96 when regressing on MAX with other variables. In Table 11, with a new definition of MAX, the MAX coefficient is -0.1158 with a t-stat of -3.22 when regressing only on MAX and -0.1053 with a t-stat of -2.39 when accounting for other variables. As a result, the robustness test supports the initial result that MAX affects the stock returns negatively. High MAX stocks tend to show lower returns in a subsequent month. It is important to notice that this tendency is only observed at the individual stock level and may change if looked at on the other level, e.g., portfolio or market.

Moreover, in Table 4, the MAX coefficients are not significant, while in Table 11, when checking the robustness, the MAX coefficients become significant at a 5% confidence level. It means that changing the definition of MAX to only 5 days, strengthens the relation between MAX and return.This may be because when accounting for one-day MAX, the range and magnitude of MAX are very high compared to the following month's returns, and thus, the relation between them is not so strong. However, when MAX is taken as an average of five days, the magnitude of the variable lies closer to month return figures and can predict the return of the following month more effectively. All the other coefficients of the regressions do not change or change slightly: they have the same significance level and direction of effect as in Table 4.

When regressing the MAX of the following month on the MAX of the previous month in Table 5, the coefficients were 0.2123 with a t-stat of 20.00 when regressing only on the previous MAX and 0.1065 with a t-stat of 8.30. In robustness test Table 12, the coefficient of MAX is 0.4718 with t-stat 16.94 when regressing only on MAX and 0.2406 with t-stat of 8,17 when controlling for other variables.

The test result concludes that despite the change of approach, MAX still has a strong effect on the maximum daily return of the subsequent month. The effect is slightly less in the 5-day MAX definition, but it is still highly significant and high. Therefore, after checking for robustness, it can be stated that the maximum daily return may have a highly negative effect on the next month's maximum daily return. All other coefficients of the regressions do not change or change slightly: they have the same significance level and direction of effect as in Table 5.

In order to check the robustness of sentiment level effect on the returns and MAX, we perform the same steps as in sections 5.4 and 5.5. However, we come up with two new approaches to construct the portfolios. The first one includes creating value-weighted quintile portfolios and the other includes creating equal-weighted quintile portfolios.

Tables 13 and 14 present the analysis results of quintile MAX portfolios' returns and alphas. Table 13 shows total results, while in Table 14, the data are sorted based on the sentiment level index in the previous month.

Overall, the direction of the MAX effect and sign of the difference in alphas and returns in Table 13 is the same as in the original analysis: the higher decile or quintile portfolios tend to show higher excess returns and roughly the same FF4F alphas. The difference in excess monthly returns between the first and fifth quintile portfolios is 0.41% on average, while the difference in Fama-French-Carhart four-factor model alphas is -0.02%. These figures are slightly smaller than in Table 7, where we test our original hypothesis (0.59% excess return difference and -0.05% alphas difference between decile 10 and decile 1). Alphas are not significant on the 5% confidence level for all quintiles ($|t$-statistics$| < 2$). This is very similar to Table 7, where no alphas were significant as well.

These results indicate that the FF4F model can predict the returns of value-weighted portfolios if the data are not sorted based on the sentiment level index. The higher excess return of higher MAX portfolios is caused not by unobserved factors but by stock and firm characteristics, such as size, momentum, market beta and book-to-market ratios. Higher MAX quintile portfolios also show higher volatility and the same Sharpe ratio as lower MAX quintiles. Therefore, the price of risk is the same for all portfolios.

Thus, after concluding the robustness check, it can be claimed that we get a robust result of higher MAX value-weighted portfolios generating higher excess return but only due to difference in stock characteristics, as no portfolio generates significant alpha.

Then, in Table 16 we proceed with the same algorithm for equal-weighted portfolios. The results seem very similar to what we achieved earlier for equal-weighted decile portfolios. Both excess returns and alphas are lower for higher MAX portfolios: the difference between excess returns of fifth and first equal-weighted quintiles is -0.88% with a t-stat of -2.32, while the same number for FF4F alphas difference is -0.75% with a t-stat of -2.42.

Therefore, Table 16 supports results achieved earlier for decile equal-weighted portfolios as all the tendencies and trends are the same, and the difference in alphas is negative and significant.

Table 14 reports the same data as Table 13 but is sorted by sentiment level index of the previous month. The results of the robustness test are very similar to the original model. The difference between the tenth and first quintile's excess returns is 0.72% in the low sentiment state, while the difference in alphas is 0.12%. For the high sentiment, the difference is 0.29% and -0.26%, respectively. Compared to table 8, where we conducted the original testing of the hypothesis, these numbers have smaller magnitude (original low sentiment difference: 1.61% excess returns and 0.85% alphas, original high sentiment difference: 0.45% excess returns and -0.05% alphas difference).

However, the overall trend is the same: for the low sentiment, the difference in returns is higher while there is a higher chance that a significant difference in alphas of the quintile MAX portfolios exists in a low sentiment state. The alphas are still insignificant for most of the portfolios. Nonetheless, t-statistics in low sentiment states are much higher for most portfolios, which implies higher of their alpha being significant.The Sharpe ratios for all high MAX quintiles are lower despite the state of the market. However, in the high sentiment states, the difference in Sharpe ratios is much larger.

In Table 15, we perform the same steps as in Table 14, but now, we inspect equal-weighted portfolios instead of the value-weighted ones. The table further supports our observations for equal-weighted portfolios: the alphas and excess returns decrease towards high MAX quintile portfolios, and the magnitude of the MAX effect is greater in low sentiment state. If the difference in alphas in high sentiment state is -0.55% with a t-stat of -1.30, in low sentiment state, it is -0.89% with a t-stat of -1.99.

As a result of the robustness test, we can say that the MAX effect's magnitude is higher in a low sentiment state of the market.

6 Conclusion

In this paper, we examined the MAX effect and possible influence it can have on the Swedish stock market. The primary question of this paper was whether stocks with higher daily returns in a month tend to generate a lower return in the future in the Swedish stock market.

We found some support for this claim based on the analysis of stock data for a 30-year long sample. The results state that the MAX effect has a negative influence on stock returns. This effect is more strong on the portfolio level rather than the firm level. However, it only appears if the portfolios are equal-weighted, and it does not show any significant effect on value-weighted portfolios. These results are robust after changing the MAX definition from a one-day return to the arithmetic mean of five max returns in a month and creating quintile portfolios sorted by MAX instead of decile MAX-sorted portfolios.

Our additional question was whether stocks that exhibit high MAX in one month tend to retain it. Again, we discovered results in support of this hypothesis. First of all, our results of Fama-Macbeth regression on MAX of the current month over MAX of the previous month indicate that there is a strong dependence between these two. Moreover, our results for the transition matrix, where all the probabilities for stocks to move between decile MAX portfolios, show that the probability for stocks to stay in the highest MAX portfolio is extraordinarily high.

We also developed a robustness check for the results, where we changed the MAX definition from one-day maximum return in the previous month to an average of five maximum daily returns over the same period. The results support our initial conclusions and show high dependency between the MAX of the previous period and the current one.

Finally, we studied if following the month with a high sentiment level, the difference between Fama-French-Carhart four-factor model alphas of high and low MAX portfolios is greater. We achieved the results that not only do not support this hypothesis but also indicate the opposite.

The outcome of our MAX decile portfolio analysis shows that the difference between the highest MAX decile and the lowest MAX decile abnormal returns is only present if the sentiment of the previous month is low. These results are robust after creating quintile portfolios instead of decile ones and still gives the same result.

Our analysis opens several new possible ways to develop this topic further. One of them is to analyze the MAX effect on a broader scale: the Nordic countries. There is no doubt that Sweden is very closely tied with its neighbors, both culturally and economically. It would be interesting to see how MAX affects stock returns in the whole region and whether trends outlined in this paper exist in the Nordic region. However, this would require much more data gathering and cleaning.

Another possible way to develop our findings is to find new ways to expand and upgrade the sentiment level index and see if any other price anomalies are dependent on it. For instance, the sentiment level index could be created using different set of data or sentiment proxies. Moreover, other market anomalies can be analyzed to see if the anomaly effect is weakened or strengthened in one sentiment state or the other.

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Appendix

Table 11: Firm-level Cross-sectional Return Regression(Robustness Test)

MAX	BETA	SIZE	BM	MOM	REV	ILLIQ
-0.1158						
(-3.22)						
	-0.0005					
	(-0.57)					
		0.0006				
		(2.72)				
			-0.0030			
			(-2.10)			
				0.0075		
				(6.26)		
					0.0110	
					(1.94)	
						-186.91
						(-0.38)
-0.1053	-0.0004	0.0001	-0.0013	0.0068	0.0127	-465.56
(-2.39)	(-0.39)	(0.40)	(-0.95)	(4.75)	(1.97)	(-1.05)

We created this table following Bali et al. (2011). Every month from November 1993 to December 2019, we run a firm-level regression of the return on subsets of lagged predictor variables including arithmetic mean of 5 maximum daily returns in the previous month an other seven variables that are defined in the Appendix. The table reports the time-series averages of the cross-sectional regression coefficients and their associated t-statistics.

Table 12: Cross-sectional Predictability of MAX (Robustness Test)

MAX	BETA	SIZE	BM	MOM	REV	ILLIQ
0.4718						
(16.94)						
	-0.0011					
	(-0.91)					
		-0.0069				
		(-33.27)				
			-0.0013			
			(-1.10)			
				-0.0044		
				(-2.39)		
					-0.0144	
					(-3.84)	
						1281.369
						(2.68)
0.2406	0.0009	-0.0060	-0.0046	0.0001	-0.0043	214.17
(8.17)	(1.48)	(-30.94)	(-4.52)	(0.11)	(-1.36)	(0.80)

We created this table following Bali et al. (2011). Every month from November 1993 to December 2019, we run a firm-level regression of the next month's MAX on subsets of lagged predictor variables including arithmetic mean of 5 maximum daily returns in the previous month an other seven variables that are defined in the Appendix. The table reports the time-series averages of the cross-sectional regression coefficients and their associated t-statistics.

Table 13: Returns and alphas of MAX portfolios (quintiles, value-weighted)

Quintile	Excess Return (%)	Std.Dev. (%)	Sharpe Ratio	FF4F Alpha (%)	Alpha t-stats	Beta	Beta t-stats
1	1.34	4.48	0.30	0.35	(1.97)	0.79	(20.94)
2	1.02	5.10	0.20	-0.29	(-1.72)	0.97	(27.16)
3	1.07	5.85	0.18	-0.35	(-1.80)	1.09	(26.92)
4	1.61	8.94	0.18	0.22	(0.61)	1.23	(16.17)
5	1.75	8.73	0.20	0.33	(0.78)	1.20	(13.61)
$5-1$	0.41			-0.02			
	(0.85)			(-0.05)			

The table shows characteristics of quintile portfolios sorted by the MAX effect every month. The sample period is from January 2001 to December 2019. The excess return shows the mean return in excess of the risk-free rate (repo rate) and Std.Dev. column is standard deviation of excess return. Sharpe Ratio is excess return divided by its standard deviation. The FF4F Alpha shows Fama-French-Carhart alpha with its t-statistics in column Alpha t-stats. Columns 7 and 8 are market betas of FF4F and its t-statistics. The last row $(5-1)$ shows the average returns and alphas of a portfolio that longs the High MAX quintile and shorts the Low MAX quintile, as well as t-statistics for the difference. All returns are expressed in percent per month.

Table 14: Returns of MAX portfolios following high and low sentiment states (quintiles, value-weighted)

Quintile	Excess Return (%)	Std.Dev. (%)	Sharpe Ratio	FF4F Alpha (%)	Alpha t-stats	Beta	Beta t-stats
Panel A. High sentiment							
1	1.15	4.73	0.24	0.29	(1.17)	0.85	(15.66)
2	1.13	5.07	0.22	0.13	(0.53)	1.00	(19.02)
3	0.88	5.84	0.15	-0.17	(-0.67)	1.10	(19.64)
4	1.06	7.69	0.14	-0.05	(-0.10)	1.17	(11.61)
5	1.44	8.99	0.16	0.03	(0.07)	1.30	(12.50)
$5-1$	0.29			-0.26			
	(0.44)			(-0.49)			
Panel B. Low sentiment							
1	1.56	4.25	0.37	0.40	(1.54)	0.75	(14.54)
2	0.97	5.13	0.19	-0.70	(-2.87)	0.97	(19.80)
3	1.39	5.75	0.24	-0.42	(-1.44)	1.07	(18.40)
4	2.27	9.97	0.23	0.76	(1.37)	1.28	(11.55)
5	2.27	8.23	0.28	0.52	(0.78)	1.04	(7.75)
$5-1$	0.72			0.12			
	(1.06)			(0.18)			

The table shows characteristics of quintile portfolios sorted by the MAX effect every month. The table is sorted in two panels based on the sentiment level of the market. Panel A includes observations with high sentiment in the previous month and Panel B includes low sentiment observations. The sample period is from January 2001 to December 2019. The excess return shows the mean return in excess of the risk-free rate (repo rate) and the Std.Dev. column is standard deviation of excess return. The Sharpe Ratio is excess return divided by its standard deviation. The FF4F Alpha shows Fama-French-Carhart alpha with its t-statistics in column Alpha t-stats. Columns 7 and 8 are market betas of FF4F and its t-statistics. The last row $(5-1)$ of each panel shows the average returns and alphas of a portfolio that longs the High MAX quintile and shorts the Low MAX quintile, as well as t-statistics for the difference. All returns are expressed in percent per month.

Table 15: Returns of MAX portfolios following high and low sentiment states (quintiles, equal-weighted)

Quintile	Excess Return (%)	Std.Dev. (%)	Sharpe Ratio	FF4F Alpha (%)	Alpha t-stats	Beta	Beta t-stats
Panel A. High sentiment							
1	1.27	4.86	0.26	0.35	(2.11)	0.85	(23.04)
2	1.13	5.29	0.21	0.11	(0.67)	0.97	(27.55)
3	1.06	6.30	0.17	-0.01	(-0.04)	1.08	(19.97)
4	0.85	6.72	0.13	-0.15	(-0.62)	1.12	(20.47)
5	0.50	7.76	0.06	-0.20	(-0.52)	0.99	(11.30)
$5-1$	-0.77			-0.55			
	(-1.55)			(-1.30)			
Panel B. Low sentiment							
1	1.91	5.08	0.38	0.30	(0.98)	0.81	(13.32)
2	1.40	5.19	0.27	-0.30	(-1.70)	0.91	(25.67)
3	1.66	6.28	0.26	-0.25	(-1.12)	1.04	(23.34)
4	1.44	7.43	0.19	-0.30	(-1.34)	1.13	(25.25)
5	1.10	7.89	0.14	-0.60	(-1.81)	1.12	(16.95)
$5-1$	-0.81			-0.89			
	(-1.48)			(-1.99)			

The table shows characteristics of quintile portfolios sorted by the MAX effect every month. The table is sorted in two panels based on the sentiment level of the market. Panel A includes observations with high sentiment in the previous month and Panel B includes low sentiment observations. The sample period is from January 2001 to December 2019. The excess return shows the mean return in excess of the risk-free rate (repo rate) and the Std.Dev. column is standard deviation of excess return. The Sharpe Ratio is excess return divided by its standard deviation. The FF4F Alpha shows Fama-French-Carhart alpha with its t-statistics in column Alpha t-stats. Columns 7 and 8 are market betas of FF4F and its t-statistics. The last row $(5-1)$ of each panel shows the average returns and alphas of a portfolio that longs the High MAX quintile and shorts the Low MAX quintile, as well as t-statistics for the difference. All returns are expressed in percent per month.

Table 16: Returns and alphas of MAX portfolios (quintiles)(equal-weighted)

Quintile	Excess Return (%)	Std.Dev. (%)	Sharpe Ratio	FF4F Alpha (%)	Alpha t-stats	Beta	Beta t-stats
1	1.57	4.97	0.32	0.31	(1.82)	0.83	(22.86)
2	1.24	5.23	0.24	-0.10	(-0.87)	0.93	(36.74)
3	1.33	6.29	0.21	-0.12	(-0.73)	1.06	(30.69)
4	1.08	7.12	0.15	-0.25	(-1.53)	1.12	(32.21)
5	0.70	7.95	0.09	-0.44	(-1.69)	1.07	(19.70)
$5-1$	-0.88			-0.75			
	(-2.32)			(-2.42)			

The table shows characteristics of quintile portfolios sorted by the MAX effect every month. The sample period is from January 2001 to December 2019. The excess return shows the mean return in excess of the risk-free rate (repo rate) and Std.Dev. column is standard deviation of excess return. Sharpe Ratio is excess return divided by its standard deviation. The FF4F Alpha shows Fama-French-Carhart alpha with its t-statistics in column Alpha t-stats. Columns 7 and 8 are market betas of FF4F and its t-statistics. The last row ($5-1$) shows the average returns and alphas of a portfolio that longs the High MAX quintile and shorts the Low MAX quintile, as well as t-statistics for the difference. All returns are expressed in percent per month.