Journal of Business and Management Studies
ISSN: 2709-0876
DOI: -------------
Journal Homepage: www.al-kindipublisher.com/index.php/jbms

JBMS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

MAX Effect and Investor Sentiment: Evidence from the Swedish Stock Market

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| ABSTRACT
Motivated by existing literature on the impact of maximum daily returns (MAX) on subsequent stock returns and its connection to market sentiment, we investigate the potential effect of MAX on stock performance in Sweden and its relationship with market sentiment. Portfolio-level analyses provide evidence that MAX negatively affects the returns of stocks listed in Sweden, while firm-level cross-sectional regressions indicate that MAX has little to no effect on individual stock returns. Furthermore, the results indicate that the magnitude of the MAX effect is more pronounced when sentiment in the Swedish stock market was low in the previous month. The findings also suggest that high-MAX stocks are likely to retain their high MAX in future months. Finally, all findings remain robust across variations in portfolio sorting methodologies and alternative definitions of MAX.

| KEYWORDS
MAX Effect, Extreme Returns, Investor Sentiment, Lottery-type Stocks, Stock Return Predictability, Sweden Stock Market

| ARTICLE INFORMATION
ACCEPTED: 15 March 2025 **PUBLISHED:** 17 April 2025 **DOI:** 10.32996/jbms.2025.7.2.13

1. Introduction
MAX effect refers to the negative relationship between a stock's maximum daily return within a month and its return in the subsequent month. This phenomenon has been extensively studied by economists over the past decade, with tests conducted across various countries and regions. In most cases, MAX has been shown to have a significant impact on stock pricing. The potential tendency of investors to favor lottery-like stocks has opened avenues for numerous studies. However, this phenomenon has yet to be explored in the Nordic region, particularly in the Swedish stock market. Moreover, while the relationship between market sentiment and the MAX effect has been established in several countries, no such investigation has been conducted in Sweden.

The primary research question addressed in this study is:
Q1: Is there a negative relationship between the maximum daily return (MAX) and future stock returns in the Swedish stock market?

To answer this question, we collect data from the Swedish stock market and form decile portfolios each month based on MAX, performing a comparative analysis of their returns. Following this, we conduct stock-level Fama-MacBeth regressions to examine the effect of the previous month's MAX on the current month's MAX and returns. After addressing the primary research question, we construct a sentiment index using Swedish macroeconomic and stock market data to investigate the influence of sentiment levels on the MAX effect. Additionally, we analyze the differences in monthly returns between decile portfolios sorted by both MAX and sentiment levels. Based on this, our additional research questions are:
Q2: Are stocks that exhibit a high MAX in one month more likely to exhibit a high MAX in the following month?
Q3: Following a month with high sentiment, how do the Fama-French-Carhart four-factor model alphas of high-MAX and low-MAX portfolios differ?

We answer these questions by running a regression of the current month's MAX on the previous month's MAX, along with a set of additional independent variables, to determine whether the previous month's MAX can predict the current month's MAX. Additionally, we construct a probability matrix to illustrate the likelihood of stocks switching their MAX decile in subsequent months. We then create a sentiment index using Principal Component Analysis (PCA), enabling us to analyze the MAX effect under different sentiment conditions.

This research offers several important contributions to the existing literature on stock price anomalies and investor behavior in the Swedish equity market. First, it establishes a clear link between the MAX effect and stock returns in the Swedish stock market. Our results align with those of Bali et al. (2011), confirming the negative effect of MAX on returns and the strong dependence of MAX on the previous month's MAX value. This provides a deeper understanding of price anomalies and has practical implications for predicting future stock returns and assessing whether certain stocks are overpriced.

Second, we find that the Swedish stock market shares certain characteristics with the U.S. stock market while also exhibiting unique features. Specifically, the MAX effect has a greater impact at the portfolio level than at the individual stock level and shows limited influence on value-weighted portfolios. These findings highlight market-specific behaviors and contribute to a broader understanding of how the MAX effect operates in different financial environments.

Third, we develop a sentiment index and investigate its relationship with the MAX effect, following the approach of Baker and Wurgler (2006). To the best of our knowledge, this relationship has not been extensively explored in the Swedish market. Our findings reveal that the difference in portfolio returns becomes more pronounced during periods of low sentiment, suggesting that investor sentiment significantly influences the strength of the MAX effect.

Finally, this research sheds light on broader tendencies and patterns in investor behavior and stock pricing within the Swedish stock market. By examining both the MAX effect and investor sentiment, we provide new insights into how behavioral factors interact with price anomalies, contributing to a more comprehensive understanding of stock market dynamics.

Our findings reveal that the MAX effect is present in the Swedish stock market at the portfolio level but not at the individual stock level. The evidence indicates that the returns of equal-weighted portfolios are influenced by the maximum daily return of the previous month. Furthermore, stocks with high MAX values tend to retain their high MAX over time. When incorporating the sentiment index, we observe that during periods of low sentiment, the difference in excess returns between portfolios is more pronounced. In contrast, during high-sentiment periods, both the variation in returns and the magnitude of unexplained returns diminish.

Overall, we uncover several interesting and unique characteristics of the Swedish stock market, including the presence of the MAX effect, the persistence of high MAX values in stocks, and the dependence of MAX dynamics on sentiment conditions. These findings offer opportunities for further examination and provide a foundation for future research extensions.

2. Literature Review

The role of extreme positive returns in the cross-sectional pricing of stocks and the term "MAX effect" was first introduced by Bali et al. (2011). They describe the MAX effect as the relationship between a stock's maximum daily return during a month (MAX) and its lower future returns. In their paper, they provide two key explanations for the existence of the MAX effect: first, the lack of diversification in investor portfolios, and second, a preference for lottery-like stocks, which are low-priced stocks with high idiosyncratic volatility and high idiosyncratic skewness (Kumar, 2009). Taking these factors into account, Bali et al. (2011) found that investors are more likely to pay a premium for stocks that demonstrate extreme positive returns. As a result, these stocks tend to deliver lower future returns. Conversely, stocks with extreme negative one-day returns exhibit the opposite behavior, showing higher future returns as investors undervalue them. This conclusion aligns with cumulative prospect theory (Tversky and Kahneman, 1992) and the optimal beliefs framework (Brunnermeier et al., 2007).

Subsequent research has reinforced the persistence of the MAX effect across various regions and expanded the geographical scope of the investigation. For instance, Fong and Tah (2014) demonstrate that a MAX strategy—longing a value-weighted portfolio of high-MAX stocks and shorting a value-weighted portfolio of low-MAX stocks—yields 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) introduced the concept of a sentiment index. By sentiment, the authors refer to beliefs about future cash flows and investment risks that are not supported by the available facts. They argue that it is costly to bet against prevailing sentiment, which limits the ability of rational investors, or arbitrageurs, to force prices back to their fundamental values as standard models would predict. Therefore, the authors suggest that there are limits to arbitrage and establish a connection between the

MAX effect and overall market sentiment which is supported by recent research emphasizing the role of investor sentiment in financial anomalies (Tashakkori et al., 2024).

Baker and Wurgler (2006) also developed a methodology for constructing a sentiment index using a macroeconomic approach. They describe potential components and proxies for this index, such as trading volume, investor surveys, and dividend premiums. The authors emphasize that there is no single correct method for estimating sentiment levels; rather, various proxies can be used depending on data availability and their relevance to different areas of the market (e.g., households, investment funds, and the stock market as a whole).

Cheema et al. (2020) and Han and Li (2017) further developed the concept introduced by Baker and Wurgler (2006) by creating a sentiment index through the estimation of the first principal component from the residuals of three individual sentiment proxies: the price-to-earnings ratio (PE), turnover ratio (TO), and the number of newly opened individual investor accounts (IIA). Baker and Wurgler (2006) suggested that the residuals from the orthogonalization procedure can serve as proxies for the irrational component of investor sentiment, thus allowing the PCA and residuals method to accurately determine the sentiment index.

Expanding the geographical scope of Bali et al. (2011), Walkshäusl (2014) and Aboulamer and Kryzanowski (2016) investigated the MAX effect in EU countries and Canada, respectively. However, the conclusions of these studies differ. While Walkshäusl (2014) found evidence of the MAX effect in the EU stock market, Aboulamer and Kryzanowski (2016) reported no such effect in Canada, suggesting that Canadian investors do not favor stocks with high maximum daily returns.

Despite the extensive research on the MAX effect across various regions, it has not yet been examined in the Swedish market. Furthermore, the presence and direction of the MAX effect may vary depending on a country's specific market characteristics. Therefore, it is valuable to investigate whether this effect exists in Sweden. Additionally, the relationship between sentiment and the MAX effect remains underexplored—a dynamic that reflects broader findings in the literature, such as the role of investor behavior in shaping market inefficiencies (Askarzadeh et al., 2024a). This gap in the literature motivated us to examine this connection, as it has only been analyzed in a few countries, excluding Sweden.

In this paper, we explore whether the MAX effect is present in the Swedish stock market and whether it is linked to the sentiment index, which we construct as part of our analysis.

3. Data

In our research, we use a list of Swedish company stocks covering the period from January 1994 to December 2019. The stock data were acquired from the FinBas database. We use daily stock price data to calculate the returns and maximum daily returns (MAX) for each stock. The stock prices at the end of each month are used to calculate the monthly returns and other characteristics, such as illiquidity, size, idiosyncratic volatility, momentum, skewness, and book-to-market ratio, as described in the Methodology section. We use market values, book values, and trading volumes to calculate these ratios, all of which were obtained from the FinBas database. Figures in different currencies were converted to Swedish Krona using Riksbank exchange rates.

We exclude stocks with less than 10 observations per month from the sample to ensure data quality. Additionally, stocks that had been listed on the market for less than two years were excluded, as their inclusion would result in insufficient data points for the Fama-MacBeth regressions, affecting the representativeness of the results. Moreover, several data errors were identified due to typographical mistakes in the database. For example, one stock increased exactly 100 times in one day and decreased by exactly 100 times the following day. Since such movements are highly improbable in real-market conditions, we adjusted these values to align with the stock's overall performance history. After cleaning the data and calculating the necessary ratios, the dataset was sufficient to test our first hypothesis.

To test the additional hypothesis, we constructed a sentiment index. For this purpose, we obtained the price-to-earnings (PE) ratios of all Swedish companies from DataStream. These ratios were then value-weighted to calculate the overall Swedish market PE ratio. To verify the accuracy of the data, we cross-checked the PE ratios with data from Morningstar Direct. The results were highly consistent, confirming the reliability of our calculations. Consequently, we decided to use the DataStream dataset for our analysis. We also gathered data on Swedish mutual funds' net cash flows from Morningstar Direct. Finally, turnover data were obtained from FinBas, consistent with the data used in testing our first hypothesis. However, for the sentiment index, the turnover data were value-weighted to reflect the Swedish stock market more accurately.

In addition to stock-level data, we collected macroeconomic data from various sources to construct the sentiment index. Specifically, we gathered M3 growth data from Statistics Sweden's website, the repo rate and the Euro-to-Swedish Krona exchange rate from Riksbank's website, industrial production growth in Sweden from Eurostat's database, and the consumer confidence index from the Organization for Economic Co-operation and Development (OECD) database. After cleaning and organizing the data, we compiled a continuous time series spanning from January 2001 to December 2020. These data were sufficient to test our hypotheses.

4. Methodology

4.1 The MAX effect and Cross-section of Stock Returns

4.1.1 Data Construction

As previously mentioned, we obtained the monthly and daily stock data from the FinBas dataset. Our analysis covers the period from January 1994 to December 2019, as some variables, such as turnover, are unavailable before this period. We believe that the length of this time period is sufficient to construct representative econometric models to test our hypotheses.

The dataset, however, provides only stock price data and does not include stock returns. Therefore, we acquired the last price data (instrument LAST in 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, ensuring the comparability of prices within a time series over time. This measure was chosen because it allows us to capture all price changes within the specified time period. Additionally, only stocks traded on the Stockholm Stock Exchange in SEK were included in the dataset. Consequently, we assume that this sample accurately represents the behavior of publicly traded Swedish companies.

After loading the data and converting them to a consistent format, we calculated the returns for all selected stocks using the following return formula:

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

where $R_{i,t}$ is the return of the stock i in time period t and $LAST_{i,t}$ is the last traded price of the stock i in time period t. After performing this procedure for both the monthly and daily data, we calculate the maximum daily return of each stock for every month. This value is then merged with the monthly data to serve 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 (1993), is the cumulative return of each stock in the previous 11 months starting from month $t-2$ 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, which is calculated as follows:

$$ILLIQ_{i,m} = 1/D_{i,m} \sum_{t=1}^{D_{i,m}} \frac{|R_{i,t}|}{VOLD_{i,t}}$$

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

Size of a firm, following Bali et al. (2011), is defined as the natural logarithm of the market value of equity, which is computed as the stock's price multiplied by the number of shares outstanding, expressed in SEK millions. If a firm's market value was not reported in Swedish Krona, we converted it using Riksbank's monthly exchange rate data.

Book-to-market Ratio (BM) is the ratio of a company's book value to its market capitalization. We computed this variable using monthly market capitalization data and yearly book value data from the FinBas database, which was collected from companies' annual reports. *Beta*, following Bali et al. (2011), is estimated via assuming a single factor return generating process:

$$R_{i,d} - r_{f,d} = a_i + b_i(R_{m,d} - r_{f,d}) + e_{i,d}$$

where $R_{i,d}$ is the return on stock *i* on day *d* and, $R_{m,d}$ is the market return on day *d*, $r_{f,d}$ is the risk-free rate on day *d*, and $e_{i,d}$ 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 b_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*:

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

4.1.3 Descriptive Statistics

Figure 1 depicts the number of stocks used in forming the decile portfolios from January 1994 to December 2019. As expected, due to a higher number of new listings compared to delistings each year, there is an upward trend in the number of stocks. The dataset begins with 90 stocks and grows to 321 by the end of the period, with an average of 257 stocks throughout. For more reliable results, we excluded stocks that had been traded for less than 24 months, which explains the decline in stock count during the final two years.

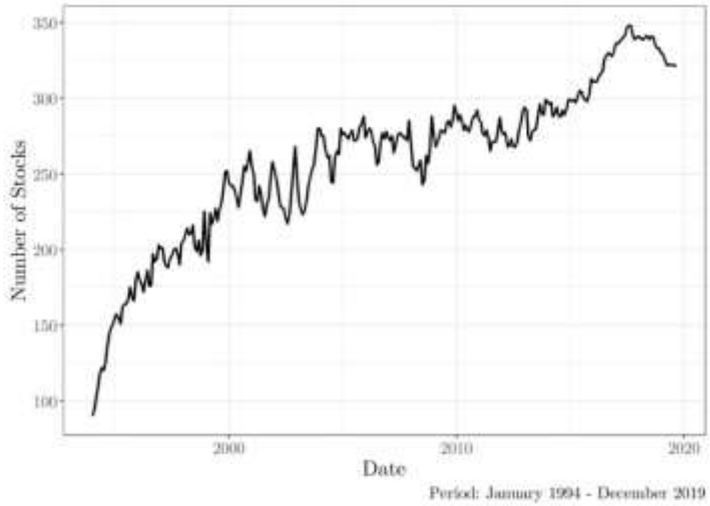

Figure 1: Number of Stocks in the Sample

Value-weighted MAX portfolios are formed monthly from January 1994 to December 2019 by sorting stocks on the Stockholm Stock Exchange based on their maximum daily return in the previous month (MAX). Decile 1 (D1) represents the portfolio of stocks with the lowest MAX in the previous month, while Decile 10 (D10) includes stocks with the highest MAX over the same period.

Table 1 presents the summary statistics of the analyzed sample of Swedish stocks. As shown in Panel A, there are, on average, 25 to 26 firms in each decile at any given time. The market share of the portfolios indicates that the closer to D1, the larger the market share. Portfolios D1–D3 (Lower MAX) account for more than 48% of the total market capitalization on average, whereas portfolios D8–D10 (High MAX) represent almost 12%.

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 monthly from January 1994 to December 2019 by sorting stocks on the Stockholm Stock Exchange based on their maximum daily return in the prior month. Decile portfolio 1 (D1) includes stocks with the lowest MAX, while decile portfolio 10 (D10) includes the highest-MAX stocks. Panel A presents the average number of stocks per decile and the average percentage of market capitalization represented by stocks in the corresponding decile. Panel B reports the average (across each decile over the entire period) of the median (across deciles and months) values of stock attributes for every decile portfolio. These attributes include 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).

Panel B provides an overview of several general attributes of the firms within each decile portfolio. Each attribute represents the average (calculated across each decile over the entire period) of the median (calculated across deciles and months) values of that attribute. The methodology for constructing these variables is discussed in detail in Section 4.1.2. For example, the average spread of MAX returns between decile portfolios 10 and 1 is 4.43%.

It is also notable that average company capitalization and average stock price exhibit a steep declining trend from D1 to D10. The average median share price and capitalization in D1 are 47.4 SEK and 7.82 billion SEK, respectively, whereas for D10, these figures drop to 21.0 SEK and 0.51 billion SEK, respectively.

Beta in Panel B represents the market beta of each decile portfolio. Beta is lowest for D1 (0.50) and increases up to D4. From D4 to D10, beta stabilizes at a similar level, around 0.65–0.67. The average book-to-market (BM) ratio often considered a firm distress factor Fama and French (1992) tends to decrease as we move from D1 to D10, declining from 0.6 to 0.5.

Illiquidity is measured using the formula developed by Amihud (2002). A clear pattern can be observed across the deciles: illiquidity increases as we move toward D10. For D10, the average illiquidity is $17.51*10^{-8}$, while for D1, it is $0.80*10^{-8}$.

Finally, average idiosyncratic volatility (IVOL) is calculated following the formula provided by Bali et al. (2011). Consistent with Kumar (2009), average idiosyncratic volatility tends to rise from the first to the tenth decile portfolio. For D1, IVOL is 1.36%, while for D10, it reaches 3.31%.

4.1 Sentiment Level Index Creation

To develop the sentiment index, we primarily applied the method used by Baker and Wurgler (2006), while also referencing Han and Li (2017) and Fong and Toh (2014) for complementary guidance.

To measure sentiment, we first identified several proxies: the market turnover ratio (TURN), dividend premium (DIV), and net aggregate flow to mutual funds (FMF). As noted by Han and Li (2017), there are no definitive or universally accepted measures of market sentiment. Sentiment proxies are highly country-specific and are influenced by data availability. Below, we discuss each of the sentiment proxies used to construct the sentiment index.

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

Dividend Premium (DIV): According to the Catering Theory of Dividends proposed by Baker and Stein (2004), the decision to pay dividends is influenced by prevailing investor demand for dividend-paying stocks. Baker and Wurgler (2007) suggest that there may be an inverse relationship between the premium for dividend-paying stocks and investor 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 non-payers.

Dividend data were obtained from FinBas. First, companies are sorted into two groups each month based on whether they paid dividends during that month. Then, the monthly value-weighted market-to-book ratio is calculated for both payers and non-payers using the following formula:

$$MB_t = \frac{(1/BM_{i,t}) - MV_{i,t}}{\sum_{i=1}^{n} MV_{i,t}}$$

where MB_t is the value-weighted market-to-book ratio of dividend payers or non-payers in month *t*, $BM_{i,t}$ is the book-to-market ratio of company *i* at time *t*, and $MV_{i,t}$ is the market value of company *i* at time *t*, with *n* companies in month *t* within the chosen subset (payers or non-payers).

The dividend premium is then calculated using the following formula:

$$DIV_t = ln\left(MB_t^p\right) - ln\left(MB_t^{np}\right)$$

where DIV_t is the dividend premium in month *t*, MB_t^p is the 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, the author finds that mutual fund flows increase when individual investors become more bullish in both the previous and current periods. While Baker and Wurgler (2006) use the closed-end fund discount as a proxy for sentiment, the low number of closed-end funds in Sweden led us to replace it with mutual fund flows.

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

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

where $NAV_{i,t}$ is the value of net assets under management for fund i in month t and r_t is the return of fund i in month t. We calculate the net aggregate flow to all mutual funds each month by summing the net flows to all individual mutual funds.

Overall, the three described proxies serve as valuable components for constructing an investor sentiment index, as they tend to fluctuate with market conditions and effectively capture the mood of the Swedish stock market. Moreover, all these variables are available throughout the sample period, with no missing values, artificial data points, or interruptions.

To accurately construct a local sentiment index for the Swedish stock market, we follow several steps outlined below. First, we examine all the sentiment proxies for the presence of trends unrelated to market sentiment, following Baker and Wurgler (2007). We identify a deterministic upward trend in both the turnover ratio and the net aggregate flow to mutual funds. This trend is associated with the overall growth of the Swedish stock market over the sample period and is not linked to market sentiment. To eliminate this trend and ensure valid, representative sentiment proxies, we normalize these variables by dividing them by their respective five-month moving averages. This approach, developed by Baker and Wurgler (2007) and Chen et al. (2014), also ensures that all proxies remain stationary throughout the sample period.

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

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

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

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

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:

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

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 key challenge in forming the sentiment index is addressing the relative timing of the variables. In other words, some variables may reflect sentiment earlier or later than others. Therefore, following Baker and Wurgler (2006), we estimate the first principal component (PCA) of six proxies: $TURN_t$, DIV_t, FMF_t, and their one-month lags, $TURN_{t-1}$, DIV_{t-1}, FMF_{t-1}. Next, we examine the correlations between the created index and these six variables. According to Table 2, which presents these correlations, we select $TURN_t$, DIV_{t-1} and FMF_{t-1} to include in our final PCA, as they exhibit higher correlations with the first-stage index compared to their counterparts.

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

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

As noted in Baker and Wurgler (2007), sentiment proxies consist of both an irrational component and a rational one. The rational component is influenced by macroeconomic conditions and the overall state of the economy. Investors receive information about these factors, which in turn affects their sentiment. To minimize and filter out the rational component, we follow the approach suggested by Baker and Wurgler (2006) and Verma and Soydemir (2009). This approach involves regressing each sentiment proxy on a selected set of macroeconomic variables and then using the residuals from these regressions to construct the sentiment index, as these residuals are assumed to represent the irrational component of the sentiment proxies.

The macroeconomic variables used to regress the sentiment proxies include changes in the money supply (M3), changes in industrial orders in Sweden, the Euro-to-SEK exchange rate, and the Swedish repo rate. These variables were selected because they are the primary macroeconomic factors available consistently throughout the sample period without missing values or breaks and because they capture a broad range of economic influences. Moreover, the frequency of these variables matches that of the three sentiment proxies, ensuring consistency in the analysis. Based on these considerations, we concluded that these regressors provide a sufficient and accurate representation of macroeconomic influences on sentiment and its proxies.

Next, we perform principal component analysis (PCA) on the residuals of DIV, TURN, and FMF, extracting the first principal component as the local Swedish sentiment index. The first principal component should effectively capture the variation in individual proxies and provide an accurate representation of the Swedish sentiment index.

The resulting PCA is:

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

Panel A in Table 3 presents the summary statistics for the factors used to construct the sentiment index, along with the index itself. The arithmetic means and standard deviations of the three components used to create the sentiment index are 0 and 1, respectively, as they were standardized prior to index construction to ensure comparability and facilitate their use in PCA analysis. The same scaling was applied to the sentiment index itself.

Table 3: Descriptive Statistics of PCA Model

Panel A. Summary statistics

Variable	Obs.	Mean	St. dev.	Median	Min	Max
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

Variable	*Ret*	S_t^{PCA}	*TURN*	*DIV*	*F MF*
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 de-trended 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.

The mean monthly market excess return is 0.79%, with a standard deviation of 5.20%, resulting in a Sharpe ratio of 0.15. This indicates that the price of risk is low in the Swedish stock market, suggesting limited compensation for taking on additional risk. This low price of risk also reflects the relatively high risk aversion of Swedish investors compared to those in other countries.

Panel B in Table 3 displays the correlation matrix of the variables from Panel A. As shown in the table, the correlation between the sentiment index and the residuals of the three proxies (FMF, TURN, and DIV) is relatively high, justifying the creation of the sentiment index. Furthermore, there is no significant correlation among the variables in the table, indicating their independence and validating their use as proxies in constructing the sentiment index using the chosen approach.

5. Empirical Results

5.1 Future Returns and MAX

Table 4 reports the regression coefficients for the relationship between current month returns and a subset of stock characteristics from the previous month. In other words, we conducted Fama-MacBeth regressions to examine the cross-sectional relationship between MAX and other variables from the prior month and their impact on returns in the following month.

We run the following monthly cross-sectional regression:

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

where $R_{i,t+1}$is the return on stock i in month *t+1*. The rest of the variables are defined as Section 4.1.2. Table 4 reports the time-series averages of the coefficients δ_1 to δ_7 over 312 months. The Newey-West t-statistics are provided in parentheses below each coefficient. The average of δ_1, obtained from regressing next month's returns on MAX alone, is -0.0225 with a t-statistic of -1.67. This value becomes -0.0219 with a t-statistic of -0.96 when we regress next month's returns on MAX along with other variables in the regression.

The coefficients on the individual control variables are noteworthy. The size effect is small but statistically significant. The value effect, represented by δ_7, is very small, negative, and significant. Stocks exhibit medium-term momentum, as indicated by a positive and significant coefficient. However, there is no significant relationship between short-term reversal or illiquidity and future stock returns. The coefficient on Beta is close to zero, which contradicts the predictions of the CAPM model.

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)

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 and 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.

The last row of Table 4 provides the full specification, including MAX and the six other variables. In this setting, the coefficient of MAX is -0.0219 and statistically insignificant, which is consistent with the direction of the relationship reported by Bali et al. (2011).

Although most variables are not significant at the 5% level (|*t-statistics*| < *2*), several conclusions can be drawn from Table 4. First, the insignificance of the MAX coefficient, both when considered alone and in the presence of other variables, suggests that the MAX effect is not strong at the individual stock level in the Swedish stock market. However, if the effect is present, its direction aligns with the findings of Bali et al. (2011), who reported a negative relationship between MAX and returns. In Table 4, the coefficient is -0.0225 when regressing next month's returns solely on MAX and -0.0219 when including other variables. Thus, while we cannot conclusively confirm that MAX has a negative effect on future returns, the possibility of such an effect remains.

Interestingly, among the variables in our regression, only momentum and reversal are statistically significant at the 5% confidence level. This finding suggests that future returns in the Swedish stock market are strongly influenced by returns over the previous 12 months. Moreover, higher returns in previous months, on average, lead to higher returns in the current month. Specifically, a 1% increase in a stock's return in the previous month, on average and controlling for other variables, increases the stock's return in the current month by 0.0069%.

Two additional variables worth noting are the book-to-market ratio and firm size. A higher book-to-market ratio is associated with lower returns in the following month, while larger firms, as measured by market capitalization, tend to have higher stock returns. Although the coefficients for these variables are statistically significant when considered in isolation, they lose significance when other variables are included in the regression. This suggests that the effects of these factors likely depend on the presence of other variables in the model.

Although the MAX coefficient is negative, its t-statistics are too low to draw confident conclusions about MAX's effect on individual stock returns. After conducting the analysis and estimating the Fama-MacBeth regression of current-month returns on the previous month's MAX, we find no significant evidence of a negative relationship between a stock's return and its maximum daily return in the prior month at the individual stock level in the Swedish stock market.

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 following equation presents the regression:

$$MAX_{i,t+1} = h_{0,t} + h_{1,t}MAX_{i,t} + h_{2,t}BETA_{i,t} + h_{3,t}SIZE_{i,t} + h_{4,t}BM_{i,t} + h_{5,t}MOM_{i,t} + h_{6,t}REV_{i,t} + h_{7,t}ILLIQ_{i,t}$$

where $MAX_{i,t+1}$ is the return on stock i in month $t+1$. The rest of the variables have been defined in Section 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.

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)

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 and 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.

As shown in Table 5, the MAX of the previous month is significant both on its own and when included with other variables, with t-statistics of 20.0 and 8.30, respectively. The same applies to firm size, which has t-statistics of -43.75 and -35.10, respectively. The book-to-market ratio is not significant when considered on its own, with a t-statistic of 1.90, but becomes significant in the regression with other variables, where it has a t-statistic of -6.74. The high coefficients for illiquidity are explained by the fact that the illiquidity variable itself is very small in magnitude compared to the other variables.

In Table 5, most variables significantly influence the next month's MAX, with the most notable being the MAX of the previous month. The coefficient is positive and significant at the 5% confidence level. Specifically, a 1% increase in the previous month's MAX, on average, increases the current month's MAX by 0.1065%, while controlling for other variables. This result supports the theory that high-MAX stocks tend to retain their MAX over time.

Further supporting this claim is the evidence presented in Table 6, which shows that stocks across all MAX levels tend to remain in the same decile or move just one decile up or down. While stocks in all MAX deciles have a 12% to 18% probability of remaining in the same decile, stocks in decile 10 (D10), representing the highest MAX, have a 30% chance of staying in that decile—twice as high as the other deciles. Thus, although most stocks are most likely to remain in the same decile, the significantly higher probability for D10 stocks strongly supports the claim that stocks with high MAX values in the past are likely to maintain high MAX values in the future.

Regarding other coefficients in Table 5, it is worth noting that firm size has a substantial impact on the following month's MAX. The size coefficient is highly significant and negative, indicating that companies with larger market capitalizations tend to exhibit lower one-day maximum returns. This finding aligns with the summary statistics in Table 1, which show a clear trend of smaller companies being more frequently found in higher MAX deciles. This result is also intuitive, as larger companies typically have lower price volatility and are less likely to experience sharp price spikes, making them less likely to exhibit high MAX values.

Based on the regression results and the probability table in Table 6, we find a significant positive relationship between the MAX of the previous month and the MAX of the current month. Therefore, we support the hypothesis that stocks exhibiting a high MAX in one month are more likely to exhibit a high MAX in the following month.

5.3 Sentiment Level Index

After conducting the PCA using the method outlined in Section 4.2, we calculate the sentiment index for each month using the calculated PCA equation. We then input the corresponding proxies' residuals for each month. Following this, we compute the median of the resulting values (which is -0.1524) and subtract it from the PCA calculation for each month. The resulting differences are presented in Figure 2.

It is important to note that the absolute value of the sentiment index does not directly represent the market's sentiment. Instead, whether the index is above or below the median reflects the relative sentiment level in the stock market. To simplify this, 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 classify 120 months as having high sentiment and 120 months as having low sentiment.

In our research, we utilize this index to categorize the sample into two groups based on the binary variable. Specifically, we use the sentiment index from the previous month: if its value is 1, the observation is assigned to the first group (high sentiment); if 0, it is assigned to the second group (low sentiment). Sentiment serves as an instrument to test our supporting hypothesis, allowing us to assess whether sentiment influences the MAX effect. Our findings reveal that the strength of the MAX effect varies significantly depending on sentiment conditions, ranging from highly pronounced to barely noticeable—a result that will be explored in greater detail later in the text.

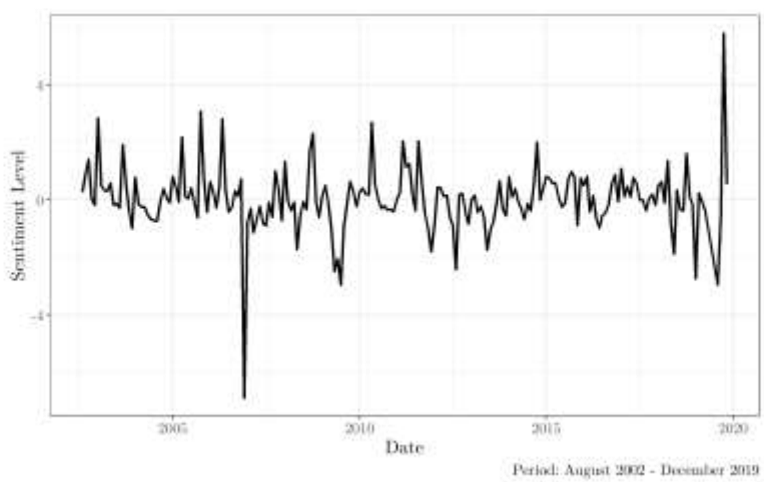

Figure 2: Sentiment Level

Figure 2 illustrates the resulting sentiment index, providing a visual representation of the PCA analysis outcome. While this visualization aids in understanding the sentiment index, the values on the Y-axis—representing deviations from the mean—should not be interpreted as absolute indicators of sentiment levels.

Moreover, since there is no universally established method for constructing a sentiment index, the chosen approach may not align with every individual's interpretation of sentiment. Additionally, some may disagree with the estimated sentiment index for specific dates. However, sentiment is inherently a behavioral concept, and perceptions of the index at any given time may vary across individuals.

In constructing the sentiment index, we carefully gathered data from various sectors of the Swedish financial market and macroeconomic indicators to create an index as representative as possible with the available data. Furthermore, we closely followed the methodology outlined in Baker and Wurgler (2006) to ensure that all relevant factors were captured in the sentiment index's formulation.

5.4 Deciles Returns

Table 6 reports the probabilities of stocks moving from one decile, sorted by the previous month's MAX, to another. The rows represent the initial decile, while the columns indicate the deciles to which stocks move. These probabilities were calculated by dividing the number of times a stock from the current decile moved to a specific decile by the total number of times that stock was in the initial decile.

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

As shown in the table, stocks tend to remain in the same decile over time or move to neighboring deciles. The 10th decile, representing the highest MAX stocks, stands out. Stocks in this decile have a 30.4% chance of remaining there, compared to an 11–15% probability for stocks in other deciles. This suggests that high-MAX stocks are more likely to continue exhibiting high MAX in future months. This finding is consistent with the regression results presented in Table 5, which show a similar outcome.

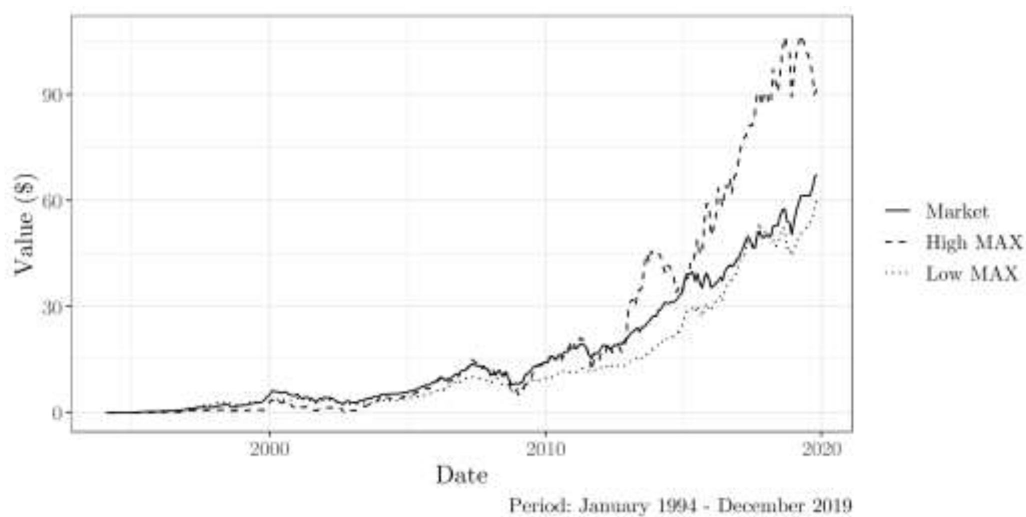

Figure 3: Value of $1 investment in January 1994 throughout the study period

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

Table 7 shows that higher MAX deciles tend to produce higher excess returns, without accounting for sentiment. This trend appears to contradict the results obtained from the regression in Table 4. However, this discrepancy is explainable. First, the observations in the regression in Section 5.1 are equally weighted, meaning each stock contributes equally to the results. In contrast, Table 7 and Table 8 analyze portfolios rather than individual stocks, while Table 4 and Table 5 focus on firm-level results. Finally, the models used in Table 4 and Table 7 differ in structure. The regression in Section 5.1 accounts for all Fama-French-Carhart (FF4F) model factors, whereas Table 7 presents only the excess returns.

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 presents the characteristics of decile portfolios sorted by the MAX effect each month. The sample period spans from January 2001 to December 2019. Excess Return represents the mean return in excess of the risk-free rate (repo rate), while the Std. Dev. column shows the standard deviation of the excess return. The Sharpe Ratio is calculated by dividing the excess return by its standard deviation. FF4F Alpha indicates the Fama-French-Carhart alpha, with its corresponding t-statistics reported in the Alpha t-stats column. Columns 7 and 8 display the market betas from the FF4F model and their respective t-statistics. The last row (10-1) reports the average returns and alphas of a portfolio that takes a long position in the High MAX decile and a short position in the Low MAX decile, along with the t-statistics for the differences. All returns are expressed as percentages per month.

It is worth noting that the standard deviation of portfolio returns increases alongside excess returns. This leads to a higher price of risk and, consequently, a lower Sharpe ratio for the higher MAX portfolios.

In all portfolios, the alphas are insignificant at the 5% confidence level, as previously mentioned. However, the betas for the same decile portfolios are highly significant, with t-statistics around 20 for all portfolios. This indicates that the FF4F model effectively explains portfolio returns on its own.

Notably, the market betas in Table 7 tend to increase from low to high MAX deciles. This suggests that stocks in the higher MAX deciles are more sensitive to market conditions than those in the lower deciles. This finding aligns with Table 1, which shows that firm size decreases from the first to the tenth decile. Therefore, higher deciles consist of smaller companies, which are generally more affected by market fluctuations than the larger firms found in the lower deciles.

Furthermore, the low significance of the alpha values suggests that there are no unexplained return factors for any of the portfolios. All returns can be explained by momentum, book-to-market ratio, market capitalization, and market beta. Thus, MAX does not have a significant effect on these portfolios or their returns.

Regarding the difference between the tenth and first decile portfolios, the latter exhibits lower excess returns on average but nearly the same alpha. Since the alphas are individually insignificant, their difference is also insignificant, equaling -0.05% with a t-statistic of -0.11. Therefore, we can conclude that despite the difference in excess returns, there is no observable influence of MAX on decile value-weighted portfolio returns, and the FF4F model effectively explains these returns.

The situation is markedly different when we examine the equal-weighted decile portfolios. Table 8 presents the same results as Table 7, but in this case, each stock within the portfolios is given equal weight.

In contrast to the value-weighted portfolios, excess returns decrease as we move from D1 to D10, while portfolio return volatility increases. This results in a clear downward trend in Sharpe ratios. The betas of all portfolios remain significant at the 5% confidence level, and market betas tend to be higher for higher MAX portfolios, consistent with the findings in Table 7.

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 presents the characteristics of decile portfolios sorted by the MAX effect each month. The sample period spans from January 2001 to December 2019. Excess Return represents the mean return in excess of the risk-free rate (repo rate), while the Std. Dev. column shows the standard deviation of the excess return. The Sharpe Ratio is calculated by dividing the excess return by its standard deviation. FF4F Alpha refers to the Fama-French-Carhart alpha, with its corresponding t-statistics reported in the Alpha t-stats column. Columns 7 and 8 display the market betas from the FF4F model and their respective t-statistics. The last row (10−1) reports the average returns and alphas of a portfolio that takes a long position in the High MAX decile and a short position in the Low MAX decile, along with the t-statistics for the differences. All returns are expressed as percentages per month.

However, portfolio alphas—or abnormal returns—are now significant and tend to decrease for portfolios with higher MAX. The downward trend in alphas is consistent across deciles. Specifically, the difference in alphas between the tenth and first decile portfolios is -0.99%, with a t-statistic of -2.73. Similarly, the difference in excess returns between these portfolios is -1.09%, with a t-statistic of -2.43.

These results indicate that the FF4F model cannot fully explain the returns of these portfolios. Consequently, we attribute the unexplained alpha to the MAX effect, as the stocks were sorted based on this variable, which is not explicitly accounted for in the FF4F model. Therefore, we conclude that the MAX effect is present in Swedish equal-weighted decile portfolios, and its direction suggests that higher MAX portfolios generate lower returns and produce negative alpha.

There is a significant difference between the returns of equal-weighted and value-weighted portfolios regarding both the direction and magnitude of the MAX effect. While value-weighted portfolios show no significant MAX effect and their returns are well explained by the FF4F model, the equal-weighted portfolios display a MAX effect consistent with Bali et al. (2011) in the U.S. stock market. Specifically, portfolios of stocks with higher MAX tend to generate lower returns and exhibit unexplained negative alpha not predicted by the FF4F model.

This effect aligns with the findings of the regression model in Section 5.1, but its magnitude is more pronounced at the portfolio level. We believe the difference between these portfolio designs is explained by the role of firm size. As shown in Table 1, higher MAX companies tend to be smaller in size. In equal-weighted portfolios, such companies' stocks receive a larger share than they would in value-weighted portfolios, amplifying the influence of smaller, high-MAX firms. Additionally, extreme MAX companies receive larger portfolio allocations, further contributing to the negative effect on returns. According to the regression in Section 5.1, these companies are more likely to negatively affect subsequent returns. In contrast, value-weighted portfolios give more weight to larger, lower-MAX, and non-extreme-MAX companies, thereby mitigating the MAX effect. As a result, no significant difference in unexplained returns is observed in value-weighted portfolios.

5.5 Deciles Returns Relation with Sentiment

Sorting by sentiment level significantly alters the results described in Table 7. Panel A of Table 9 represents the high-sentiment state of the stock market for value-weighted portfolios. Overall, the trends and directions of the effects in this panel align with those observed in Table 7. Excess returns tend to increase from decile 1 to decile 10, along with the standard deviation of excess returns. As a result, the Sharpe ratio decreases from low to high MAX deciles. However, the rate at which the Sharpe ratio decreases is less consistent than in Table 7; it remains lower for higher MAX deciles but fluctuates around 0.17.

Regarding the alphas and betas from the FF4F model in Panel A of Table 9, their patterns mirror those in Table 7. Almost all alphas are insignificant, except for the second decile, where the t-statistic is high enough to consider the alpha borderline significant (t-stat = 1.89, alpha = 0.56%). The market betas for all portfolios remain highly significant; however, the sharp increase in beta from D1 to D10 seen previously is no longer present.

Table 9: Returns and alphas of MAX portfolios following high and low 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	(13.68)
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 presents the characteristics of decile portfolios sorted by the MAX effect each month. The data is divided into two panels based on the sentiment level of the market. Panel A includes observations from months with high sentiment in the previous month, while Panel B includes observations from months with low sentiment. The sample period spans from January 2001 to December 2019. Excess Return represents the mean return in excess of the risk-free rate (repo rate), while the Std. Dev. column shows the standard deviation of the excess return. The Sharpe Ratio is calculated by dividing the excess return by its standard deviation. FF4F Alpha refers to the Fama-French-Carhart alpha, with its corresponding t-statistics reported in the Alpha t-stats column. Columns 7 and 8 display the market betas from the FF4F model and their respective t-statistics. The last row (10−1) of each panel reports the average returns and alphas of a portfolio that takes a long position in the High MAX decile and a short position in the Low MAX decile, along with the t-statistics for the differences. All returns are expressed as percentages per month.

The difference in decile returns is 0.45%, while the difference in alphas is -0.05%, mirroring the results in Table 7. Once again, insignificant alphas and highly significant market betas indicate that the FF4F model can accurately explain portfolio returns, with no evidence of abnormal returns. Thus, despite differences in excess returns, all returns are explained by portfolio characteristics, and MAX does not influence portfolio returns in a high-sentiment state.

Panel B of Table 9 illustrates the performance of value-weighted deciles in a low-sentiment state. In this scenario, excess returns increase even more as we move to the tenth decile. However, the decline in Sharpe ratios is less pronounced. While Sharpe ratios remain higher for the first two decile portfolios, there is no clear pattern beyond that, despite the continued increase in return volatility with higher MAX portfolios.

Betas remain significant and continue to increase with higher decile portfolios. However, alphas are now borderline significant for about half of the portfolios. Therefore, we can no longer conclude that portfolios produce no abnormal returns or that the FF4F model fully explains the returns.

The difference in excess returns between decile 10 and decile 1 is now 1.61%. Moreover, the difference in alphas between these portfolios is 0.85%, which is close to being statistically significant. This suggests that the difference is not fully explained by the FF4F model and can be attributed to the MAX effect, as the portfolios were sorted based on this variable. As a result, we can conclude that the MAX effect is present only during low-sentiment periods in the Swedish stock market for value-weighted decile portfolios. In such periods, high MAX stocks tend to earn more.

Turning to Table 10, which is structured identically to Table 9, several key differences emerge. First, excess returns are now lower for high MAX portfolios, and this trend persists regardless of the market's sentiment level. In both panels, return volatility increases toward higher MAX portfolios, leading to steadily decreasing Sharpe ratios.

All market betas remain significant across both panels, consistent with Table 9. However, in Table 10, alphas are lower for higher MAX portfolios. These alphas are borderline significant, and their significance appears relatively stable regardless of the sentiment level in the stock market.

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	(-1.14)	1.03	(17.03)
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)	1.07	(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 presents the characteristics of decile portfolios sorted by the MAX effect each month. The data is organized into two panels based on the market's sentiment level. Panel A includes observations from months with high sentiment in the previous month, while Panel B includes observations from months with low sentiment. The sample period spans from January 2001 to December 2019. Excess Return represents the mean return in excess of the risk-free rate (repo rate), while the Std. Dev. column shows the standard deviation of the excess return. The Sharpe Ratio is calculated by dividing the excess return by its standard deviation. FF4F Alpha refers to the Fama-French-Carhart alpha, with its corresponding t-statistics reported in the Alpha t-stats column. Columns 7 and 8 display the market betas from the FF4F model and their respective t-statistics. The last row (10−1) of each panel reports the average returns and alphas of a portfolio that takes a long position in the High MAX decile and a short position in the Low MAX decile, along with the t-statistics for the differences. All returns are expressed as percentages per month.

In Table 10, the difference in excess returns between the tenth and first decile portfolios is -0.77% (t-stat = -1.29) in the high-sentiment state and -0.88% (t-stat = -1.08) in the low-sentiment state. Similarly, the difference in alphas between these portfolios is -0.55% (t-stat = -1.02) in the high-sentiment state and -0.82% (t-stat = -1.11) in the low-sentiment state.

Overall, although the direction of the MAX effect differs between value-weighted and equal-weighted portfolios—as explained in Section 5.4—its magnitude is consistently greater during low-sentiment periods. Therefore, we conclude that the difference in portfolio alphas is more pronounced in low-sentiment states.

5.6 Robustness Tests

To verify the robustness of our findings, we conducted several tests for each of our hypotheses. First, to test the robustness of our first and second hypotheses—whether MAX affects next month's returns and whether the previous month's MAX can predict the next month's MAX—we modified our definition of MAX. Instead of using the highest one-day return within the month, we redefined MAX as the arithmetic mean of the five days with the highest daily returns. This approach allows us to assess whether the effect persists when we account for multiple high-return days, minimizing the influence of potential outliers associated with a single-day spike. This method helps determine if the observed effects are sensitive to the MAX definition.

We performed the same regressions as in Sections 5.2 and 5.3, with the only difference being the new MAX definition. The results are presented in Table 11 and Table 12. In the original analysis (Table 4), the MAX coefficient was -0.0225 with a t-statistic of -1.67 when regressing next month's returns solely on MAX, and -0.0219 with a t-statistic of -0.96 when including other variables. In contrast, using the new MAX definition (Table 11), the MAX coefficient is -0.1158 with a t-statistic of -3.22 when regressing solely on MAX, and -0.1053 with a t-statistic of -2.39 when controlling for other variables. These results support our initial finding that MAX negatively affects stock returns—high MAX stocks tend to exhibit lower returns in the subsequent month. However, it is important to note that this tendency is observed only at the individual stock level and may differ when examined at the portfolio or market level.

Furthermore, while the MAX coefficients in Table 4 were not statistically significant, the robustness test results in Table 11 show that the MAX coefficients are significant at the 5% confidence level. This suggests that redefining MAX as the average of the top five daily returns strengthens the relationship between MAX and returns. One possible explanation is that using a single-day MAX results in a wider range and greater variability, which may weaken the observed relationship with monthly returns. In contrast, averaging over five days reduces this variability, bringing the MAX values closer to the magnitude of monthly returns, thereby improving predictive power. All other regression coefficients remained consistent or changed slightly, maintaining the same significance levels and directional effects as observed in Table 4.

When regressing the following month's MAX on the previous month's MAX in Table 5, the original coefficients were 0.2123 with a t-statistic of 20.00 when regressing solely on the previous MAX, and 0.1065 with a t-statistic of 8.30 when including other variables. In the robustness test (Table 12), the coefficients increased substantially: the MAX coefficient is 0.4718 with a t-statistic of 16.94 when regressing solely on MAX, and 0.2406 with a t-statistic of 8.17 when controlling for other variables.

The test results conclude that despite the change in approach, MAX still has a strong effect on the maximum daily return of the subsequent month. While the effect is slightly weaker using the 5-day MAX definition, it remains highly significant and substantial. Therefore, after performing the robustness check, it can be stated that the maximum daily return has a significant negative effect on the next month's maximum daily return. All other regression coefficients either remain unchanged or exhibit slight variations, maintaining the same significance levels and directional effects as observed in Table 5.

To test the robustness of the sentiment level effect on returns and MAX, we followed the same procedures as in Sections 5.4 and 5.5. However, we introduced two new approaches to constructing portfolios: the first involves creating value-weighted quintile portfolios, and the second involves creating equal-weighted quintile portfolios.

Table 13 and Table 14 present the analysis results of quintile MAX portfolios' returns and alphas. Table 13 shows the overall results, while Table 14 sorts the data based on the sentiment level index from the previous month.

Overall, the direction of the MAX effect and the signs of the differences in alphas and returns in Table 13 are consistent with the original analysis: higher quintile portfolios tend to exhibit higher excess returns and roughly the same FF4F alphas. The average difference in excess monthly returns between the first and fifth quintile portfolios is 0.41%, while the difference in Fama-French-Carhart four-factor model alphas is -0.02%. These figures are slightly smaller than those in Table 7, where the original hypothesis was tested (0.59% excess return difference and -0.05% alpha 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.

Table 14 reports the same data as Table 13, but sorted by the sentiment level index of the previous month. The results of this robustness test are very similar to those from the original model. The difference in excess returns between the fifth and first quintiles is 0.72% in the low sentiment state, while the difference in alphas is 0.12%. In the high sentiment state, the differences are 0.29% for excess returns and -0.26% for alphas. Compared to Table 8, where we conducted the original hypothesis testing, these numbers are of smaller magnitude (original low sentiment differences: 1.61% for excess returns and 0.85% for alphas; original high sentiment differences: 0.45% for excess returns and -0.05% for alphas).

However, the overall trend remains consistent: in low sentiment states, the difference in returns is larger, and there is a greater likelihood of a significant difference in the alphas of quintile MAX portfolios. While alphas remain insignificant for most portfolios, t-statistics in low sentiment states are notably higher, implying a greater chance of alpha significance. The Sharpe ratios for all high MAX quintiles are lower regardless of the market state, though in high sentiment states, the difference in Sharpe ratios is more pronounced.

In Table 15, we perform the same analysis as in Table 14, but now we examine equal-weighted portfolios instead of value-weighted ones. This table further supports our observations for equal-weighted portfolios: both alphas and excess returns decrease as we move toward higher MAX quintile portfolios, and the magnitude of the MAX effect is greater in low sentiment states. Specifically, the difference in alphas in the high sentiment state is -0.55% with a t-statistic of -1.30, while in the low sentiment state, the difference is -0.89% with a t-statistic of -1.99.

These results indicate that the FF4F model effectively predicts the returns of value-weighted portfolios when the data is not sorted based on the sentiment level index. The higher excess returns of higher MAX portfolios are driven 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 exhibit higher volatility but maintain similar Sharpe ratios compared to lower MAX quintiles. Thus, the price of risk is consistent across all portfolios.

Next, in Table 16, we applied the same methodology to equal-weighted portfolios. The results closely mirror those previously obtained for equal-weighted decile portfolios. Both excess returns and alphas are lower for higher MAX portfolios: the difference in excess returns between the fifth and first equal-weighted quintiles is -0.88% with a t-statistic of -2.32, while the corresponding difference for FF4F alphas is -0.75% with a t-statistic of -2.42.

Therefore, Table 16 supports the results obtained earlier for equal-weighted decile portfolios, as all tendencies and trends remain consistent, and the difference in alphas is both negative and significant. Following the robustness check, we can conclude that higher MAX value-weighted portfolios generate higher excess returns due to differences in stock characteristics, as no portfolio generates significant alpha.

6. Conclusion

In this paper, we investigated the MAX effect and its potential influence on the Swedish stock market. The primary research question was whether stocks with higher maximum daily returns within a month tend to generate lower future returns in the Swedish stock market.

Our analysis of a 26-year stock data sample provides some support for this claim. The results indicate that the MAX effect negatively influences stock returns, with a stronger impact at the portfolio level than at the firm level. However, this effect is only present in equal-weighted portfolios and does not exhibit any significant influence on value-weighted portfolios. These findings remain robust even after modifying the MAX definition from a one-day return to the arithmetic mean of the five highest daily returns in a month and when constructing quintile portfolios sorted by MAX instead of decile MAX-sorted portfolios.

An additional question we explored was whether stocks that exhibit a high MAX in one month tend to retain it in the following month. Our findings provide strong support for this hypothesis. First, the results of the Fama-MacBeth regression of the current month's MAX on the previous month's MAX indicate a strong dependence between the two. Furthermore, our transition matrix analysis, which tracks the probabilities of stocks moving between decile MAX portfolios, reveals that the likelihood of stocks remaining in the highest MAX portfolio is exceptionally high.

To further validate our findings, we conducted a robustness check by redefining MAX from the one-day maximum return in the previous month to the average of the five highest daily returns over the same period. The results remained consistent with our initial conclusions, reinforcing the strong dependency between the MAX of the previous period and the current one.

Finally, we examined whether, following a month with a high sentiment level, the difference between the Fama-French-Carhart four-factor model alphas of high and low MAX portfolios would be greater. However, our results not only fail to support this hypothesis but also suggest the opposite effect.

The results of our MAX decile portfolio analysis indicate that the difference in abnormal returns between the highest and lowest MAX deciles is only observed when the sentiment in the previous month is low. This finding remains robust even when constructing quintile portfolios instead of decile ones, yielding the same outcome.

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 sets 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.

Future research could examine how firm-level characteristics and governance such as international diversification (Askarzadeh et al., 2024b) contribute to return anomalies. Similar mechanisms may underlie the MAX effect, especially across markets with varying governance standards.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
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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)

Each month, from November 1993 to December 2019, we conducted a firm-level regression of returns on a subset of lagged predictor variables, including the arithmetic mean of the five highest daily returns from the previous month and seven other variables defined in the Appendix. The table reports the time-series averages of the cross-sectional regression coefficients along with 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)

Each month, from November 1993 to December 2019, we conducted a firm-level regression of the next month's MAX on a subset of lagged predictor variables, including the arithmetic mean of the five highest daily returns from the previous month and seven other variables defined in the Appendix. The table reports the time-series averages of the cross-sectional regression coefficients along with their associated t-statistics.

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

Decile	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 presents the characteristics of quintile portfolios sorted by the MAX effect each month. The sample period spans from January 2001 to December 2019. Excess Return represents the mean return in excess of the risk-free rate (repo rate), while the Std. Dev. column reports the standard deviation of the excess return. The Sharpe Ratio is calculated by dividing the excess return by its standard deviation. FF4F Alpha refers to the Fama-French-Carhart alpha, with its corresponding t-statistics shown in the Alpha t-stats column. Columns 7 and 8 display the market betas from the FF4F model and their respective t-statistics. The last row (5−1) reports the average returns and alphas of a portfolio that takes a long position in the High MAX quintile and a short position in the Low MAX quintile, along with the t-statistics for the differences. All returns are expressed as percentages per month.

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

Decile	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	-0.25	(-0.70)	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	-0.22	(-0.64)	1.07	(18.40)
4	2.27	9.07	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)

Decile	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	-0.13	(-0.62)	1.02	(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	-0.19	(-1.34)	1.13	(25.25)
5	1.10	7.89	0.14	-0.64	(-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)

Decile	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 presents the characteristics of quintile portfolios sorted by the MAX effect each month. The sample period spans from January 2001 to December 2019. Excess Return represents the mean return in excess of the risk-free rate (repo rate), while the Std. Dev. column reports the standard deviation of the excess return. The Sharpe Ratio is calculated by dividing the excess return by its standard deviation. FF4F Alpha refers to the Fama-French-Carhart alpha, with its corresponding t-statistics shown in the Alpha t-stats column. Columns 7 and 8 display the market betas from the FF4F model and their respective t-statistics. The last row (5−1) reports the average returns and alphas of a portfolio that takes a long position in the High MAX quintile and a short position in the Low MAX quintile, along with the t-statistics for the differences. All returns are expressed as percentages per month.