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The Performance of Stocks Earning Extreme Single-Day Returns: Evidence from Sweden

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ABSTRACT

In 2011, Bali et al. presented evidence that stocks with extreme one and multi day-returns significantly underperform stocks with less extreme returns in the following month. They attributed this to investors exhibiting a preference for stocks with lottery-like payoffs. Motivated by this, we examine the relation between extreme positive daily returns and returns in the subsequent month in the Swedish stock market. Using a sample containing stocks listed on the largest Swedish stock exchange, NASDAQ OMX, from January 1984 to December 2018, we find significant evidence of a negative relation between positive extreme returns and subsequent returns. The negative relation is robust to controls for size, book-to-market, liquidity, momentum and short-term reversal as well as idiosyncratic volatility, skewness and lottery-characteristics on portfolio-level. Multivariate regression analysis suggests that past extreme returns only show a significantly negative relation with future returns when we control for other firm characteristics. The negative cross-sectional relation is more significant and more economically relevant during recessions and insignificant during expansionary periods and varies considerably within our sample period. Excluding microcaps makes the relation insignificant for value-weighted portfolios. We conclude that the underperformance of stocks with extreme daily returns in the Swedish market may be driven by a combination of very short-term reversal, cumulative prospect theory and an increased inclination to gamble during economically bad times. Limits to arbitrage may prevent arbitrageurs from exploiting and correcting potential mispricings.

Keywords: *MAX Effect, Extreme returns, Cross-section of returns, Lottery-like payoffs, Behavioral Finance*

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Content

Tables and Figures

1) Introduction

Conventional financial theory is based on the assumption that investors are rational and only willing to take risks when compensated with higher returns. These mean-variance optimizing investors are well diversified and thus not affected by idiosyncratic (firm-specific) risk. Consequently, investors should only be rewarded for taking systematic (non-diversifiable) risk (Sharpe (1964), Lintner (1965), and Mossin (1966)). Seeking out stocks that increase exposure to idiosyncratic risk is therefore unnecessary because there is no theoretical gain in expected returns when doing so.

Empirical analysis, however, regularly finds anomalies that contradict the notions of modern portfolio theory. Goetzmann and Kumar (2008) note that U.S. individual investors are often underdiversified and Calvet et al. (2006) find similar evidence for Swedish households. This implies that taking idiosyncratic risk increases the risks of individuals' portfolios and should in fact be compensated. Contradictory to this theory, Ang et al. (2006) discover a seemingly puzzling negative relationship between idiosyncratic volatility and returns on the U.S. stock market.

In 2011, Bali, Cakici, and Whitelaw investigated the returns of stocks depending on the highest one and multi-day returns they earned in the previous month. They found that stocks with the most extreme positive daily returns significantly underperform stocks with less extreme returns in the following month. This MAX effect is robust to a variety of commonly known risk-factors and appears to explain the negative relationship between idiosyncratic volatility and future returns.

Bali et al. (2011) attribute the poor performance of high MAX stocks to one of the foundations of behavioral finance: Kahneman and Tversky's (1992) cumulative prospect theory. The theory states that individuals are risk-seeking when it comes to low-probability gains but risk-averse when it comes to low-probability losses. Thus, they are willing to pay a higher price for a small chance of extreme gains but will have to be heavily compensated for a small chance of extreme losses. In accordance with this theory, Bali et al. (2011) find positive returns for stocks with extreme minimum returns in the previous months, though of a lower significance than the MAX returns. As a consequence, stocks with positively skewed returns should be more expensive and earn lower returns while stocks with negatively skewed returns should outperform the rest.

This matches earlier findings of Kumar (2009), who discover that some individual investors prefer stocks with lottery-like characteristics, meaning high idiosyncratic skewness, idiosyncratic volatility and a low price. These stocks underperform stocks with non-lottery-like features. Similarly, Han and Kumar (2013) find that the MAX effect is primarily present in stocks with a higher share of retail trading and Cheon and Lee (2017) note that it is stronger in countries with higher levels of individualism.

Seemingly contradictory evidence has been found about the relationship between MAX and sentiment (investor confidence). Fong and Toh (2014) find it to be higher in times of high sentiment independent of macroeconomic variables in the U.S. and explain that with an increased desire to gamble. Berggrun et al. (2019) find the MAX effect to be especially pronounced during recessions in Brazil and attribute it to individuals' higher propensity to gamble in bad times.

On the other hand, Baars and Mohrschladt (2019) argue that the MAX effect is not driven by cumulative prospect theory, but rather by investors' overreaction to the positive news, as MAX is not persistent enough to make the stocks attractive to such investors and the effect is only strong in stocks far from their 52-week high.

Different evidence has linked the MAX effect to non-behavioral market microstructure effects and extreme short-term reversals and argues it is not economically significant after excluding microcaps (Aboulamer and Kryzanowski, 2016 & Hou et al., 2018).

Motivated by this anomaly and its potential implications on investor behavior in Sweden, we analyze the relationship between MAX and returns in the most relevant Swedish stock market index, NASDAQ OMX, from 1984 to 2018 and evaluate its robustness and interaction with other factors. We analyze which of the various explanations are most appropriate for explaining the MAX effect in Sweden and whether MAX has explanatory power in the cross section of returns. We chose the Swedish stock market because it has so far been neglected in most major studies on the MAX effect as both Annaert et al. (2013) and Walkshäusl (2014) restrict multi-country analysis to European Economic Area countries, and while Cheon and Lee (2017) include it in their cross-country analysis, it spans a shorter timeframe and does not focus on the Swedish stock market specifically.

Our primary aim is to investigate the predictive power MAX has on the cross section of expected returns in Sweden by isolating it from different variables which could explain the effect. We analyze which of the behavioral and technical explanations seem most suitable for explaining the performance of high MAX stocks in Sweden, how the magnitude of the effect changes during economic cycles, and whether the effect is limited to small and micro-caps.

The methodology of Bali et al. (2011) serves as our framework, but we extend the study by considering alternative explanations and studying the persistence of the MAX effect during subperiods as well as during expansionary and recessionary periods. Like Bali et al. (2011), we focus primarily on the significance of the Difference Portfolio, which would buy stocks in the highest MAX decile and sell stocks in the lowest MAX decile. We use univariate and bivariate portfolio sorting techniques as well as Fama and Macbeth (1973) regressions to establish the relationship between extreme daily returns and subsequent stock returns on the Swedish stock market.

Following past research, we focus on three main research questions:

1. Does the MAX effect exist in Sweden?
2. Are high MAX stocks overpriced due to their lottery-like payoffs or due to commonly known firm-specific risk factors?
3. Is the MAX effect more pronounced during recessionary periods?

The remainder of our paper is organized as follows. In chapter two, we review literature on the MAX effect, its persistence across markets and potential explanations for it. In chapter three, we present the data and the methodology we used for analyzing the MAX effect in Sweden. In chapter four, we present and discuss our empirical results and its limitations, before we conclude our main findings in chapter five.

2) Literature Review

In this section we present existing research on the MAX effect, including its global persistence and potential explanations for its impact on the cross-section of returns. We begin by presenting the findings of Bali et al. (2011). These serve as a reference throughout much of our thesis. We follow with an overview of papers which have found evidence of the MAX effect in different markets and present their explanations. We round out the section with evidence that calls into question the existence of the MAX effect.

Bali et al. (2011) find that portfolios buying stock which earned extreme daily returns over the previous month yield a statistically significant negative performance in the following month using data from the NYSE, AMEX and NASDAQ. This holds true for both value-weighted and equal-weighted portfolios and is robust to excluding microcaps or stocks with infrequent trading. They find that stocks with high maximum returns tend to be smaller, more volatile and less liquid than stocks with lower MAX while showing a positive reversal and a negative momentum. Controlling for these factors and additional firm characteristics does not weaken the significance of the MAX effect however. Furthermore, they find that the negative relation between idiosyncratic volatility and returns found by Ang et al. (2006, 2009) becomes insignificant after controlling for MAX.

Annaert et al. (2013) analyze the MAX effect in a sample of thirteen European countries, representative of the Euro area, and find a weak relationship between MAX and future returns with significant alpha differences between the high- and low-MAX decile only for equal-weighted portfolios. They argue that this could be partly explained by high-MAX stocks showing lower momentum and higher reversal leading to a negative bias when only controlling for MAX. When controlling for these characteristics using bivariate sorts, they find significant alpha and increased return differences for both the equally- and the value-weighted portfolios. They assert that controlling for different firm characteristics is important to detect the actual MAX effect. Like Bali et al. (2011), they find high-MAX stocks to be highly persistent, supporting the explanation that the effect exists due to a preference for lottery-like assets.

Walkshäusl (2014) analyzes the MAX effect in 11 countries which are part of the European Monetary union over the period from 1990 to 2011 and finds a significant MAX effect. However, his sample does not include any Nordic markets.

Since the returns discussed throughout our paper represent extremely positive or negative outcomes, they may proxy for investors exhibiting positive skewness preference. However, Bali et al. (2011) are unable to explain the effect with any backward-looking skewness measure nor with expected skewness. They argue that the effect persists because exploiting it would require investors to short-sell stocks with high volatility and illiquidity. This strategy would involve high transaction costs and short positions in stocks with high volatility and positive skewness which would make it risky.

Berggrun et al (2019) find evidence of the MAX effect in Brazil and analyze the role of the state of the economy in investors' propensity to seek lottery-like returns. The authors document a significant negative MAX effect only in periods following weak economic activity. They explain these results with the theory that recessions engender a greater inclination to gamble and speculate.

Barinov (2018) proposes a rationale in which MAX stocks can serve as insurance against aggregate volatility for well-diversified investors: when market volatility rises, a hedge on lottery-like payoffs could save an otherwise losing portfolio. Barinov notes that if this is the case then MIN stocks, those with the most strongly negative single-day return in a month, should see low subsequent returns similar to those of their MAX counterparts. If investors are looking for stocks with high idiosyncratic volatility as insurance it should not matter in which direction that volatility manifested itself in a given month. Thus, stocks with high MIN and MAX in the previous month should both underperform. On the other hand, if investors are irrationally overweighting the likelihood of the extreme-return scenarios, they should be avoiding MIN stocks similarly to how they appear to prefer MAX stocks, which would imply higher returns for stocks with high MIN returns in previous months. Barinov finds the former to be true, which is inconsistent with Ali et al.'s findings (2020 - 1), that the MAX effect diminishes when investors expect high overall volatility in the near future.

Ali et al.'s (2020 - 1) results implicitly contradict Berggrun et al.'s results; a bad state of the economy is more likely to correlate with high market volatility, yet such a scenario would weaken the MAX effect according to Ali et al.´s (2020 -1) findings (because of high-fear periods) and amplify it according to Berggrun's (because of gambling tendencies).

Stambaugh et al (2012) identify an arbitrage asymmetry, the fact that short sellers face both greater risks and greater impediments than purchasers, as a potential culprit of the aggregate negative effect of idiosyncratic volatility on returns. Idiosyncratic volatility increases the magnitude of returns, positive or negative, but it does so less significantly for the positive returns of underpriced stocks. This results in low returns on aggregate for all stocks with high idiosyncratic volatility.

Byun et al (2019) further examine the behavioral component and hypothesize that the MAX effect is driven by overreaction rather than cumulative prospect theory. Further, they argue that the 52-week high acts as a perceived price ceiling for a given stock, echoing Birru (2015). They find that when a lottery-like stock's current price is near its highest point over the past year, it tends to be underpriced, whereas if it is far off that mark, it is likely to be overpriced. The MAX effect only exists for stocks that are well under their 52-week highs. They argue that this could be because investors are reluctant to believe that stocks close to their high will continue achieving high returns connected to the behavioral bias anchoring.

Aboulamer and Kryzanowski (2016) find no evidence of the MAX effect and discover a positive relationship between idiosyncratic volatility and future returns in Canada. They argue that this is due to the absence of short-term return reversals in the Canadian market; they consider sharp, very short-term return reversals the primary reason for the MAX effect in other markets.

Ali et al. (2020 - 2) find a positive statistically significant relationship between high maximum returns and subsequent stock return in the Singapore stock market. This relationship can be explained by a positive IVOL effect however. This finding follows standard financial theory. The authors conclude that investors on the Singapore market are less affected by behavioral biases.

Hou et al. (2018) fail to replicate significant return differences between the high-MAX and the low-MAX deciles using only the NYSE after excluding microcaps for the value-weighted MAX portfolios. They argue that many market anomalies, including the MAX effect, are only relevant in microcaps, which make up 60.7% of American stocks but only 3.2% of the total market capitalization, so the effects are primarily driven by market microstructure effects that do not impact the market as a whole.

3) Data and Methodology

3.1) Data

For our study we use data from the Finbas database of the Swedish House of Finance Research Data Centre ranging from 1983 to 2018 (SHOF, 2021). The dataset includes stocks listed on the Stockholm Stock Exchange (Nasdaq OMX). We obtain daily and monthly adjusted and unadjusted closing prices, monthly market capitalization, book values and volume data. The closing prices are adjusted for splits, dividends and other corporate events. In addition, we use daily and monthly Fama and French factors calculated for the Swedish market by the Swedish House of Finance, which includes all variables of the Fama-French and Carhart four-factor model. (SHOF, 2021)

Table 1: Number of monthly Stocks over time

	Number of Stocks
Total	1,371
Minimum	176
Maximum	486
Average	318
Median	324

For a small number of observations, values are stated in currencies different from SEK. To convert those, we use exchange rate data from Wharton Research Data Services (WRDS, 2021). [1]

Every month, we exclude firm-months for which we do not have return data for at least 12 months and firm-months that are missing their lagged market capitalization. In addition, we exclude all firm-months with missing trading days in the previous month as those companies´

[1] For 12 firm-months with bookvalues in Icelandic Crona (ICK), we use data from the website Online Currency Converter (2021)

MAX is not fully comparable and may be overestimated. Volume data is systematically missing before September 1993 and book values are unsystematically missing, so the results for these metrics are not fully comparable across the time series.

Additionally, we use the NBER-based Recession indicator for Sweden (FRED, 2021), a binary monthly variable, to analyze the persistence of the MAX and MIN effect during expansionary and recessionary business cycles. The recession indicator is provided by the Federal Reserve Bank of St. Louis and based on data from the OECD.

3.2) Relevant Variables

In the following section we describe some of the measures we use to determine lottery-like features of stocks as well as control variables which are used to determine whether high MAX-stocks do indeed have lottery-like features and whether MAX is just a proxy for well-known market characteristics.

Return

To calculate simple daily returns, we divide the bid price by the last daily bid price subtracted by one. When calculating monthly returns, we divide the bid price by the last month's bid price subtracted by one.

$$R_t = \frac{P_t}{P_{t-1}} - 1$$

The bid prices are adjusted for corporate actions such as stock splits or dividends, thus no further adjustment is necessary.

MAX and MIN

Following Bali et al. (2011), we define MAX(N) as the average of the N maximum daily returns for a stock i within a month t.

$$MAX(N)_{i,t} = \frac{1}{N}\left(R_{i,d}\right),$$

$$d = 1,2\ \dots, D_t, \qquad N = 1,2,3,4,5$$

where D_t is the number of trading days.

Similarly, we define MIN(N) as the average of N minimum daily returns for a stock i within a month t.

$$MIN(N)_{i,t} = \frac{1}{N}\left(R_{i,d}\right),$$

$$d = 1,2\ \dots, D_t, \qquad N = 1,2,3,4,5$$

Beta

To account for nonsynchronous trading, we calculate beta by regressing daily excess stock returns against the current excess market return as well as its lead and lag as introduced by Scholes and Williams (1977) and Dimson (1979)

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

Where $R_{i,d}$ is the return of the stock *i* on day *d*, $r_{f,d}$ is the risk-free rate on day *d* and $R_{m,d}$ is the market return on day *d*. The market beta of a stock *i* in month *t* is defined as:

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

Idiosyncratic Volatility

Following Ang et al. (2006), we define idiosyncratic volatility as the residual standard error of the daily excess returns regressed on the Fama and French (1993) three-factor model.

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{mkt,i}MKT_t + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \varepsilon_{i,d},$$

where $R_{i,d} - r_{f,d}$ is the excess return of stock *i* on day *d* and MKT_t, SMB_t and HML_t are the factor returns for market, size, and book-to-market.

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

Size

As size, we define the total market capitalization of the company, meaning the market capitalization of all its stock classes added together at the end of the formation period (t-1). We argue that this better accounts for the risk connected to companies with smaller market capitalization compared to larger ones. Following Bali et al. (2011), we use the natural logarithm of market value in regressions.

Momentum (MOM)

Like Bali et al. (2011) we define the momentum variable following Jegadeesh and Titman (1993) as the cumulative return of a stock over the previous 11 months starting two months ago. Using corporate action adjusted prices this is:

$$MOM_{i,t} = \frac{P_{t-2}}{P_{t-12}} - 1$$

Short-Term Reversal (REV)

Following Jegadeesh (1990), we define reversal for a stock in month *t* as the previous months return of that stock (the return in month *t-1*).

Illiquidity (ILLIQ)

We use the stock illiquidity measure developed by Amihud (2002) which defines illiquidity as the absolute monthly stock return divided by its trading volume

$$ILLIQ_{i,t} = \frac{|R_{i,t}|}{VOLD_{i,t}}$$

Total Skewness (TSKEW)

We compute total skewness of stock i for month t using the daily returns of the previous year

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

Where D_t is the total number of trading days in period t, $R_{i,d}$ is the return on stock i on day d, μ_i is the mean of returns of stock i in period t, and σ_i is the standard deviation of returns of stock i in period t.

Systematic (SSKEW) and Idiosyncratic (ISKEW) Skewness

We use the definition by Harvey and Siddique (2000), defining systematic skewness (SSKEW) as the slope coefficient of the squared market excess return from a regression of the excess return from stock *i* on the excess return of the market and the squared market excess return.

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{mkt,i} MKT_t + SSkew_i MKT_t{}^2 + \varepsilon_{i,t}$$

We define idiosyncratic skewness (ISKEW) as the skewness of the daily residuals (Harvey and Siddique, 2000).

Lottery Stock Index (LIDX)

LOTT is defined as the sum of the vigintile assignments according to the IVOL, ISKEW, and stock price measures, divided by 60 in order to scale it from 0 to 1. The LOTT measure is motivated by Kumar (2009) to identify lottery stocks.

3.3) Portfolio Sorting and Regression Approach

In the following section, we present our approach, to determine the cross-sectional influence of MAX on future returns. In all cases, we present our results with Newey-West (1987) adjusted t-statistic to control for autocorrelation and heteroscedasticity.

3.3.1) Univariate Portfolio Analysis

Following Bali et al. (2011), we implement a portfolio sorting strategy to assess the cross-sectional relation between MAX or MIN returns in the previous month and returns. For that we use an L/M/N strategy where L describes the length of our estimation period in months, M describes the waiting period after the estimation of parameters and N describes the holding period (as described by Ang et al. 2006) of 1/0/1. That means we form portfolios based on the last month's maximum daily returns and rebalance these portfolios every month. Like Bali et al. (2011) we form decile portfolios and calculate value- and equal-weighted returns. A downside of this approach is the relatively low number of stocks per portfolio per month (32 on average). However, as the MAX effect is most pronounced in the extremes, sorting in quintiles would make the results less reliable.

When calculating value-weighted (VW) returns, the stock returns are weighted by their market capitalizations at the date of portfolio formation (the end of the previous month) within each decile, while equal-weighted (EW) returns are calculated as a simple mean. We regress the excess returns of every decile portfolio as well as the zero-cost portfolio that is long the highest decile (10) and short the lowest decile (1) on the factor returns of the Fama French (1993) and Carhart (1997) – 4 Factor Model. The difference portfolio is used to measure the relationship between MAX, MIN and subsequent stock market returns.

$$r_{i,t} = \alpha_i + \beta_{mkt,i}MKT_t + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{MOM,i}MOM_t + \varepsilon_{i,d},$$

In further analysis we also adapt the strategy to a 3/0/1 and a 6/0/1 portfolio, meaning we form it based on the MAX in the previous 3 or 6 months to determine the persistence of MAX when using longer formation periods.

3.3.2) Bivariate Portfolio Sorting

To determine whether the MAX effect persists after controlling for different effects, we form quintiles in the control variables described earlier and then sort the stocks into deciles within each of these control groups. When doing this, we slightly deviate from the approach of Bali et al. (2011) who formed control groups in deciles. That is because our sample has a significantly lower number of stocks per month. Even so every of the MAX deciles within each control group only contains an average of 6 stocks per month. Like Bali et al. (2011), we take the simple averages of the control groups for every respective decile of MAX to ensure we have similar levels of the control variable within each decile. We do not report the values of all individual double-sorted portfolios as the conditional nature of the portfolio formation makes the interpretation of the differences between the control groups uncertain (Bali et al. 2016).

3.3.3) Fama and Macbeth Regression

While portfolio analysis is helpful in analyzing the cross-sectional relation between two variables without making assumptions about the nature of the relationship under investigation, it has the drawback of only allowing a limited set of controls when examining the relationship between variables (Bali et al. 2016).

Thus, to determine the persistence and cross-sectional predictability of MAX by firm characteristics and lottery-like features and the impact of MAX on Returns in the Swedish market, we use the regression approach first implemented by Fama and Macbeth (1973). This way, we can control for the effect of multiple pairs of independent variables on the variable of interest at the same time while univariate and bivariate portfolio analysis allows us to control for a maximum of two variables. The downside of this approach is that we have to assume a relation between the variables of interest (Bali et al., 2016). We follow the common assumption of a generally linear relationship between the variables while using the natural logarithm of SIZE and Book to Market. We follow Bali et al. (2011) and orthogonalize IVOL in multivariate regressions which contain both MAX and IVOL, as its high cross-sectional correlation with MAX would create a multicollinearity problem. Furthermore, when analyzing the cross-sectional relation between MAX and future returns we follow Fu (2009) and winsorize all independent variables at the 0.5% and 99.5% level to reduce the impact of outliers.

We run both an ordinary least squares (OLS) Fama and Macbeth regression and a weighted least squares regression (WLS), weighted by the square root of the previous month's market capitalization. The WLS controls for the effect of small and microcap outliers on OLS regressions and thus achieves more economically relevant results (Hou et al. 2018).

4) Results

In the following chapter, we present and discuss our results based on our previously presented methodology. In the first sections, we will analyze the existence of the MAX effect in Sweden using the base portfolio approach, analyze typical features of high MAX stocks, look at alterations of the base portfolio approach and determine the influence of the timing of the highest return within the month. Subsequently, we will examine whether the MAX effect remains significant after controlling for various firm characteristics and lottery-like features of stocks through bivariate dependent portfolio sorting. Following that, we test the significance of MAX in combination with multiple variables through Fama and Macbeth (1973) regressions before analyzing the persistence within time periods and depending on the business cycle. Finally, we analyze the significance of the MAX effect after the introduction of further robustness checks

4.1) Performance of Portfolios Univariately Sorted by MAX

Table 1 shows the results of the univariate portfolio sorting by MAX. All high-MAX portfolios earn lower returns than the lower-MAX portfolios, but the return differences are not statistically significant. While the alphas for all difference (high MAX - low MAX) portfolios are negative, they are only statistically significant for MAX(2) and (5) at the 5% level and for MAX(3) at the 10% level. The MAX(1) and MAX(4) value-weighted difference portfolios do not generate statistically significant alphas, and none of the equal-weighted difference portfolios have statistically significant alphas. Thus, while we do find evidence of the MAX effect in Sweden, it is substantially weaker than found by Bali et al. (2011) in the US. Interestingly, like in the US, the deciles 2-4 show a better performance than the portfolio of lowest-MAX stocks (decile 1) while the returns of the 9th MAX decile show a considerably better performance than the highest MAX decile.

Table 2. Summary statistics for returns on portfolios of stocks sorted on multi-day maximum returns

We form monthly decile portfolios from 1984 to 2018 by sorting stocks on the average of the N highest daily returns over the previous month. Portfolio 10 (1) is the portfolio with the highest (lowest) maximum multi-day return over the previous month. Newey-West adjusted t-statistics are reported in parenthesis. The last two rows present the differences in monthly returns between the first and last deciles and the differences in the four-factor Cahart (1997) Alpha. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Value-weighted returns on MAX(N) portfolios

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX(N)	0.75	0.79	0.89	0.89	0.82
2	1.26	1.29	1.25	1.11	1.22
3	1.21	1.37	1.38	1.29	1.17
4	1.07	1.20	1.29	1.42	1.52
5	1.15	1.07	1.06	0.93	0.89
6	1.46	1.31	1.07	1.20	1.14
7	1.07	1.21	1.27	1.28	1.15
8	0.68	0.86	0.96	1.06	1.04
9	1.08	1.13	0.86	0.62	0.63
High MAX(N)	0.45	0.11	0.29	0.59	0.33
Return Difference	-0.30 (-0.66)	-0.68 (-1.44)	-0.61 (-1.22)	-0.30 (-0.57)	-0.50 (-0.99)
Alpha Difference	-0.49 (-1.19)	-0.93** (-2.19)	-0.83* (-1.89)	-0.55 (-1.21)	-0.89** (-2.18)

Equal-weighted returns on MAX(N) portfolios

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX(N)	1.48	1.46	1.47	1.48	1.42
2	1.70	1.56	1.54	1.52	1.67
3	1.57	1.71	1.68	1.60	1.53
4	1.55	1.51	1.57	1.64	1.63
5	1.54	1.65	1.54	1.56	1.50
6	1.45	1.24	1.47	1.51	1.57
7	1.08	1.39	1.25	1.25	1.29
8	1.11	1.15	1.16	1.19	1.24
9	0.85	0.88	0.85	0.86	0.85
High MAX(N)	1.12	0.90	0.91	0.85	0.76
Return Difference	-0.36 (-0.72)	-0.56 (-1.08)	-0.56 (-1.07)	-0.63 (-1.18)	-0.66 (-1.24)
Alpha Difference	-0.16 (-0.42)	-0.34 (-0.89)	-0.37 (-0.93)	-0.44 (-1.10)	-0.49 (-1.22)

Notes: *$p<0.1$ **$p<0.05$ ***$p<0.01$

This hump shape is a lot more pronounced in the Swedish market but comparable to that found by Annaert et al (2013) in other European markets. If one were to take the alpha difference between the 3rd and the 10th deciles, all MAX(N) would have significant alpha differences at least at the 10% level and the MAX(2) and MAX(3) even at the 1% level.

Looking at the EW portfolios, a similar return pattern is observable, but neither the return differences nor the alpha differences are significant. The low significance of MAX is similar to the results from Annaert et al. (2013), who find no significant results for VW portfolios and only significant results for the MAX(1) and (2) EW. The fact that MAX(1) and MAX(3) have insignificant alphas while the other MAX levels do not, indicates a lower robustness of the MAX effect in Sweden than in the U.S.

4.2) Characteristics and Persistence of MAX stocks

To determine whether the MAX effect could be explained by investors' lottery-seeking preferences and preference for skewness, we investigate the summary statistics of portfolios sorted into the respective deciles. High MAX stocks appear to be on average a lot smaller, less liquid and have a higher market beta than stocks in the lower MAX deciles which are considered lottery-like features. Further, they are showing positive short-term reversal and negative momentum. This mostly mirrors the findings of Bali et al. (2011) and Annaert et al. (2013). Looking at the average weight of each decile within the whole market, the decrease in the higher MAX deciles is evident with the average high MAX portfolio only consisting of 2.2% of the total market capitalization despite making up 10% of the stocks. This indicates that the MAX effect might be primarily driven by small stocks or even confined to microcap stocks.

Table 3. ***Summary Statistics of MAX(N=1) Portfolio***

The table reports for each MAX decile the average of the median values of the following characteristics across the months in the month of portfolio formation. MAX is the maximum daily return within the month, Size describes the market capitalization, BM the Book-to-Market ratio, Illiquidity, describes Amihuds illiquidity measure, IVOL is the idiosyncratic volatility, REV the return in the formation month, MOM the return in the 11 months before portfolio formation and Market Weight the average part of the total Market Capitalization the stocks in the portfolio make up

Decile	Max	Size* (SEK 10^7)	Price (SEK)	BM	Illiquidity (10^9)	IVOL	Beta	REV	MOM	Market Weight
Low Max	1.43	158.42	119.34	0.63	0.79	0.82	0.21	-1.53	13.08	12.72
2	2.42	259.31	124.61	0.57	0.60	1.17	0.49	-1.11	13.68	17.03
3	3.02	228.64	113.84	0.57	0.76	1.37	0.60	-0.35	12.69	15.64
4	3.61	180.28	105.65	0.56	0.81	1.54	0.65	0.11	12.74	13.96
5	4.24	147.09	96.59	0.56	1.14	1.75	0.72	0.55	12.23	11.53
6	4.99	119.19	87.95	0.55	1.62	1.99	0.73	1.17	11.67	9.61
7	5.94	98.21	76.28	0.56	2.71	2.27	0.81	1.80	10.58	7.70
8	7.28	71.36	68.53	0.57	4.98	2.68	0.83	2.66	8.69	5.67
9	9.67	47.88	54.73	0.61	9.74	3.38	0.87	3.92	6.45	3.93
High Max	16.58	24.49	36.59	0.64	39.29	5.59	0.86	7.48	-1.45	2.20

Looking at more obviously lottery-like features of high-MAX stocks, it is apparent that Idiosyncratic Skewness and Total Skewness increase from the lowest- to the highest-MAX portfolios, while systematic skewness increases for high-MAX stocks. The decreasing systematic skewness for high MAX stock indicates that these stocks are more affected by market crashes, but systematic skewness only defines a small part of the total skewness.

Table 4. ***Lottery Features of Max(N=1) Portfolio***

The table reports for each MAX decile the average of the median values of Systematic Skewness (SSKEW), Idiosyncratic Skewness (ISEKW), Total Skewness (TSKEW), the difference to its price to the 52-high (NH) and the lottery stock index (LIDX).

Decile	SSkew	ISkew	TSkew	NH	LIDX
Low Max	-2.36	0.37	0.31	1.17	0.32
2	-2.46	0.25	0.18	1.19	0.33
3	-2.54	0.27	0.19	1.22	0.37
4	-2.62	0.30	0.22	1.23	0.40
5	-2.79	0.33	0.26	1.27	0.45
6	-3.37	0.36	0.29	1.30	0.49
7	-3.55	0.42	0.34	1.36	0.54
8	-4.13	0.48	0.41	1.44	0.60
9	-4.19	0.61	0.54	1.55	0.67
High Max	-4.84	1.04	0.98	1.75	0.78

Furthermore, stocks in the highest MAX decile tend to be the furthest from their 52-week high indicating that anchoring could be a factor and might even drive the MAX effect (Blau et al, 2017)

If MAX stocks earn lower returns due to investors preferring their positive skewness and lottery-like payoffs, we would expect MAX to be persistent in stocks over time. To analyze this, we first examine the average month-to-month portfolio transition matrix (Table 4). The diagonal of the matrix shows the probability of a stock finding itself in the same decile in one month as it was in the previous month. Without persistence, the transition probabilities for all deciles would be about 10%. Instead, they concentrate at and around the diagonal, and at the two extreme deciles (the upper left and bottom right corners), the values even exceed 30%: stock whose MAX is in the top decile this month has a 31% chance of being in the same decile next month. A stock in the highest MAX decile has a 60% chance in one of the top 3 MAX deciles in the subsequent period. The same can be seen for stocks in the lowest MAX decile. This indicates that investing in high-MAX stocks to earn lottery-like pay-offs in the subsequent period would be a valid consideration, which mirrors the findings of Bali et al. (2011) and Annaert et al. (2013).

Table 5. ***Average Monthly transition matrix of MAX(N=1) Deciles***

This table shows the average portfolio transition probability of a stock in Percent. On the left are the decile portfolios that the stocks belong to in period t (-1) and in the numbered columns are the probabilities that they will be in the specified decile portfolio during the next month.

Decile (t-1)	1	2	3	4	5	6	7	8	9	10
Low Max	31.0	14.5	11.2	9.3	7.7	6.3	5.6	5.4	4.2	4.9
2	15.5	16.3	13.7	12.0	10.8	8.6	7.4	6.5	5.2	4.0
3	11.2	13.8	13.9	13.0	11.4	10.2	8.5	7.4	6.1	4.7
4	9.5	12.6	12.7	12.6	11.6	10.3	9.5	8.6	7.1	5.5
5	7.7	10.2	11.2	11.4	11.8	11.6	11.0	10.3	8.5	6.1
6	6.3	9.8	9.8	11.2	11.6	11.7	11.8	10.8	9.6	7.2
7	5.5	7.8	8.9	10.0	11.3	11.5	12.6	12.1	11.2	9.1
8	5.1	6.7	8.4	8.5	9.6	11.0	12.3	12.9	14.0	11.4
9	4.7	4.8	5.7	7.3	8.5	10.8	11.6	13.4	16.1	17.0
High Max	5.3	3.5	4.1	4.7	6.0	7.1	8.9	12.1	17.3	30.8

To further explore the persistence and predictability of MAX, we follow Bali et al. (2011) and run a monthly firm-level, cross-sectional Fama-Macbeth (1973) regression of MAX and six control variables. Except for beta, all variables appear to have significant explanatory power. A high MAX return seems to be a good predictor for a high MAX in the next month but IVOL has the highest explanatory power. Furthermore, consistent with the summary tables, smaller and more illiquid stocks are more likely to have a higher MAX returns while stocks with higher momentum or reversal are less likely to have a high MAX in the following period. This indicates that investors who are looking for lottery-like payoffs could reasonably expect stocks with high MAX returns to show similar behavior in the subsequent month, which supports the explanation through cumulative prospect theory.

Table 6. *Cross-sectional predictability of MAX*

Cross-Sectional Predictability of MAX(1). Each month we run a firm-level cross-sectional regression of the Maximum daily Return in that month (MAX(N=1)) to the MAX(1) in the previous month and 6 lagged predictor variables Beta, SIZE, the log of a firm's market capitalization, B/M, the Book-to-Market ratio, MOM, the return over the previous year excluding the last month, REV, the previous months return, ILLIQ, Illiquidity calculated following Amihud (2002) and IVOL, idiosyncratic volatility . The table reports the coefficients with Newey-West (1987) adjusted t-statistics in parenthesis and the mean adjusted r-squared of the regressions.

				Dependent variable:				
MAX(1)	Beta	SIZE	B/M	MOM	REV	ILLIQ	IVOL[2]	Adjusted R-Squared
0.346***								11.37%
(20.10)								
	0.0002							2.20%
	(0.21)							
		-0.010***						7.17%
		(-10.81)						
			0.006***					1.25%
			(3.25)					
				-0.027***				2.08%
				(-4.79)				
					-0.023**			2.93%
					(-2.42)			
						5,336.26***		3.97%
						(4.56)		
							1.404***	16.24%
							(20.92)	
0.361***	0.0012	-0.0043***	-0.0029***	-0.0065***	-0.044***	2,653.28***	1.404***	25.54%
(22.95)	(-0.23)	(-10.38)	(-5.29)	(-3.03)	(-6.80)	(3.11)	(16.57)	

Note: *p**p***p<0.01

[2] Like Bali et al. (2011) we orthogonalize IVOL in multivariate regressions as its high cross-sectional correlation with MAX creates a multicollinearity problem

4.3) Testing for MIN Effect

If the MAX effect is driven by cumulative prospect theory, we would expect stocks with highly negative returns to show the opposite effect as investors would overweigh the small probability of a large loss connected to holding high MIN stocks and thus undervalue these stocks. The returns of portfolios formed based on the MIN in the previous month, do show this pattern with higher returns for stocks with highly negative returns in the previous month but neither the return differences nor the alpha differences are statistically significant.

This is at least directionally consistent with Kahneman and Tversky's cumulative prospect theory (1992) but not significant enough to make strong conclusions. The fact that the MIN effect is weaker than the MAX effect is consistent with the findings of Bali et al. (2011) and might be connected to the fact that arbitrageurs would not have to take a risky short position to profit from this effect. However, the results would be consistent with the theories that MAX is driven by short-term reversal or investor overreaction as well.

Table 7. ***Value-Weighted Returns on Portfolios of Stocks Sorted on Multi-Day Minimum Returns***

We form monthly decile portfolios from 1984 to 2018 by sorting stocks on the average of the N minimum daily returns over the previous month. Portfolio 10 is the portfolio with the lowest (absolute highest) minimum multi-day return over the previous month. Newey-West adjusted t-statistics are reported in parenthesis. The last two rows present the differences in monthly returns between the first and last deciles and the differences in the four-factor Fama-French and Cahart (1997) Alpha. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Decile	N=1	N=2	N=3	N=4	N=5
Low MIN	1.00	1.03	1.11	1.06	1.04
2	1.01	1.07	1.03	0.96	0.98
3	1.29	1.24	1.21	1.23	1.22
4	1.37	1.14	1.11	1.04	1.21
5	1.29	1.20	1.11	1.12	1.02
6	1.20	1.07	1.52	1.39	1.38
7	1.02	1.42	1.47	1.45	1.50
8	1.17	0.89	0.70	0.92	1.19
9	1.01	0.76	0.77	0.62	0.57
High MIN	1.37	1.55	1.62	1.54	1.43
Return Difference	0.38 (0.68)	0.52 (0.91)	0.51 (0.87)	0.48 (0.81)	0.39 (0.62)
Alpha Difference	0.44 (0.79)	0.56 (1.05)	0.49 (0.97)	0.46 (0.92)	0.36 (0.69)

Notes: **p<0.1 **p<0.05 ***p<0.01*

4.4) MAX Effect with Longer Formation Periods

Given the persistence and cross-sectional predictability of MAX, investors seeking lottery-like payoffs might invest in stocks that have shown high MAX returns not just over the previous months but also over a longer period. Its demonstrated persistence suggests that the MAX effect ought to be significant for longer formation periods as well. To test whether this holds true, we consider an alternative measure of MAX which averages the MAX(N) over the last 3 and 6 months. (Table 15 in appendix). While high-MAX portfolios formed with this measure still tend to underperform, the differences in return to the low MAX are very small and sometimes even positive and the generated alphas insignificant. This differs from the findings of Bali et al. (2011) who still find significant return and alpha differences for longer formation periods in the US. The fact that this measure of lottery-like payoffs does not generate significant alpha differences could indicate that the MAX effect in the Swedish market is not primarily driven by lottery-seeking investors with skewness preferences but rather by short-term anomalies or other risk factors.

4.5) MAX Effect Depending on the Date of the MAX

Since the MAX effect in the Swedish market does not stay consistent when measuring MAX over longer time periods, we now analyze whether the MAX effect is stronger depending on the day the MAX occurs within the month. For that, we subdivide our stocks in the high-MAX portfolios into stocks where the maximum return happens in the first and where it happens in the second half of the month.[3]

We find that the MAX effect is distinctly stronger when the highest daily maximum return happens in the second part of the month. The alphas are significant at the 1% level and 5% level and the return differences are significant at the 5% and 10% level for all but MAX(1). On the other hand, high-MAX stocks which have their maximum return in the first part of the month do not show any underperformance with alphas very close to zero and returns which are even slightly higher than those of the low MAX portfolio. This is different from the findings of Bali et al. (2011) who did not find evidence of return differences when controlling for which day the highest MAX happened on. This finding weakens the idea that cumulative prospect

[3] Because we are splitting the portfolios according to the day of MAX after calculating the deciles, some months (15 out of 419) are missing observations of stocks in every decile. These are excluded from the below calculation. This does not affect the magnitude of the return differences.

theory and preferences for stocks with lottery-like payoffs (Tversky and Kahneman. 1992) drive the MAX effect in the Swedish market.

Stocks with positive daily extreme returns during the second half of the month are likely to earn high returns in the second half of the month. The large difference between MAX returns appearing early or late in the month could point to very sharp short-term reversals of one or two weeks being responsible for the MAX effect (Jegadeesh (1990) and Lehmann (1990)). This would be consistent with findings of Huang et al. (2010) who conclude that the puzzling negative relationship between IVOL and future returns in the US stock market can be explained by a sharp reversal of returns for stocks with extreme returns. It also supports Aboulamer and Kryzanowski (2016) who find no significant MAX effect in Canada and attribute that to the absence of return reversals in the Canadian stock market.

Table 8. ***Value-Weighted Returns on Portfolios of Stocks sorted on multi-day maximum Returns depending on whether MAX happened in the first or the second part of the month***

We form monthly decile portfolios from 1984 to 2018 by sorting stocks on the average of the N highest daily returns over the previous month. Portfolio 10 (1) is the portfolio with the highest (lowest) maximum multi-day return over the previous month. Newey-West adjusted t-statistics are reported in parenthesis. After sorting, we divide the stocks within the decile portfolios depending on whether the highest monthly return happened in the first or the second half of the month. The last two rows present the differences in monthly returns between the first and last deciles and the differences in the four-factor Cahart (1997) Alpha. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Summary Statistics for portfolios which have their highest MAX in the *first Half of Month*

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	0.84	0.87	0.99	0.86	0.80
2	1.80	1.55	1.47	1.46	1.58
…					
9	1.00	1.26	0.82	0.70	0.81
High MAX	1.21	1.20	1.36	1.34	1.13
Return Difference	0.37 (0.80)	0.33 (0.65)	0.38 (0.67)	0.48 (0.84)	0.34 (0.63)
Alpha Difference	0.03 (0.06)	-0.003 (-0.01)	0.10 (0.18)	0.27 (0.49)	0.05 (0.09)

Notes: **p<0.1 **p<0.05 ***p<0.01*

Summary Statistics for portfolios which have their highest MAX in the *second Half of Month*

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.06	1.03	1.07	1.01	1.07
2	1.20	1.26	1.25	1.15	1.17
…					
9	0.67	0.88	0.89	0.76	0.90
High MAX	0.25	-0.35	-0.51	-0.20	-0.21
Return Difference	-0.82	-1.38**	-1.58**	-1.21*	-1.27*
	(-1.20)	(-2.18)	(-2.44)	(-1.77)	(-1.83)
Alpha Difference	-0.80	-1.37**	-1.71***	-1.43**	-1.57**
	(-1.45)	(-2.46)	(-2.95)	(-2.35)	(-2.50)

Notes: *p<0.1 **p<0.05 ***p<0.01*

4.6) Controlling for Firm Characteristics

To test whether the MAX effect is driven by other commonly known risk factors and firm characteristics, namely size, book-to-market ratio, momentum, short-term return reversals, and illiquidity or idiosyncratic volatility, we perform bivariate portfolio sorts. For that we first sort the portfolios in quintiles of the relevant control group and then within each control group we rank stocks based on their MAX. Like Bali et al. (2011), we only report the averages of these control groups for brevity and to form portfolios with dispersion in MAX but similar levels of the control group. Due to the difference in MAX returns depending on whether the highest return happened in the first or the second half of the month, we also control for the return in the second half of the month in case of very sharp short-term reversals.

Remarkably, after controlling for different firm characteristics, the return and alpha differences between the high MAX and the low MAX portfolios increase in magnitude and significance, even for MAX(1) and (3), which did not show significant alpha differences earlier. When controlling for size, the alphas for the difference portfolio of MAX(2) to MAX(5) are significant at the 1% level and the MAX(1) alpha at the 5% level. Similarly, after controlling for beta, momentum, and book-to-market all alpha differences are significant at least at the 10% level and to a high degree even at the 1% level. When sorting for IVOL, the alpha of MAX(1) remains insignificant, but the alphas of MAX(2) to (5) are significant at the 1% level indicating that MAX is not a proxy for IVOL. Testing for short-term reversal on the other hand, the previously most significant alpha difference for MAX(2) becomes insignificant, while the other alphas are significant at the 5% level. Most surprisingly, despite the finding that the MAX effect is only significant when the MAX appears in the second half of the month, double sorting for the return during the second half of the month does not decrease the magnitude of the MAX effect: the difference portfolios for all levels of MAX retain negative alphas at the 10% and 5% level.

The increasing significance of MAX when controlling for the effect of different variables seems puzzling initially, but it mirrors the results of Bali et al. (2011) and Annaert et al. (2013), both of whom find the significance of the alpha and return differences increasing when controlling for firm characteristics. In part this can likely be explained by the fact that some characteristics of high MAX stocks such as a negative momentum or a positive short-term reversal are negatively correlated to returns thus, they could cloak the MAX effect in univariate portfolio sorts.

The fact that after controlling for IVOL, MAX(1) stays insignificant but the other MAX measures increase in significance and that controlling for REV makes MAX(2) insignificant may also indicate that the different measures of MAX are correlated to and possibly explained by different effects. Furthermore, a limitation of bivariate portfolio sorting is that it only allows testing for two characteristics simultaneously.

Another limitation of these results is that due to the small number of stocks per control group and the high negative correlation of MAX and size, the procedure of taking the average returns of each control group for each level of MAX is likely to overweight small stocks significantly especially when testing for SIZE, even though it may disentangle MAX from the size effect itself; in average, the smallest 60% of stocks constitute less than 5% of the total market capitalization.

Table 9. *Portfolios sorted on MAX after controlling for firm characteristics*

We form monthly decile portfolios from 1984 to 2018 by first sorting stocks in quintile portfolios of the respective control variables SIZE, the total market capitalization, short term reversal, IVOL, the idiosyncratic volatility over the previous month, the Book-to-market ratio, the firms market beta, momentum, illiquidity following Amihud´s (2002) illiquidity measure and the return in the second half of the previous month. We form decile portfolios of MAX (N) within each control group. We report the average returns across the five control groups to produce decile portfolios with dispersion in the variable of interest but with similar levels of the control variable. Portfolio 10 (1) is the portfolio with the highest (lowest) maximum multi-day return over the previous month. The last two rows present the differences in monthly returns between the first and last deciles and the differences in the four-factor Cahart (1997) Alpha. Newey-West (1987) adjusted t-statistics are reported in parentheses.

VW Portfolios sorted by MAX after controlling for SIZE

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.14	1.20	1.14	1.17	1.13
2	1.71	1.50	1.65	1.65	1.64
3	1.63	1.61	1.64	1.65	1.64
4	1.42	1.62	1.50	1.50	1.47
5	1.34	1.53	1.64	1.49	1.51
6	1.29	1.51	1.25	1.40	1.38
7	1.30	0.99	1.14	1.16	1.13
8	1.05	0.97	0.79	0.81	0.74
9	0.47	0.43	0.66	0.56	0.64
High MAX	0.44	0.41	0.26	0.28	0.24
Return Difference	-0.71**	-0.79**	-0.89**	-0.89**	-0.89**
	(-2.27)	(-2.37)	(-2.35)	(-2.23)	(-2.20)
Alpha Difference	-0.60**	-0.75***	-0.88***	-0.90***	-0.90***
	(-2.37)	(-3.00)	(-3.21)	(-3.28)	(-3.32)

VW Portfolios sorted by MAX after controlling for short-term reversal (REV)

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.08	1.08	1.13	1.12	1.09
2	1.46	1.46	1.39	1.41	1.49
3	1.40	1.42	1.38	1.28	1.29
4	1.41	1.61	1.39	1.40	1.36
5	1.71	1.42	1.48	1.58	1.55
6	1.42	1.28	1.39	1.39	1.33
7	1.05	1.09	0.99	1.05	0.99
8	0.88	0.93	0.93	1.00	1.06
9	0.93	0.80	0.96	1.03	0.86
High MAX	0.38	0.52	0.36	0.37	0.31
Return Difference	-0.70*	-0.55	-0.76*	-0.75	-0.79
	(-1.83)	(-1.26)	(-1.65)	(-1.51)	(-1.63)
Alpha Difference	-0.62**	-0.47	-0.71**	-0.67**	-0.69**
	(-2.12)	(-1.58)	(-2.24)	(-1.99)	(-2.11)

Notes: *p<0.1 **p<0.05 ***p<0.01

VW Portfolios sorted by MAX after controlling for IVOL

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.16	1.49	1.49	1.44	1.43
2	1.06	1.13	0.93	1.03	1.13
3	1.19	1.07	1.29	1.11	1.16
4	1.26	0.97	0.96	1.19	1.07
5	0.76	1.15	1.14	0.92	0.95
6	1.39	1.12	0.86	1.15	1.10
7	1.32	1.11	1.01	0.96	0.91
8	0.94	0.57	0.90	1.13	1.17
9	0.46	0.92	0.83	0.83	0.74
High MAX	1.05	0.84	0.66	0.81	0.89
Return Difference	-0.11	-0.65**	-0.83**	-0.63**	-0.53*
	(-0.40)	(-2.15)	(-2.58)	(-1.99)	(-1.65)
Alpha Difference	-0.33	-0.85***	-1.07***	-0.91***	-0.80***
	(-1.27)	(-3.18)	(-3.66)	(-3.20)	(-2.80)

VW Portfolios sorted by MAX after controlling for Book-to-Market

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.20	1.17	1.10	1.19	1.12
2	1.72	1.66	1.66	1.46	1.52
3	1.38	1.45	1.55	1.53	1.57
4	1.23	1.47	1.39	1.44	1.47
5	1.44	1.44	1.26	1.35	1.20
6	1.41	1.35	1.37	1.16	1.12
7	1.04	0.83	0.90	1.08	1.10
8	0.96	0.90	1.05	0.92	0.90
9	0.40	0.62	0.63	0.56	0.60
High MAX	0.66	0.33	0.21	0.19	0.30
Return Difference	-0.54	-0.84**	-0.90**	-0.99**	-0.83**
	(-1.55)	(-2.41)	(-2.51)	(-2.49)	(-2.14)
Alpha Difference	-0.50*	-0.85***	-0.92***	-0.99***	-0.84***
	(-1.76)	(-2.83)	(-2.94)	(-3.09)	(-2.67)

Notes: *p<0.1 **p<0.05 ***p<0.01

VW Portfolios sorted by MAX after controlling for Beta

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.19	1.15	1.22	1.19	1.22
2	1.13	1.14	1.31	1.22	1.33
3	1.31	1.43	1.44	1.40	1.22
4	1.19	1.34	1.18	1.31	1.35
5	1.30	1.08	1.22	1.32	1.30
6	1.30	1.20	1.07	1.09	1.12
7	1.08	0.92	0.97	0.98	1.08
8	0.79	0.83	0.83	0.89	0.90
9	0.84	0.44	0.47	0.52	0.59
High MAX	0.22	0.45	0.54	0.38	0.32
Return Difference	-0.96***	-0.70**	-0.67*	-0.81**	-0.90**
	(-2.86)	(-2.09)	(-1.82)	(-2.08)	(-2.29)
Alpha Difference	-0.85***	-0.57**	-0.54*	-0.69**	-0.80***
	(-3.13)	(-2.22)	(-1.88)	(-2.35)	(-2.72)

VW Portfolios sorted by MAX after controlling for Illiquidity

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.19	1.16	1.19	1.26	1.26
2	1.17	1.09	1.28	1.34	1.36
3	1.27	1.21	1.29	1.12	1.12
4	0.98	1.33	1.09	1.24	1.19
5	1.16	0.94	1.05	0.94	0.78
6	0.84	1.02	0.91	1.04	1.19
7	0.86	0.92	0.91	1.00	1.00
8	0.71	0.69	0.71	0.53	0.52
9	0.31	0.43	0.39	0.49	0.55
High MAX	0.43	0.45	0.32	0.25	0.26
Return Difference	-0.77**	-0.71*	-0.86*	-1.00**	-1.01**
	(-2.14)	(-1.75)	(-1.94)	(-2.25)	(-2.25)
Alpha Difference	-0.96***	-0.90***	-1.08***	-1.28***	-1.23***
	(-3.31)	(-2.73)	(-3.70)	(-4.26)	(-4.04)

VW Portfolios sorted by MAX after controlling for Momentum

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	0.98	1.01	1.04	1.00	1.04
2	1.42	1.37	1.39	1.43	1.34
3	1.30	1.31	1.28	1.39	1.37
4	1.18	1.35	1.44	1.53	1.32
5	1.10	1.10	1.36	1.15	1.28
6	1.13	1.10	1.16	1.12	1.10
7	0.78	1.01	0.81	0.89	0.83
8	1.01	0.76	0.71	0.70	0.63
9	0.67	0.64	0.64	0.65	0.62
High MAX	0.17	0.44	0.46	0.47	0.43
Return Difference	-0.81**	-0.57	-0.58	-0.53	-0.62
	(-2.31)	(-1.50)	(-1.44)	(-1.32)	(-1.53)
Alpha Difference	-0.96***	-0.75**	-0.71**	-0.68**	-0.79**
	(-3.08)	(-2.30)	(-2.13)	(-2.06)	(-2.47)

Notes: *p<0.1 **p<0.05 ***p<0.01

VW Portfolios sorted by MAX after controlling for Return of the second half of the previous month

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.04	1.13	0.97	0.99	1.10
2	1.26	1.15	1.20	1.24	1.30
3	1.32	1.26	1.34	1.31	1.34
4	1.43	1.65	1.55	1.45	1.41
5	1.20	1.30	1.40	1.32	1.27
6	1.34	1.19	1.12	1.21	1.02
7	1.38	1.14	1.08	1.16	1.15
8	1.03	0.99	1.24	1.22	1.36
9	0.73	0.69	0.55	0.60	0.61
High MAX	0.33	0.15	0.25	0.35	0.38
Return Difference	-0.71*	-0.98**	-0.72*	-0.64	-0.73*
	(-1.79)	(-2.36)	(-1.71)	(-1.49)	(-1.73)
Alpha Difference	-0.54**	-0.91***	-0.63**	-0.61*	-0.68**
	(-1.99)	(-3.30	(-2.26)	(-1.94)	(-2.20)

Notes: *p<0.1 **p<0.05 ***p<0.01

In addition, bivariate dependent sorts are not always powerful enough to disentangle the true effect in highly correlated variables (Bali et al. 2011). Particularly in the case of reversal over the last month and the second half of the month, it is reasonable to assume that the correlation between the control variable and MAX will be highest in the highest control group quintile. This problem is enhanced by the fact that we are only able to use five control groups compared to the ten MAX deciles due to the limited number of stocks in our sample.

4.7) Controlling for Lottery Characteristics

Cumulative prospect theory argues that investors tend to overvalue stocks with a small probability of large high returns while they tend to undervalue stocks with a small probability of an extreme negative return (Barberis and Huang 2008) and thus prefer positively skewed returns. As stocks in the high-MAX portfolios tend to have a more positive idiosyncratic and total skewness, this skewness preference might explain the underperformance of those stocks.

To determine whether these effects can explain the returns we double sort the stocks as described on idiosyncratic skewness, systematic skewness and the lottery stock index (LIDX) which combines idiosyncratic skewness, price and idiosyncratic volatility (Kumar, 2009). None of the skewness measures is able to fully explain the alpha differences between high- and low-MAX portfolios, with all alphas significant at 10% level for either measure and even at the 1% level when sorted on systematic skewness. Sorting by the lottery stock index brings alpha differences comparable to the univariate portfolio sorting with only the alphas of MAX (2,3,5) significant, but with larger return differences.

This matches earlier findings by Bali et al. (2011). It indicates that the MAX effect is unlikely to be explained only by skewness preference in the Swedish market. However, we are only able to use backwards-looking skewness measures which might not be adequate in capturing this effect. [4]

[4] The lack of volume data through much of our sample and the requirement for five years of backwards-looking return data would allow the calculation of expected skewness following Boyer et al. (2010) only for a small subsample. This would make the results on this measure difficult to compare.

Table 10 - *Portfolios sorted on MAX after controlling for lottery characteristics*

We form monthly decile portfolios from 1984 to 2018 by first sorting stocks in quintile portfolios of the respective control variables ISKEW, idiosyncratic skewness, SSKEW and LIDX, the lottery stock index which accounts for idiosyncratic skewness, idiosyncratic volatility and price following Kumar (2009). We form decile portfolios of MAX (N) within each control group. We report the average returns across the five control groups to produce decile portfolios with dispersion in the variable of interest but with similar levels of the control variable. Portfolio 10 (1) is the portfolio with the highest (lowest) maximum multi-day return over the previous month. The last two rows present the differences in monthly returns between the first and last deciles and the differences in the four-factor Cahart (1997) Alpha. Newey-West (1987) adjusted t-statistics are reported in parentheses.

VW Returns on Portfolios of Stocks sorted on multi-day maximum Returns after controlling for ISKEW

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.14	1.14	1.20	1.14	1.21
2	1.54	1.54	1.57	1.53	1.48
3	1.71	1.45	1.55	1.42	1.56
4	1.53	1.81	1.58	1.74	1.64
5	1.38	1.54	1.63	1.63	1.64
6	1.40	1.37	1.38	1.43	1.59
7	1.32	1.40	1.44	1.14	1.13
8	1.45	1.04	1.05	1.24	1.28
9	0.97	0.80	1.06	0.93	0.90
High MAX	0.34	0.58	0.46	0.38	0.47
Return Difference	-0.80*	-0.56	-0.75	-0.76	-0.73
	(-1.79)	(-1.16)	(-1.47)	(-1.47)	(-1.40)
Alpha Difference	-0.93***	-0.72**	-0.96**	-1.03***	-1.02***
	(-2.80)	(-2.04)	(-2.55)	(-2.75)	(-2.65)

VW Returns on Portfolios of Stocks sorted on multi-day maximum Returns after controlling for SSKEW

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.15	1.05	1.19	1.18	1.14
2	1.51	1.55	1.37	1.47	1.40
3	1.47	1.73	1.70	1.61	1.67
4	1.98	1.62	1.49	1.57	1.55
5	1.40	1.58	1.83	1.72	1.43
6	1.27	1.49	1.58	1.65	1.67
7	1.43	1.32	1.22	1.28	1.29
8	1.13	1.21	1.12	1.19	0.99
9	1.05	1.12	1.04	1.17	1.35
High MAX	0.42	0.23	0.37	0.26	0.19
Return Difference	-0.73**	-0.82***	-0.82**	-0.93*	-0.96**
	(-2.11)	(-2.63)	(-2.29)	(-1.89)	(-1.97)
Alpha Difference	-0.93***	-1.23***	-1.05***	-0.92***	-0.92***
	(-3.39)	(-4.04)	(-3.42)	(-2.94)	(-3.00)

VW Returns on Portfolios of Stocks sorted on multi-day maximum Returns after controlling for LIDX

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	0.98	1.03	1.03	1.04	1.01
2	1.50	1.48	1.46	1.46	1.34
3	1.61	1.53	1.34	1.40	1.34
4	1.20	1.25	1.59	1.49	1.54
5	1.17	1.19	1.18	1.30	1.35
6	1.26	1.08	1.16	1.43	1.51
7	1.04	1.17	1.05	1.00	1.06
8	0.94	0.76	0.80	0.93	0.84
9	0.60	0.25	0.35	0.36	0.42
High MAX	0.37	0.30	0.29	0.39	0.26
Return Difference	-0.61	-0.73*	-0.74*	-0.65	-0.76*
	(-1.58)	(-1.85)	(-1.74)	(-1.43)	(-1.66)
Alpha Difference	-0.49	-0.68**	-0.73**	-0.60	-0.78**
	(-1.46)	(-2.16)	(-2.08)	(-1.62)	(-2.17)

Notes: *p<0.1 **p<0.05 ***p<0.01

4.8) Fama and Macbeth Ordinary Least Squares Regression Analysis

Since bivariate portfolio sorting only allows controlling for one additional risk factor at a time, we use the Fama and Macbeth (1973) regression approach to determine whether MAX remains significant after controlling for various additional risk factors together. For that, we run monthly firm-level cross-sectional regressions of returns and several lagged predictor variables including MAX(5). We chose MAX (5) because it has shown the highest significance in explaining future returns in portfolio level analysis and appears a good indicator of a stock with lottery-like payoffs. To reduce the effect of outliers, we follow Fu (2009) and winsorize the values at the 0.5% and 99.5% marks for all independent variables every month.

In the univariate specification, MAX has a negative slope coefficient with a statistically significant t-stat of |-2.12|. IVOL has a slightly negative but insignificant slope when regressed by itself but interestingly becomes very significant with a positive slope coefficient while the significance of MAX increases to |-2.28|. This mirrors the findings of Bali et al. (2011) and once again indicates that MAX is not in fact driven by IVOL but shows a different effect.

Regressions of MAX (5) in combination with beta, size and book-to-market show similar significance levels. However, when combined with momentum, the significance of MAX decreases to a barely significant t-statistic of |-1.69|, and when regressing it together with reversal it becomes fully insignificant. In a regression with both reversal and momentum, the coefficient of MAX decreases further and its t-statistics decrease to |-0.21| while both REV and MOM are highly significant. In the full specification, MAX is less insignificant but does not manage to meet any relevant significance levels.

This would indicate that MAX is not a significant risk factor on the Swedish stock market, but the low returns of high MAX stocks are primarily driven by short-term reversal and to a lesser degree by momentum. Given the obvious correlation between earning high multi-day returns, the relationship seems intuitive. However, a Fama and Macbeth (1973) OLS regression comes closest to an equal-weighted portfolio approach, where stocks with small market capitalization are overrepresented and the result suffers from the influence of extreme outliers.[5] In our earlier analysis we found significant alpha differences only for our value-weighted portfolios so these results are widely consistent with our earlier findings.

Table 11. ***Firm-level cross-sectional regression***

Each month from 1984-2018, we run a firm-level cross-sectional regression of the return in that month on subsets of lagged predictor variables including MAX(5), IVOL and 6 control variables. Regressions including ILLIQ include only the period from 1993-2018 as we do not have ILLIQ data for earlier periods. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their respective Newey-West (1987) adjusted t-statistics.

MAX	IVOL	Beta	SIZE	BM	MOM	REV	ILLIQ
-0.0997**							
(-2.12)							
	-0.0326						
	(-0.54)						
-0.1191**	0.4386**						
(-2.28)	(2.56)						
		0.0001					
		(0.12)					
-0.1214**		0.0012					
(-2.11)		(0.72)					
			-0.0006				
			(-1.18)				
-0.1283***			-0.0009*				
(-2.81)			(-1.65)				
				0.0037**			
				(2.57)			
-0.1309***				0.0039***			
(-2.93)				(2.82)			
					0.0091***		
					(3.61)		
-0.0873*					0.0089***		
(-1.69)					(2.67)		
						-0.0397***	
						(-3.90)	
-0.0398						-0.0411***	
(-0.72)						(-3.60)	
-0.0122					0.0109***	-0.0474***	
(-0.21)					(3.44)	(-4.32)	
							3,689.10
							(1.14)
		-0.0019**	-0.0008	0.001	0.0121***	-0.0224**	-1,581.18
		(-2.55)	(-1.21)	(0.72)	(3.66)	(-2.58)	(0.45)
-0.0886		0.0012	-0.0007	0.0033***	0.0118***	-0.0500***	
(-1.39)		(0.66)	(-1.23)	(2.77)	(4.09)	(-4.89)	
-0.0647		-0.0014**	-0.0008	0.001	0.0118***	-0.0199*	1,260.872
(-1.07)		(-2.20)	(-1.55)	(0.77)	(4.10)	(-1.86)	(0.34)
-0.0748	-0.0441	-0.0015**	-0.0008	0.0009	0.0120***	-0.0194	1,292.60
(-1.14)	(-0.30)	(-2.22)	(-1.47)	(0.71)	(3.62)	(-1.53)	(0.41)
Note:							$^{*}p^{**}p^{***}p<0.01$

5 By the nature of weighting the squared residuals an OLS is even more affected by outliers than equally weighted portfolios, which tend to be more present in microcaps. (Harvey et al. 2021)

4.9) Fama and Macbeth Weighted Least Squares Regression

To further test the significance of the MAX effect and determine whether short-term reversal appears to make it insignificant primarily due to its strong effect on small firms and microcaps, we run the Fama and Macbeth (1973) regression using weighted least squares (WLS), weighted by the square root of market capitalization in the previous month. This makes the results more economically relevant and statistically reliable, as a regression based on OLS significantly overweights microcaps and thus is more prone to discovering anomalies that cannot be taken advantage of due to trading frictions and illiquidity (Hou et al. 2018).

In this regression approach, the coefficient of MAX is negative but insignificant in the univariate regression of MAX(5) on return. Given the hump-shaped return curve of the value-weighted MAX deciles, this rather weak relationship seems reasonable as the effect of an increasing MAX does not appear to be strictly linear. However, it is a lot lower than that found by Walkshäusl (2014) for other European markets. In combination with IVOL, both MAX and IVOL show a very low significance.

Surprisingly, while MAX is insignificant on its own, combining it with idiosyncratic volatility and other control variables makes it a lot more significant with a t-statistic of |-2.24| in the full specification and of |-1.95| when excluding illiquidity (which is missing before 1993) in addition to having more negative coefficients. Similarly, the effect of IVOL becomes a lot more significant when adding additional variables. This is consistent with the results of our bivariate dependent portfolio sorting where we noticed a highly increased significance of the MAX portfolios when controlling for other effects, but given that we were only able to test on one effect at a time it nonetheless seems remarkable. Neither idiosyncratic skewness nor systematic skewness appear to be able to explain the significance of MAX in a multivariate regression setting.

Table 12. *Firm-level cross-sectional regression - value weighted*

Each month from 1984-2018, we run a firm-level cross-sectional regression of the return in that month on subsets of lagged predictor variables including MAX(5) and control variables weighted on the square root of the previous months market capitalization. The control variables include IVOL, Beta, SIZE, the natural logarithm of a firms total market value, BM, the natural logarithm of a firms Book-to-Market ratio, REV, the previous months return, REV-2W, the return of the second half of the previous month , ILLIQ, illiquidity by Amihud´s (2002) illiquidity measure as well as systematic skewness (SSKEW) and idiosyncratic skewness (ISKEW). The firm-months are weighted by the square root of their previous months market capitalization. Regressions including ILLIQ include only the period from 1993-2018 as we do not have ILLIQ data for earlier periods. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their respective Newey-West (1987) adjusted t-statistics.

	Dependent variable: Return										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
MAX (5)	-0.0567	-0.0401	-0.0160	-0.0438	-0.1687*	-0.2235**	-0.1522*	-0.1531*	-0.1952**	-0.1384*	-0.1892**
	(-0.69)	(-0.54)	(-0.18)	(-0.52)	(-1.95)	(-2.24)	(-1.87)	(-1.90)	(-2.14)	(-1.74)	(-2.10)
IVOL		-0.0566					-0.5389***	-0.5573***	-0.4028*	-0.5381***	-0.3879*
		(-0.32)					(-2.73)	(-2.85)	(-1.77)	(-2.92)	(-1.76)
Beta					0.0011	-0.0002	0.0001	-0.00001	-0.0009	-0.0001	-0.0010
					(0.82)	(-0.11)	(0.06)	(-0.01)	(-0.58)	(-0.06)	(-0.68)
Size					-0.0011	-0.0012	-0.0019***	-0.0019***	-0.0017**	-0.0017**	-0.0016**
					(-1.56)	(-1.59)	(-2.70)	(-2.63)	(-2.52)	(-2.35)	(-2.42)
BM					0.0009	0.0006	0.0009	0.0011	0.0003	0.0011	0.0007
					(0.83)	(0.56)	(0.88)	(1.06)	(0.33)	(0.99)	(0.67)
MOM					0.0099***	0.0079**	0.0113***	0.0128***	0.0090***	0.0123***	0.0108***
					(3.06)	(2.13)	(3.62)	(4.03)	(2.66)	(3.90)	(3.11)
REV			-0.0257*		-0.0272**	-0.0188	-0.0057	-0.0054	-0.0035	-0.0102	-0.0018
			(-1.86)		(-2.12)	(-1.15)	(-0.33)	(-0.28)	(-0.14)	(-0.54)	(-0.08)
REV - 2w				-0.0575***			-0.0876***	-0.0820***	-0.0680***	-0.0760***	-0.0627***
				(-3.62)			(-4.31)	(-4.06)	(-2.82)	(-3.97)	(-2.64)
ILLIQ						10,485.6700					7,544.8160
						(1.12)					(0.97)
ISKEW								-0.0003		-0.0002	-0.0001
								(-0.42)		(-0.24)	(-0.11)
SSKEW									0.00001	0.000000	-0.00004
									(0.04)	(0.0006)	(-0.18)

Note: *p**p***p<0.01

The results may in part be explained by the nonlinearity of the MAX effect in the base case which may be reduced when combining it with the relevant control variables in a multivariate regression. While Bali et al. (2011) find MAX is highly significant in predicting future returns in the US stock markets on its own, the significance level increases when regressing it with the control variables. Similarly, Annaert et al. (2013) find MAX significant only at the 10% level on its own while the significance increases in combination with control variables. Thus, while MAX appears to have a significantly negative effect on future returns when combined with various control variables, it is insignificant on its own in a value-weighted regression. Therefore, we cannot conclude that MAX has distinct significant explanatory power when predicting future returns in the Swedish stock market.

4.10) Persistence of the MAX Effect During Subsamples

To analyze the persistence of MAX over time, we divide our sample into three equal-length time periods (*Table 18 in the appendix*). Interestingly, the significance of the MAX effect varies widely over time. In the first period from 1984-1994, the difference portfolio between the high- and low-MAX does not generate any significant alphas and the return difference is even negative for some of the MAX (N). However, this is not due to a good performance of the high-MAX portfolio but rather a consequence of the bad performance of the low-MAX portfolio during that time period. In the intermediate period from 1995 to 2006 on the other hand, all difference portfolios generated significantly negative alphas at the 1% level and the 5% level. While high-MAX stocks still performed poorly, the low-MAX portfolio achieved very high returns in this period. In the last period, from 2007 to 2018, the return difference between the low- and high-MAX portfolios as well as the alpha differences increase steadily from MAX(1) to MAX(5) but are only significant at the 10% level for MAX(4) and MAX(5). This could point to MAX being driven by IVOL or reversal during that period as those would also steadily increase from MAX(1) to MAX(5).

The high variability of the MAX effect over time further indicates that the choice of sample period can significantly impact the results. Had we started our analysis beginning ten years later, all MAX levels would be of a much higher significance. This could explain the lower significance of our results compared to Walkshäusl (2014) for example, who uses a measurement period from 1990 to 2011 when testing the MAX effect in Europe. The differences in magnitude could be driven by time-varying effects such as differing business cycles or sentiment.

4.11) Persistence of the MAX Effect Depending on the State of the Economy

While theoretical models such as Palfrey and Wang's (2012) predict a higher appetite for speculative assets during good states of the economy, most empirical evidence indicates that investors are more drawn to gambling behavior during bad states. Therefore, we would expect the MAX effect to be more pronounced during recessions than during expansionary periods if the causes of the MAX effect are behavioral.

Figure 1. *Excess returns of highest- and lowest-MAX Portfolios compared to the market.*
The graph shows the 24-month moving average excess returns of the portfolio consisting of stocks with the highest MAX(5), with the lowest MAX(5) and the market portfolio.

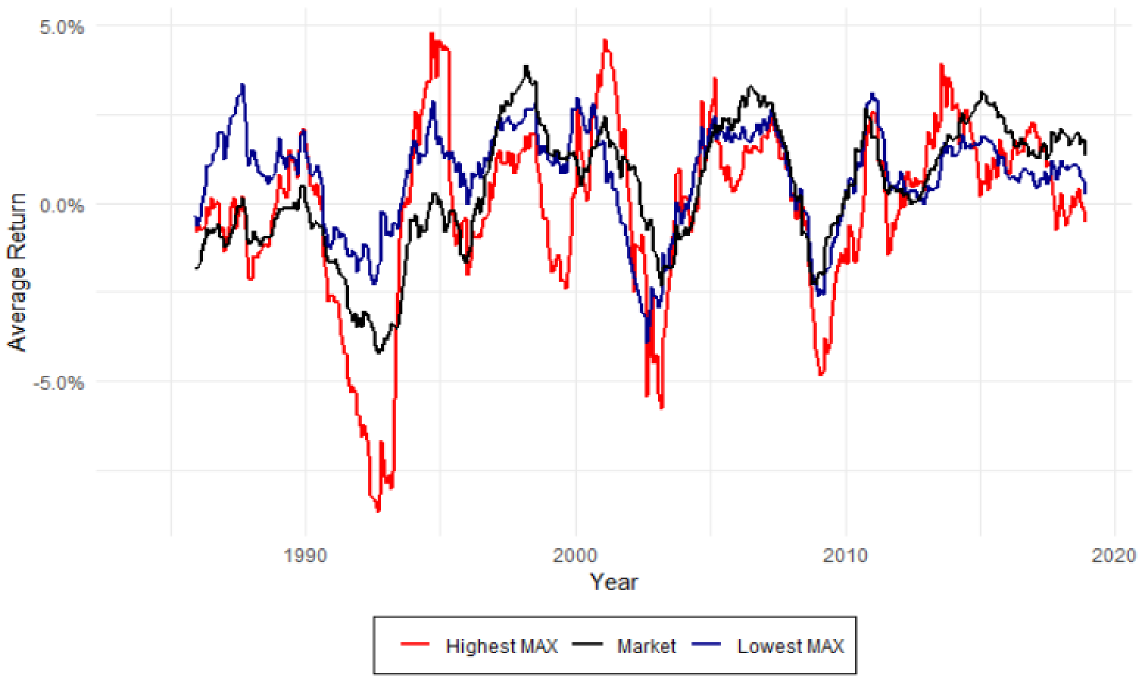

Figure 1 indicates that MAX portfolios particularly underperformed the market during major recessions, mainly the Swedish Economic Crisis from 1990-1993, the burst of the dot-com bubble (2000-2003) or the Great Recession (2007-2009) (NBER, 2021).

To analyze the magnitude of the differences between high and low MAX stocks depending on the state of the economy and in combination with other risk factors, we run monthly cross-sectional value-weighted Fama and Macbeth (1973) regressions; separately during the time period, the OECD-based recession indicator (NBER, 2021) considers recessionary and during the time the recession indicator considers expansionary using MAX(5) together with the defined control variables. Furthermore, we take a look at the portfolio-level performance of the difference portfolios during recessionary and expansionary periods.

The Fama and Macbeth (1973) regression indicates a distinct difference in the magnitude and significance of MAX depending on the economic cycle. In recessionary periods, MAX is highly significant and negative when regressed without control variables with a slope coefficient of |-0.27| and a t-statistic of |-2.55|. In combination with the earlier defined control variables it remains significant at the 5%-level.[6]

Adding idiosyncratic and systematic skewness to the regression reduces its significance barely below the 10%-level indicating that the MAX effect during recessions is partly driven by a preference for stocks with positive skewness.[7]

On the other hand, during expansionary periods the average slope coefficient of MAX(5) in a univariate regression on return is in fact positive though insignificant. When adding the control variables to the regression, the average slope coefficient turns negative but remains insignificant. Interestingly, while IVOL is insignificant during recessionary periods, it becomes highly significant and negative during expansionary periods. This could indicate that MAX is a proxy for IVOL during those periods.

[6] The higher significance level when regressed with all control variables including ILLIQ can be attributed to the fact that this regression does not include the time before 1993, during which the MAX effect was weaker.

[7] Using MAX (1 - 4) in the regression instead of MAX (5) shows similar results but MAX has a lower significance in the multivariate specifications

Table 13. *Firm-level cross-sectional regression during recessionary and during expansionary periods– value weighted*

Based on the OECD based recession indicator, we run monthly firm-level cross-sectional regressions from 1984-2018 for months which are marked as recessionary periods or as expansionary periods. The regression is run to predict return in that month on subsets of lagged predictor variables including MAX (5), IVOL, 7 control variables Beta, SIZE, the natural logarithm of a firms total market value, BM, the natural logarithm of a firms Book-to-Market ratio, REV, the previous months return, REV-2W, the return of the second half of the previous month , ILLIQ, illiquidity by Amihud´s (2002) illiquidity measure as well as systematic skewness (SSKEW) and idiosyncratic skewness (ISKEW). The firm-months are weighted by the square root of their previous months market capitalization. Regressions including ILLIQ include only the period from 1993-2018 as we do not have ILLIQ data for earlier periods. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their respective Newey-West (1987) adjusted t-statistics.

	Dependent variable: Return											
	Recessionary Periods						**Expansionary Periods**					
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
MAX	-0.2658**	-0.2223**	-0.3321**	-0.1939*	-0.2971**	-0.1802	0.1417	-0.0857	-0.1204	-0.0841	-0.1539	-0.0988
	(-2.55)	(-1.98)	(-2.30)	(-1.77)	(-2.13)	(-1.64)	(1.28)	(-0.79)	(-1.07)	(-0.77)	(-1.42)	(-0.93)
IVOL		-0.3133	-0.0716	-0.3245	-0.1078	-0.3580		-0.7530***	-0.6536**	-0.7265***	-0.6375**	-0.7090***
		(-1.13)	(-0.19)	(-1.20)	(-0.30)	(-1.34)		(-2.82)	(-2.12)	(-3.00)	(-2.19)	(-3.00)
Beta		0.0012	0.0005	0.0010	-0.0007	0.0003		-0.0005	-0.0014	-0.0004	-0.0006	-0.0001
		(0.65)	(0.19)	(0.55)	(-0.31)	(0.21)		(-0.30)	(-0.75)	(-0.23)	(-0.35)	(-0.05)
SIZE		-0.0016	-0.0025**	-0.0015	-0.0027***	-0.0014		-0.0021**	-0.0013	-0.0020**	-0.0012	-0.0018**
		(-1.48)	(-2.58)	(-1.36)	(-2.74)	(-1.31)		(-2.42)	(-1.44)	(-2.28)	(-1.27)	(-2.10)
BM		-0.0002	0.0005	-0.0004	0.0009	-0.0002		0.0020	0.0008	0.0021	0.0010	0.0022
		(-0.15)	(0.33)	(-0.30)	(0.68)	(-0.13)		(1.44)	(0.57)	(1.49)	(0.75)	(1.59)
MOM		0.0112**	0.0077	0.0108**	0.0113*	0.0120**		0.0113***	0.0111***	0.0113***	0.0121***	0.0127***
		(2.14)	(1.23)	(1.99)	(1.75)	(2.21)		(3.44)	(3.16)	(3.63)	(3.41)	(4.06)
REV - 2W		-0.1088***	-0.0993**	-0.0981***	-0.0948**	-0.0969***		-0.0675***	-0.0576*	-0.0645**	-0.0512*	-0.0562**
		(-3.34)	(-2.17)	(-3.26)	(-2.12)	(-3.31)		(-2.64)	(-1.93)	(-2.56)	(-1.68)	(-2.20)
REV		0.0078	0.0215	0.0015	0.0228	0.0024		-0.0186	-0.0131	-0.0227	-0.0092	-0.0222
		(0.30)	(0.48)	(0.05)	(0.52)	(0.08)		(-0.83)	(-0.44)	(-0.97)	(-0.33)	(-1.01)
ILLIQ			27,397.22						-8,030.06			
			(1.61)						(-1.63)			
SSKEW				-0.0002		-0.0003				0.0003		0.0003
				(-0.76)		(-1.03)				(1.45)		(1.50)
ISKEW					-0.0009	0.0003					0.0002	-0.0006
					(-0.72)	(0.30)					(0.24)	(-0.66)

Note: *p**p***p<0.01

The portfolio-level analysis offers less clear results. While stocks with high MAX underperform more in absolute terms in times of recession and the return differences are significant for MAX(N=2,3,5), the alpha difference is only significant for MAX(5) at the 5% level. During expansionary periods, high-MAX stocks earn comparable returns to low-MAX stocks, but the negative alphas of the difference portfolios indicate that this is achieved with excessive risk that is not compensated for. The alphas for MAX (2-5) are significant at the 10% level.

However, the portfolio-level analysis also shows that during recessions, low-MAX portfolios except for the lowest-MAX portfolio perform better than higher-MAX portfolios. The difference portfolio is not able to evaluate the full relationship between MAX and returns in combination with other variables unlike the Fama and Macbeth (1973) regression, however. Furthermore, interpretations of alphas when looking exclusively at recessionary periods are disputable as higher risk weightings for the same level of return would imply a better risk-adjusted performance.

While our findings are not fully conclusive, they indicate that the MAX effect is more pronounced during recessions, and particularly the underperformance of stocks with extreme previous returns is worse during these periods. During expansionary periods the MAX effect appears to be a lot weaker and is insignificant in the regression. Stocks with higher MAX even earn slightly higher returns but the portfolio-level analysis indicates that these are not high enough to compensate for the high factor loadings.

Our findings match the findings of Berggrun et al. (2019) who found a significant MAX effect only during recessions and of Kumar (2009) who finds a higher demand for lottery-type stocks in economically bad times. This may indicate that the MAX effect in Sweden is partly driven by a higher inclination to gamble during recessions.

Table 14. ***Portfolio Analysis during Expansionary and Recessionary Periods***

We form monthly decile portfolios from 1984 to 2018 by sorting stocks on the average of the N highest daily returns over the previous month depending on whether the previous month was indicated as expansionary or recessionary by the OECD based recession indicator (NBER, 2021). Portfolio 10 (1) is the portfolio with the highest (lowest) maximum multi-day return over the previous month. Newey-West adjusted t-statistics are reported in parenthesis. The last two rows present the differences in monthly returns between the first and last deciles and the differences in the four-factor Cahart (1997) Alpha. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Value-Weighted Returns on Portfolios of Stocks sorted on multi-day maximum Returns during *Expansionary* Periods

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.63	1.60	1.66	1.68	1.47
2	1.72	1.94	2.01	1.84	1.94
3	2.05	1.99	1.70	1.65	1.68
4	1.56	1.98	2.06	2.10	1.94
5	1.84	1.54	1.59	1.37	1.38
6	2.22	2.18	1.91	2.19	2.10
7	1.84	2.16	2.33	2.37	2.50
8	2.08	2.37	2.26	2.23	2.10
9	2.28	2.32	2.31	2.24	2.20
High MAX	1.80	1.47	1.68	1.74	1.58
Return Difference	0.17 (0.23)	-0.13 (-0.17)	0.02 (0.02)	0.06 (0.07)	0.11 (0.13)
Alpha Difference	-0.88 (-1.52)	-1.28** (-2.01)	-1.27* (-1.89)	-1.33** (-2.05)	-1.35** (-2.07)

Value-Weighted Returns on Portfolios of Stocks sorted on multi-day maximum Returns during *Recessions*

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	-0.11	-0.08	0.11	0.04	0.15
2	0.77	0.61	0.44	0.37	0.47
3	0.33	0.73	1.05	0.92	0.63
4	0.55	0.39	0.47	0.70	1.09
5	0.43	0.57	0.51	0.46	0.38
6	0.67	0.39	0.20	0.16	0.13
7	0.27	0.22	0.16	0.14	-0.25
8	-0.78	-0.71	-0.40	-0.15	-0.07
9	-0.18	-0.11	-0.65	-1.07	-1.01
High MAX	-0.94	-1.29	-1.17	-0.61	-0.99
Return Difference	-0.82 (-1.31)	-1.21* (-1.85)	-1.28* (-1.91)	-0.65 (-1.00)	-1.14* (-1.89)
Alpha Difference	-0.32 (-0.61)	-0.86 (-1.48)	-0.81 (-1.39)	-0.42 (-0.75)	-1.09** (-2.00)

Notes: **p<0.1 **p<0.05 ***p<0.01*

4.12) Further Robustness Checks

4.12.1) Relaxing Trading Day Requirement

To test the robustness of our base results, we test the significance when using less strict data requirements. So far, we excluded all firm-months that had missing trading days in the formation month. Loosening this to require at least 10 trading days every month adds about 5% additional data points to our sample. This adjustment does not impact the overall return distribution but slightly increases the returns of the low-MAX deciles and to a larger degree the returns of the high-MAX deciles. This decreases the significance of the MAX effect substantially with only the alpha for MAX(2) still significant at the 10% level. Thus, while the overall pattern is still visible, it is barely significant and might be due to chance. This can likely be explained by the fact that stocks with fewer trading days may have overstated MAX returns as the returns record price jumps of longer periods if one or multiple days are missing. Nonetheless, this finding puts further doubt on the robustness of the MAX effect in Sweden.

Table 15. ***Portfolio sorts with relaxed restrictions on missing trading days***

We form monthly value-weighted decile portfolios from 1984 to 2018 by sorting stocks on the average of the N highest daily returns over the previous month. Portfolio 10 (1) is the portfolio with the highest (lowest) maximum multi-day return over the previous month. Newey-West adjusted t-statistics are reported in parenthesis. Stocks with at least ten trading days in the formation period are included. The last two rows present the differences in monthly returns between the first and last deciles and the differences in the four-factor Cahart (1997) Alpha. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	0.76	0.87	0.97	0.92	0.90
2	1.26	1.34	1.24	1.13	1.28
3	1.21	1.32	1.50	1.38	1.25
4	1.07	1.27	1.19	1.33	1.35
5	1.15	0.95	0.99	1.07	1.06
6	1.46	1.32	1.15	1.18	1.26
7	1.07	1.32	1.16	1.04	0.91
8	0.68	0.80	1.00	1.19	0.80
9	1.07	0.86	0.74	0.62	0.65
High MAX	0.46	0.38	0.57	0.76	0.59
Return Difference	-0.30 (-0.67)	-0.49 (-0.96)	-0.40 (-0.72)	-0.16 (-0.27)	-0.31 (-0.53)
Alpha Difference	-0.48 (-1.18)	-0.77* (-1.73)	-0.69 (-1.45)	-0.45 (-0.89)	-0.65 (-1.33)

Notes: **p<0.1 **p<0.05 ***p<0.01*

4.12.2) Excluding Microcaps

To determine whether the MAX effect is primarily driven by small stocks, we test its persistence after excluding microcaps. We follow Fama and French (2008) who define microcaps as stocks below the 20th NYSE percentile. Because our sample consists primarily of stocks listed on the NASDAQ OMX, the most relevant stock exchange in Sweden, we consider it comparable to the NYSE in the context of the Swedish market. Thus we exclude stocks below the 20th percentile in terms of market capitalization every period.

After excluding microcaps *(table 19 in the appendix)*, the alpha and return differences in our value-weighted portfolio decrease and become insignificant. On the other hand, the return and alpha differences for the equal-weighted portfolio increase substantially, with all alpha and return differences significant at the 1% level. These findings indicate that MAX is indeed driven by small stocks in Sweden and does not affect the whole market. However, some of the smallest stocks appear not to follow the expected pattern of the MAX effect. This makes the alphas for the equal-weighted portfolio of the whole sample insignificant. This may be in part connected to outliers and measurement errors, which stocks in the smallest percentiles are most prone to.

5) Limitations

In this section we discuss limitations of our research resulting from incomplete data or our chosen methodology.

5.1) Potential Survivorship Bias

While the Finbas database gives us high quality and extensive stock market data, it does not exclude delisting returns. We follow Piotroski (2000) and assume a delisting return of 0% if a stock stops trading during a month. This may skew the results if stocks in the high or low MAX deciles have an increased or reduced chance of bankruptcy following a delisting. Given the nature of very volatile lottery-like stocks, this may have a significant impact on the results.

5.2) Incomplete Daily Fama-French Factors

The daily data containing Fama-French (1993) and Cahart (1997) factors did not have data for every trading day in our sample. In total 35 out of 419 months had at least one missing factor observation and one month had to be completely dropped because of missing factor data. This may lead to some misestimations of IVOL, Beta or Skewness for the affected months. Before deciding to use all months despite these inconsistencies, we ensured that the results do not change substantially had we excluded these months.

5.3) Small Sample Size

Given the comparably low number of stocks per month in our sample, we are only able to use five control groups in our bivariate dependent sorts unlike the ten Bali et al. (2011) used. This may lead to some of the controlled effects remaining in the double sorted portfolio especially in cases of high correlation between MAX and the control variable (i.e. REV) making the results less conclusive. Additionally, the low number of stocks per portfolio makes the results less stable to small changes in the data or outliers could have large impacts on the results. Analyzing the firms in a cross-sectional regression model allows us to look at the relationship of MAX and these control variables in more detail but at the cost of assuming the relationship between MAX and returns is linear.

5.4) Missing Control Variable Data Points

Throughout our sample we are missing certain data points necessary for calculating our control variables. Most notable, volume data are systematically missing until 1993 making portfolio sorting and regressions including illiquidity less comparable. Additionally, book values are unsystematically missing for about 6% of our data points and in rare cases values of skewness or momentum if the relevant lagged value is missing. Especially with respect to illiquidity, we might therefore misestimate the effect of the variable on the MAX effect.

6) Conclusion and Recommendations for Future Research

We analyze the return predictability of stocks depending on their lagged extreme positive daily returns in the Swedish stock market following the methodology of Bali et al. (2011). We find evidence that stocks with positive extreme daily returns in one month underperform in the subsequent month. A zero-cost portfolio buying a value-weighted portfolio of stocks in the highest MAX decile and selling a value-weighted portfolio of stocks in the lowest MAX decile yields negative risk-adjusted returns. Those are only significant for MAX based on the 2, 3, and 5 highest returns in the previous month however, and they are not significant for equal-weighted portfolios. This negative relation is robust to and increases in magnitude when controlling for the firm characteristics of size, book-to-market ratio, momentum, illiquidity, and beta as well as idiosyncratic volatility and skewness.

We find that stocks in the high-MAX decile are smaller in size and price and are less liquid than stocks in lower deciles while having a high degree of idiosyncratic volatility and positive skewness. Stocks with high (low) maximum daily returns in the previous month are more likely to earn high (low) maximum returns in the subsequent month indicating a persistence of MAX in stocks as has been found in previous research. Stocks with extreme minimum returns in the previous month show higher returns, but the difference portfolio, buying the highest-MIN and selling the lowest-MIN stocks, does not generate significant alphas.

Despite the persistence in maximum returns over time, portfolios formed using the average of maximum daily returns over periods of 3 or 6 months do not show significant alpha or return differences. In addition, the MAX effect is only existent in stocks which have their maximum return in the second half of the month, contrary to the findings of Bali et al. (2011). This could indicate that the MAX effect in Sweden is driven by extreme short-term reversals. That being said, controlling for reversal over the previous month and reversal over a shorter period by bivariate portfolio sorting is also unable to explain the MAX effect..

A firm-level cross-sectional Fama and Macbeth (1973) equal-weighted regression of lagged MAX and lagged control variables on returns shows a significant and negative slope coefficient of MAX(5). This coefficient appears to be explained primarily by short-term return reversal and to a lesser degree by momentum.

A WLS Fama and Macbeth (1973) regression weighted by size finds no significant explanatory power of MAX(5) when univariately regressed on the next month's return but a significant and negative slope coefficient when used in combination with control variables. We suspect this might be due to the nonlinearity of the MAX effect with respect to returns. Alternatively, it could indicate that MAX is a proxy for another effect which we were not able to control for.

We analyze the persistence of the MAX effect during three time periods from 1984 to 1994, from 1995 to 2006 and from 2007 to 2018. We find that the significance of the MAX effect has varied widely over time. While it is insignificant during the first period, it is highly significant in the second period and only mildly significant in the last period. The large differences in the significance over time indicate that time-varying factors may influence the MAX effect and puts a caveat on studies finding the MAX effect using short estimation periods.

Further, we find a strong and significant negative relation between MAX and future returns during recessionary periods, which is robust to the inclusion of controls for firm characteristics, return reversals, and momentum. Controlling for both idiosyncratic and systematic skewness, the MAX coefficient becomes insignificant. During expansionary periods, no significant relation between MAX and future returns is found. Portfolio-level analysis indicates a similar relationship between MAX and raw returns but a less clear one in terms of alpha. We consider this an indication that the MAX effect in Sweden may be partly driven by a greater inclination to gamble during economically bad times.

Finally, we control the robustness of the MAX under less strict data requirements and when excluding microcaps. In the first case, we consider all firm-months which have at least 10 trading days in the formation month instead of requiring trading on every day. This reduces the significance of the MAX effect for the value-weighted portfolio and only MAX(4) is significant at the 10% level while the equal-weighted portfolio remains insignificant. Excluding microcaps from our sample makes the alpha and return differences of the value-weighted portfolio insignificant. On the other hand, the significance of the alphas and returns generated by the equal-weighted high-low portfolio increases substantially to the 1% level for all

MAX(N). This indicates that MAX in the Swedish market is driven by small stocks but also that some of the smallest high MAX stocks do not follow the expected return pattern potentially due to outliers or measurement errors.

All in all, we show that while a negative cross-sectional relationship between MAX and future returns appears to exist in Sweden, it is of lower statistical significance than in other markets and it is not linear. The high sensitivity of the returns to the timing of the MAX within a month indicates that the effect is probably not primarily driven by cumulative prospect theory in Sweden. We assume extreme short-term reversal and overreaction may interact with cumulative prospect theory when explaining the effect in Sweden. The effect appears to be stronger during recessions, which may be due to a greater inclination to gamble during economically bad times. The MAX effect seems to be driven by small firms and microcaps subject to higher transaction costs and becomes insignificant for value-weighted portfolios after excluding those. High trading costs combined with the riskiness of shorting high MAX stocks may explain why the underperformance of stocks with extreme past returns has not been exploited by arbitrageurs.

For future research on the MAX effect in the Swedish market, we recommend a distinction between the extreme returns that originate from firm-specific news events and those that appear to happen by chance. Past research in other markets implies that the effect may be stronger when news is absent (Tao et al. 2020) which would provide a stronger case for behavioral explanations. Furthermore, a closer look into the types of investors who are drawn to high-MAX stocks would be interesting.

Additionally, our findings indicate a strong variation in the magnitude of the MAX effect over time. It would be interesting to explore whether similar variations exist in other markets and what drives them.

Furthermore, recent events in the U.S. showed an increased organization of retail traders who purposefully drove up stocks of heavily shorted companies (NYT, 2021). It would be interesting to analyze whether this behavior increases the magnitude of the MAX effect for smaller stocks due to heightened limits to arbitrage or whether it only reflects the effect of increased investor sentiment.

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8) Appendix

8.1) Formula to determine the optimal lag for Newey-West adjusted t-statistics:

Following Bali et al. (2016), we use the following formula:

$$4 * (\frac{T}{100})^{2/9},$$

where T is the total number of periods (months) of the respective sample.

8.2) Additional Results Tables

Table 16. ***Portfolio sorts with longer formation periods***

We form monthly value-weighted decile portfolios from 1984 to 2018 by sorting stocks on the average of the N highest daily returns over the 3 or 6 months. Portfolio 10 (1) is the portfolio with the highest (lowest) average maximum multi-day return over the previous 3 or 6 months. Newey-West adjusted t-statistics are reported in parenthesis. The last two rows present the differences in monthly returns between the first and last deciles and the differences in the four-factor Cahart (1997) Alpha. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Value-Weighted Returns on Portfolios of Stocks sorted on multi-day maximum Returns over the last 3 months

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	0.96	0.93	0.83	0.81	0.78
2	1.02	1.06	1.01	0.97	0.99
3	1.17	1.07	1.13	1.17	1.16
4	1.24	1.31	1.39	1.40	1.36
5	1.21	1.43	1.25	1.33	1.32
6	1.00	1.14	1.30	1.34	1.40
7	1.24	1.19	1.07	1.14	0.98
8	1.01	0.77	1.06	1.24	1.24
9	1.41	1.40	1.60	1.15	1.16
High MAX	0.72	0.89	0.58	0.92	0.80
Return Difference	-0.24 (-0.44)	-0.04 (-0.06)	-0.25 (-0.40)	0.12 (0.19)	0.03 (0.04)
Alpha Difference	-0.31 (-0.68)	-0.17 (-0.33)	-0.46 (-0.91)	-0.14 (-0.29)	-0.25 (-0.50)

Value-Weighted Returns on Portfolios of Stocks sorted on multi-day maximum Returns over the last 6 months

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	0.82	0.69	0.70	0.68	0.67
2	1.17	1.18	1.03	1.03	1.15
3	1.55	1.54	1.56	1.46	1.26
4	1.06	0.97	1.15	1.36	1.24
5	0.98	1.21	1.21	1.11	1.19
6	1.10	1.26	1.38	1.38	1.35
7	1.10	0.93	1.09	1.01	1.01
8	1.20	0.89	0.84	1.02	1.16
9	0.84	1.18	1.03	0.62	0.93
High MAX	0.40	0.53	0.67	0.77	0.49
Return Difference	-0.42	-0.16	-0.03	0.09	-0.18
	(-0.71)	(-0.27)	(-0.05)	(0.14)	(-0.31)
Alpha Difference	-0.55	-0.26	-0.20	-0.13	-0.45
	(-1.13)	(-0.52)	(-0.41)	(-0.28)	(-0.98)

Notes: **p<0.1 **p<0.05 ***p<0.01*

Table 17. *Portfolios sorted by SIZE*

Average market share (%) per quintile after sorting stocks by SIZE over time

Quintile	Average Market Share
Smallest	0.34
2	1.09
3	3.06
4	10.72
Largest	84.79

Table 18. *Portfolio sorts divided into 10-year subperiods*

We form monthly value-weighted decile portfolios within the defined time period by sorting stocks on the average of the N highest daily returns over the previous month. Portfolio 10 (1) is the portfolio with the highest (lowest) maximum multi-day return over the previous month. Newey-West adjusted t-statistics are reported in parenthesis. The last two rows present the differences in monthly returns between the first and last deciles and the differences in the four-factor Cahart (1997) Alpha. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Value-Weighted Returns on Portfolios of Stocks sorted on multi-day maximum Returns - 1984-1994

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	-0.07	-0.35	-0.36	-0.40	-0.47
2	1.01	1.22	1.14	1.06	1.16
3	1.44	1.32	1.39	1.29	1.08
4	1.59	1.79	1.71	1.80	1.99
5	1.56	1.54	1.52	1.41	1.35
6	2.19	1.85	1.73	1.98	1.90
7	1.52	1.76	1.61	1.70	1.71
8	0.95	1.08	1.15	1.25	0.96
9	0.75	0.56	0.47	0.32	0.97
High MAX	0.03	-0.39	0.06	0.33	-0.25
Return Difference	0.10	-0.04	0.42	0.73	0.22
	(0.10)	(-0.04)	(0.39)	(0.65)	(0.20)
Alpha Difference	0.08	-0.19	0.35	0.73	0.06
	(0.09)	(-0.20)	(0.35)	(0.72)	(0.06)

Value-Weighted Returns on Portfolios of Stocks sorted on multi-day maximum Returns -1995-2006

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.49	1.71	1.86	1.82	1.72
2	1.42	1.56	1.52	1.33	1.39
3	1.57	1.49	1.64	1.70	1.61
4	1.24	1.49	1.39	1.46	1.61
5	1.26	0.72	0.98	0.68	0.80
6	1.30	1.35	1.10	1.30	1.13
7	1.09	1.68	1.84	1.73	1.26
8	1.43	1.51	1.42	1.81	2.15
9	1.86	2.70	2.20	1.59	0.99
High MAX	0.67	0.13	0.15	0.97	0.83
Return Difference	-0.82	-1.58*	-1.71*	-0.85	-0.89
	(-0.94)	(-1.76)	(-1.82)	(-0.85)	(-0.96)
Alpha Difference	-1.66***	-2.37***	-2.44***	-1.70**	-1.91***
	(-2.67)	(-3.91)	(-3.97)	(-2.45)	(-2.74)

Value-Weighted Returns on Portfolios of Stocks sorted on multi-day maximum Returns - 2007-2018

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	0.77	0.90	1.09	1.14	1.12
2	1.32	1.08	1.07	0.94	1.10
3	0.62	1.31	1.11	0.89	0.81
4	0.42	0.38	0.79	1.01	1.01
5	0.68	0.98	0.73	0.72	0.57
6	0.96	0.76	0.45	0.37	0.45
7	0.64	0.25	0.37	0.44	0.54
8	-0.32	0.03	0.32	0.15	0.01
9	0.61	0.11	-0.10	-0.06	-0.05
High MAX	0.62	0.54	0.63	0.44	0.36
Return Difference	-0.15	-0.36	-0.46	-0.70	-0.77
	(-0.23)	(-0.51)	(-0.67)	(-1.06)	(-1.15)
Alpha Difference	-0.31	-0.64	-0.76	-1.01*	-1.16*
	(-0.49)	(-0.99)	(-1.27)	(-1.70)	(-1.97)

Notes: **p<0.1 **p<0.05 ***p<0.01*

Table 19. *Portfolio sorts after excluding Microcaps*

We form monthly decile portfolios from 1984 to 2018 by sorting stocks on the average of the N highest daily returns over the previous month. Portfolio 10 (1) is the portfolio with the highest (lowest) maximum multi-day return over the previous month. Before sorting the portfolios, we exclude all stocks within the smallest quintile of market capizalization. Newey-West adjusted t-statistics are reported in parenthesis. The last two rows present the differences in monthly returns between the first and last deciles and the differences in the four-factor Cahart (1997) Alpha. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Value-Weighted Returns on Portfolios of Stocks sorted on multi-day maximum Returns after excluding Microcaps

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	0.76	0.83	0.88	0.90	0.82
2	1.26	1.15	1.17	1.12	1.25
3	1.21	1.46	1.48	1.47	1.24
4	1.07	1.10	1.26	1.27	1.30
5	1.15	1.21	1.13	1.30	1.22
6	1.46	1.23	1.07	1.14	1.09
7	1.07	1.37	1.18	0.97	1.15
8	0.68	0.79	1.01	1.12	1.15
9	1.08	1.14	1.09	0.90	0.78
High MAX	0.45	0.76	0.60	0.70	0.73
Return Difference	-0.31 (-0.68)	-0.07 (-0.15)	-0.28 (-0.60)	-0.20 (-0.43)	-0.08 (-0.17)
Alpha Difference	-0.49 (-1.20)	-0.33 (-0.79)	-0.61 (-1.48)	-0.59 (-1.50)	-0.53 (-1.34)

Equally Weighted Returns on Portfolios of Stocks sorted on multi-day maximum Returns after excluding Microcaps

Decile	N=1	N=2	N=3	N=4	N=5
Low MAX	1.32	1.30	1.30	1.30	1.22
2	1.62	1.52	1.53	1.51	1.76
3	1.56	1.71	1.62	1.73	1.50
4	1.59	1.53	1.61	1.44	1.56
5	1.39	1.61	1.53	1.65	1.58
6	1.58	1.40	1.45	1.46	1.42
7	1.24	1.28	1.31	1.19	1.28
8	0.99	1.16	1.01	1.09	1.17
9	0.75	0.63	0.80	0.78	0.57
High MAX	0.08	-0.02	-0.03	-0.02	0.07
Return Difference	-1.24*** (-3.50)	-1.32*** (-3.57)	-1.33*** (-3.43)	-1.32*** (-3.46)	-1.16*** (-3.02)
Alpha Difference	-1.10*** (-4.03)	-1.22*** (-4.62)	-1.26*** (-4.65)	-1.26*** (-4.57)	-1.12*** (-3.96)

Notes: *p<0.1 **p<0.05 ***p<0.01