THE MAX EFFECT AND FIRM-SPECIFIC ATTENTION

HOW REVERSALS VARY WITH INVESTOR FOCUS

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The MAX Effect and Firm-Specific Attention: How Reversals Vary with Investor Focus

Abstract:

We examine the MAX effect, defined as the negative relation between extreme daily returns and subsequent stock performance, in Swedish equities from 2011 to 2024. We document a robust MAX effect in both portfolio sorts and firm-level return predictability. Using Google search volume as a proxy for firm-specific investor attention, we show that the effect varies across attention levels: MAX-related reversals arise when extreme returns coincide with abnormally low or moderate attention but disappear entirely when attention is abnormally high. Although firm-level regressions confirm that MAX predicts next-month returns, they do not detect systematic moderation by abnormal attention at the one-month horizon. Taken together, the results indicate that firm-specific attention is an important variable associated with whether reversals occur after salient price jumps, highlighting the broader role of attention in behaviorally driven return anomalies.

Keywords:

MAX Effect, Google Trends, Attention, Reversals, Behavioral Finance

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I. Introduction

Large single-day stock returns are among the most attention-grabbing events in financial markets. When a stock experiences an extreme daily price surge, it tends to drive media coverage and trigger online search activity. Although such dramatic returns may create the impression of rare, lottery-like opportunities, a growing body of research shows that these surges are systematically followed by lower future returns. This pattern is known as the MAX effect.

MAX, defined as the largest daily return of a stock within a month, has been shown to predict lower risk-adjusted returns in the following month. The effect is linked to investors' preference for lottery-like payoffs, where salient return spikes draw disproportionate attention and inflate prices before they revert toward fundamentals (Bali, Cakici, and Whitelaw, 2011).

The fact that the MAX effect varies in strength across markets and periods suggests that investors do not respond to salient price jumps in a uniform way. Prior research attributes this variation to market-wide sentiment (Mojtahedi, Mashhadi, and Savin, 2025), differences in investor composition (Aboulamer and Kryzanowski, 2016), or whether an extreme return coincides with informational events such as earnings announcements (Baars and Mohrschladt, 2021). These explanations speak to who is trading and what information is available, but they do not capture a theoretically important determinant of how investors react to salient price movements: the degree of *attention* directed at the specific firm experiencing the jump.

Firm-specific attention reflects how intensely investors focus on a stock when an extreme return occurs, shaping the speed at which price distortions may correct (Peng and Xiong, 2006; Merton, 1987). Despite its theoretical importance, this dimension has not been examined in prior MAX research. Evidence on the MAX effect in Sweden is also limited. Mojtahedi et al. (2025) document the effect in equally weighted portfolios from 1994 to 2019 but find no significant firm-level relationship, prompting an updated analysis.

We address this gap by providing updated evidence on the MAX effect in Sweden from 2011 to 2024 and examining whether firm-specific attention conditions the strength of MAX-related reversals. These objectives motivate two research questions:

1. Is the MAX effect present in Sweden between 2011 and 2024?

2. Does the MAX effect vary with firm-specific investor attention?

Literature on attention provides several reasons why behaviorally driven anomalies such as the MAX effect may vary across attention levels. Attention can signal heightened speculative interest, which increases buying pressure and contributes to temporary price distortions (Da, Engelberg, and Gao, 2011). Attention can also reflect greater investor recognition or monitoring, which accelerates information incorporation and reduces the persistence of distortions (Merton, 1987; Fang and Peress, 2009). Limited-attention models such as Peng and Xiong (2006) also emphasize that the speed of mispricing correction depends on how much attention investors devote

to processing information. Together, these frameworks suggest that attention influences both the magnitude and timing of the reversals that are central to the MAX effect, motivating our focus on firm-level attention as a conditioning variable.

To investigate our research questions, we construct a dataset of all firms listed on Nasdaq Stockholm from 2011 to 2024, combining daily return data, firm characteristics, and Google Trends search histories. At the portfolio level, we examine returns on MAX-sorted portfolios and on portfolios formed from double sorts of abnormal attention and MAX, evaluating their risk-adjusted performance using Fama–French Carhart four-factor regressions. At the firm level, we estimate monthly Fama–MacBeth cross-sectional regressions to test whether MAX predicts next-month returns and whether this predictive relation varies with firm-specific abnormal attention, proxied by standardized Google search volume.

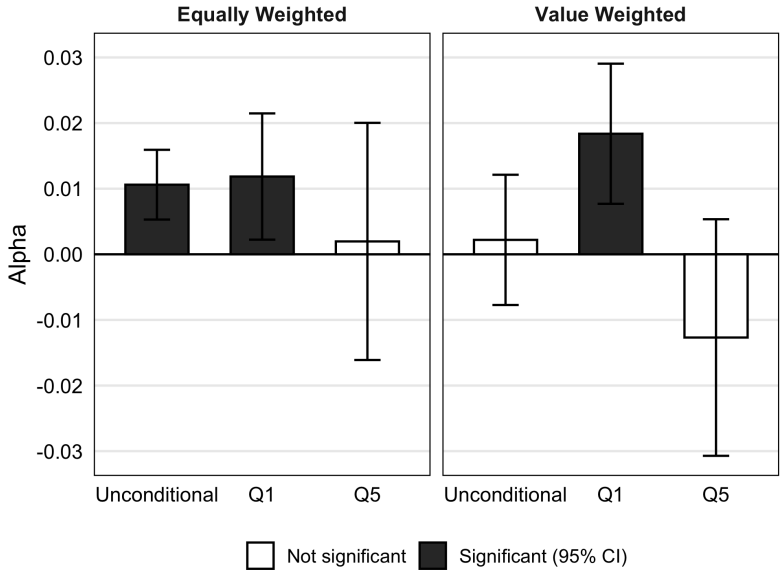


Figure 1. Long–Short Portfolio Alphas. This figure shows monthly Fama–French Carhart four-factor alphas for long–short portfolios formed on prior month maximum daily returns, evaluated both unconditionally and within different abnormal attention states. At the end of each month, we first sort stocks into quintiles based on their standardized abnormal attention from the previous month. Within each attention quintile, we then sort stocks into deciles using their prior month maximum daily return. The long–short portfolios are defined as the return on the lowest decile portfolio minus the return on the highest decile portfolio. The Unconditional portfolio applies this sort without conditioning on abnormal attention, while the Q1 and Q5 portfolios apply the sort within the lowest and highest abnormal attention quintiles.

Our main findings are that the MAX effect is present in Sweden during 2011 to 2024 and that its strength varies with the level of firm-specific attention. Figure 1 illustrates these patterns. In unconditional portfolios, long–short strategies sorted only on *MAX* yield statistically significant alphas under equal weighting but not value weighting. Conditioning on attention reveals a clearer pattern. In low-attention states (Q1), long–short alphas strengthen and remain significant under both weighting schemes, while in high-attention states (Q5), the alphas are small and statistically indistinguishable from zero. Although Figure 1 displays only the

lowest and highest abnormal attention quintiles for clarity, results for the intermediate quintile, Q3, also show positive and statistically significant long–short spreads when equally weighted. This confirms that the MAX effect is present in both low and moderate attention states, while entirely absent in high-attention environments.

These results demonstrate that attention meaningfully conditions the MAX effect. By showing that firm-specific attention is associated with whether and to what extent reversals follow extreme daily gains, our findings contribute to understanding why empirical evidence on the MAX effect varies across markets, time periods, and portfolio constructions. This evidence complements prior research on the MAX effect by identifying attention as a key conditioning factor and provides updated evidence for the Swedish equity market. More broadly, our results highlight that attention serves as a useful conditioning variable when evaluating behavioral anomalies.

The remainder of the paper is structured as follows: Section II reviews related theory and literature. Section III describes the data and variable construction. Section IV outlines the empirical methodology and presents the results. Section V reports robustness tests. Section VI concludes.

II. Theoretical Framework and Literature

A. Asset Pricing Foundations

Understanding return patterns following extreme price movements requires a framework for measuring abnormal performance. Under standard asset pricing theory, financial markets are informationally efficient, meaning that prices fully reflect available information and predictable return patterns should not persist after controlling for risk (Sharpe, 1964). The Capital Asset Pricing Model formalizes this by relating expected returns to systematic market risk. The Fama–French three-factor model extends this framework by incorporating size and value factors (Fama and French, 1992), while Carhart (1997) adds momentum. These models provide the benchmark for assessing whether stocks experiencing extreme daily returns earn abnormal subsequent returns. If extreme returns predict lower risk-adjusted returns after controlling for these factors, it is typically interpreted as evidence of behavioral forces rather than risk compensation.

Behavioral finance offers such explanations by showing how psychological biases create temporary mispricings. Cumulative prospect theory demonstrates that investors overweight small probabilities of extreme gains (Tversky and Kahneman, 1992), making rare lottery-like payoffs appear overly attractive. Barberis and Huang (2008) apply this insight to asset pricing, showing that preference for positively skewed return distributions can drive investors to overpay for stocks with lottery-like characteristics. Salience theory (Bordalo, Gennaioli, and Shleifer, 2012) reinforces this mechanism by demonstrating that vivid attention-grabbing signals distort beliefs and prompt overreaction. Together, these frameworks suggest that extreme daily returns, being both salient and suggestive of lottery payoffs, may temporarily inflate prices before subsequent correction.

B. The MAX Effect: Evidence and Variation

The MAX effect is well-established empirically. Bali et al. (2011) show that stocks with the highest maximum daily return in a month (MAX) earn significantly lower risk-adjusted returns in the following month across US equities from 1962 to 2005. This pattern appears in multiple international markets, including Australia (Fong and Toh, 2014) and Europe (Walkshäusl, 2014). However, evidence for the MAX effect in Sweden is scarce, limited to Mojtahedi et al. (2025), who document a significant MAX effect at the equally weighted portfolio level for the period 1994 to 2019.

Beyond its pervasive presence, the magnitude of the MAX effect varies across contexts. Research examining variation in the strength of the MAX effect highlights conditioning factors at multiple levels. At the market level, Mojtahedi et al. (2025) show the effect in Sweden strengthens when aggregate sentiment is low. At the firm level, Aboulamer and Kryzanowski (2016) demonstrate that the MAX effect weakens with higher institutional ownership, while Baars and Mohrschladt (2021) show that MAX-related reversals weaken substantially when extreme returns coincide with earnings announcements. These findings establish that the MAX effect is conditional, with market-wide sentiment, investor composition, and informational events all identified as moderators.

C. Investor Attention and Mispricing Persistence

Theoretical models establish that investor attention determines when mispricings persist. Limited attention frameworks emphasize that investors cannot continuously monitor all stocks, causing gradual information incorporation (Peng and Xiong, 2006). Merton (1987) demonstrates that stocks with limited investor recognition exhibit slower price adjustment regardless of available information. These models predict that both the magnitude and timing of mispricing correction depend systematically on attention levels.

Empirical evidence supports this view. Fang and Peress (2009) show that stocks receiving more media coverage incorporate information more quickly. Da et al. (2011) introduce Google search volume as a direct measure of investor attention and find that attention spikes precede short-run price increases and longer-run reversals, consistent with attention-induced trading pressure (Barber and Odean, 2008). These frameworks collectively imply that attention influences the timing of price correction, which is central to understanding variation in MAX-related reversals.

These empirical findings point to two theoretical mechanisms through which attention may influence the persistence of mispricing. Under an information hypothesis, elevated attention reflects monitoring and news processing that facilitate faster correction, implying that reversals should be stronger when attention is low. Under a price-pressure hypothesis, elevated attention reflects speculative demand that temporarily pushes prices away from fundamentals. In this case, mispricing may not correct immediately but instead unwind gradually.

D. Research Gap and Contribution

Prior research shows that the MAX effect depends on market-wide sentiment, investor composition, and firm-level informational events. Yet no study has explored how the effect varies with a theoretically foundational determinant of behavioral anomaly persistence: investor attention. We address this gap by employing a direct firm-specific attention measure based on Google search volume, capturing the demand for information about individual stocks experiencing extreme returns.

Our attention measure captures overall investor focus without distinguishing between underlying sources, such as news processing, monitoring, or speculative interest. We can therefore document how the MAX effect varies across attention levels but cannot identify which mechanisms drive this variation. We interpret our findings as associational evidence showing that attention conditions the strength and timing of MAX-related reversals. This helps explain why empirical evidence on the MAX effect varies across markets, time periods, and portfolio constructions, and highlights the broader role of attention in conditioning behaviorally driven anomalies.

III. Data

Our dataset includes all stocks listed on Nasdaq Stockholm between January 2011 and December 2024. Daily stock prices, trading volume, and accounting data are obtained from the SHOF FinBas database. Market returns are retrieved from Nasdaq's OMXSCAPGI total return index, and the Riksbank's repo rate serves as the risk-free rate. Values reported in foreign currencies are converted to SEK using daily exchange rates from the Riksbank. To ensure reliable estimation of monthly variables, we exclude firms with fewer than 24 months containing at least 10 valid daily price observations. Survivorship bias is mitigated by including all stocks ever listed during the sample period, including new listings, relistings, and delistings. The Swedish Fama–French Carhart equity factors used in the asset pricing analyses, namely size (SMB), value (HML), and momentum (MOM), are obtained from the AQR data library and matched to our sample at a monthly frequency. The market factor (MKT) is constructed from daily returns of the OMXSCAPGI total return index and the Riksbank's repo rate.

Daily closing prices, adjusted for corporate actions including stock splits, rights issues, and dividends, are used to compute daily stock returns. From these returns, we construct our main predictor, MAX, defined following Bali et al. (2011) as the largest single-day return for each stock in each month. Firm characteristics follow established definitions in the empirical asset-pricing literature. Firm size ($SIZE$) is the natural logarithm of market capitalization in SEK. Book-to-market (BM) is measured as book equity divided by market capitalization, with book equity lagged six months to account for reporting delays, consistent with Fama and French (1992). BM ratios above 10 are excluded to remove unrealistic valuation outliers. Momentum ($RET12_2$) is the cumulative return over months $t-12$ to $t-2$, following Jegadeesh and Titman (1993), while short-term reversal (REV) is the return in month $t-1$, following Jegadeesh (1990). Illiquidity ($ILLIQ$) is the Amihud (2002) ratio, computed as the monthly average of the absolute daily return divided by daily trading volume. Market beta ($BETA$) is estimated each month from a rolling

regression of daily excess stock returns on daily excess market returns, requiring at least 15 daily observations. Idiosyncratic volatility ($IVOL$) is the standard deviation of the rolling regression's residuals. To limit the influence of extreme observations, we winsorize all variables at the 1st and 99th percentiles. After applying these data-cleaning steps, we obtain our full sample.

Investor attention is measured using monthly Google Search Volume Index (GSVI), manually collected from Google Trends for each firm from January 2010 to December 2024, with searches restricted to Sweden. Search terms are based on cleaned company names, with non-distinctive suffixes such as "AB" removed. Ticker-based searches were considered but yielded insufficient data. Because GSVI values are normalized relative to each firm's own search history over the whole sample period, we follow Da et al. (2011) in constructing a standardized abnormal attention variable (ATT), ensuring comparability across firms. We define it as:

$$ATT_{i,t} = \frac{GSVI_{i,t} - \frac{1}{12}\sum_{k=0}^{11} GSVI_{i,t-k}}{\sqrt{\frac{1}{12}\sum_{k=0}^{11}\left(GSVI_{i,t-k} - \frac{1}{12}\sum_{j=0}^{11} GSVI_{i,t-j}\right)^2}}$$

This measure captures how unusual a firm's search activity is in month t relative to its own recent search history. It is computed as the difference between the current GSVI and the average of the previous twelve months, scaled by the standard deviation over the same period. In the notation, i denotes the firm, t the current month, and k and j index the twelve lagged monthly observations from 0 to 11. A higher value indicates that attention is unusually elevated for the firm, while a lower value indicates unusually low attention.

Proxying attention by GSVI introduces multiple measurement challenges: First, because search activity is sparse for many small firms, we require at least 15 monthly non-zero GSVI observations to ensure a reliable attention measure. Our GSVI filter applies only to analyses that include attention measures and is referred to as the GSVI-filtered sample. Baseline tests of the MAX effect use the full sample to establish the effect's presence before examining conditioning factors. Second, because the filter may unevenly affect different stock types and risk making the samples non-comparable, we compare variable characteristics, correlations, and main results across both samples. Third, GSVI is inherently noisy and does not guarantee to solely capture financial attention. This concern is especially pronounced for consumer-facing brands, since their search histories may reflect general web traffic rather than investor interest. For instance, higher search activity for SAS does not necessarily indicate greater financial attention, as searches may relate to airline tickets instead of its stock. To address this issue, we run robustness tests in Section V by excluding consumer-facing firms and randomizing search histories.

We merge daily price data, accounting data, Google Trends series, and factor returns into a monthly panel. After all filters, the full sample contains 64,725 firm-months and 543 unique firms, while the GSVI-filtered sample contains 47,965 firm-months and 394 unique firms.

Table I

Summary Statistics of Key Variables

This table presents the means and standard deviations (σ) for Excess Return (*RET*), maximum daily return (*MAX*), beta (BETA), natural logarithm of market capitalization in SEK (*SIZE*), book-to-market ratio (*BM*), momentum (*RET12_2*), one-month reversal (*REV*), and Amihud illiquidity (*ILLIQ*). We report summary statistics for the full sample used before applying attention filters and for the GSVI-filtered sample requiring at least 15 non-zero GSVI observations per firm. The statistics are based on monthly data for all stocks listed on Nasdaq Stockholm between January 2011 and December 2024. We also report the number of observations and unique firms for each sample.

	Full Sample		**GSVI-Filtered Sample**	
	Mean	σ	Mean	σ
RET [%]	0.83	10.96	0.97	10.40
MAX [%]	5.50	4.65	5.15	4.31
BETA	0.67	0.77	0.69	0.72
SIZE	21.45	2.36	21.75	2.27
BM	1.13	1.55	1.17	1.62
RET12_2	0.12	0.45	0.13	0.42
REV	0.01	0.10	0.01	0.10
ILLIQ $\times 10^6$	1.08	6.16	0.49	3.66
ATT	-	-	0.02	1.02
Observations	64,725		47,965	
Firms	543		394	

Table I reports summary statistics for all variables in the full sample and the GSVI-filtered sample. The distributions remain closely aligned across almost all characteristics. The GSVI-filtered sample shows a modest shift toward larger and less illiquid firms with mean *SIZE* increasing from 21.45 to 21.75 and mean *ILLIQ* decreasing from 1.08×10^6 to 0.49×10^6. Further, the GSVI-filtered sample exhibits marginally higher excess returns with mean *RET* increasing from 0.83% to 0.97%. *MAX*, *BM*, *BETA*, *RET12_2*, and *REV* display only minor numerical differences across the samples. *ATT* has a mean close to zero, 0.02, and a standard deviation close to one, 1.02, consistent with its standardization. The similarity between the samples indicates that imposing the requirement of a minimum number of non-zero GSVI observations can strengthen the attention measure while preserving the underlying economic structure of the dataset. Moreover, Figure A.1 presents how the two samples evolve over time. In the full sample, the number of firms increases from 304 at the start of the sample in 2011 to 404 by the end of 2024. After the attention filter, the GSVI-filtered sample still expands steadily, growing from 203 firms in early 2011 to 300 firms in late 2024. Figure A.2 shows that average *MAX* fluctuates without a persistent trend in both samples, with the exception of a clear spike in 2020 during the COVID shock, the potential effects of which are addressed in Section V.

Table II

Correlation Matrix of Key Variables

This table presents the contemporaneous correlations between *MAX*, standardized abnormal attention (*ATT*), beta (*BETA*), natural logarithm of market capitalization (*SIZE*), book-to-market ratio (*BM*), momentum (*RET12_2*), one-month reversal (*REV*), and Amihud illiquidity (*ILLIQ*), computed across the full sample period between January 2011 and December 2024 using the GSVI-filtered sample.

	MAX	ATT	BETA	SIZE	BM	RET12_2	REV	ILLIQ
MAX	1.00	0.14	0.05	-0.27	-0.07	-0.08	0.23	0.15
ATT	0.14	1.00	0.01	0.02	-0.02	0.08	0.08	-0.02
BETA	0.05	0.01	1.00	0.27	-0.06	0.02	0.00	-0.08
SIZE	-0.27	0.02	0.27	1.00	-0.24	0.09	0.05	-0.21
BM	-0.07	-0.02	-0.06	-0.24	1.00	-0.08	-0.04	0.04
RET12_2	-0.08	0.08	0.02	0.09	-0.08	1.00	0.04	-0.05
REV	0.23	0.08	0.00	0.05	-0.04	0.04	1.00	-0.01
ILLIQ	0.15	-0.02	-0.08	-0.21	0.04	-0.05	-0.01	1.00

Table II presents contemporaneous correlations between *MAX*, *ATT*, *BETA*, *SIZE*, *BM*, *RET12_2*, *REV*, and *ILLIQ* based on the GSVI-filtered sample. The correlation between *MAX* and *ATT* is modest at 0.14, while correlations between *ATT* and other firm characteristics are all below 0.10 in absolute value. *MAX* shows a moderate negative correlation with *SIZE*, at -0.27, and only weak associations with other variables. Table A.1 reports the same correlations for the full sample, showing highly consistent patterns. These modest correlations indicate that our variables capture distinct cross-sectional information and that multicollinearity is unlikely to affect subsequent empirical tests.

Although these correlations strengthen the reliability of our variables, one challenge is the contemporaneous measurement of *MAX* and *ATT* within the same month, which limits our ability to establish whether *ATT* is an independent conditioning factor or simply an endogenous response to extreme returns. Several features of our data help to limit this concern: First, the correlation between *MAX* and *ATT* is modest at 0.14 (see Table II), indicating that the two variables capture largely distinct sources of variation. If attention simply responded to *MAX* events, we would expect a much stronger correlation. Second, our standardization approach isolates unusual monthly search spikes relative to each firm's own historical baseline, which helps separate temporary attention changes from persistent differences in firm visibility. Third, including comprehensive firm-level controls reduces the likelihood that our attention measure proxies for other known return predictors. However, important limitations remain. Our attention measure cannot distinguish whether search activity reflects investor interest per se or differences in investor composition, for instance, firms with high retail ownership may exhibit more search activity regardless of returns. Moreover, monthly data aggregation prevents us from observing the precise timing of attention changes relative to *MAX* events within each month, hindering definitive statements about causal direction.

Taken together, the dataset is extensive, economically representative, and well

suited for studying the MAX effect and its variation with investor attention. We rely on widely used data sources and standard variable definitions, and we address key data challenges by filtering firms with insufficient observations, winsorizing extreme values, and incorporating standard control variables in our empirical specifications. These steps ensure that the subsequent analysis rests on a reliable and stable dataset.

IV. Empirical Analysis

We examine the presence of the MAX effect in Sweden and whether firm-specific attention conditions this effect in four main stages: First, in Section IV.A.1, we run portfolio-level tests to evaluate the MAX effect by sorting stocks each month into decile portfolios based on prior month MAX and estimating their abnormal performance using the Fama–French Carhart four-factor model. Second, in Section IV.A.2, we turn to firm-level evidence using monthly Fama–MacBeth regressions, where next month returns are predicted by MAX and standard firm characteristics. Third, in Section IV.B.1, we examine whether firm-specific abnormal investor attention conditions the anomaly by double sorting stocks into ATT quintiles and MAX deciles. Within each ATT quintile, we form long–short MAX portfolios and estimate Fama–French Carhart alphas. Finally, in Section IV.B.2, we extend the firm-level Fama–MacBeth model by including abnormal attention and the interaction between ATT and MAX. All significance tests employ two-tailed tests, with significance at the 5% level requiring $|t| > 1.96$.

A. The MAX Effect in Sweden

This section concerns the first two stages, exploring the MAX effect in Sweden at the portfolio and firm level. The findings from both approaches provide support for the MAX effect in Sweden during the sample period 2011 to 2024, with statistically significant results in the equally weighted portfolio analysis as well as in the firm-level regression structure.

A.1 Portfolio Analysis

Throughout the sample period, at the end of every month, all stocks are ranked on their MAX of the previous month and sorted into ten equally sized decile portfolios. These portfolios are rebalanced monthly so that portfolio 1 always contains the stocks with the lowest MAX values in the previous month, while portfolio 10 always contains those with the highest.

Table III

Summary Statistics of MAX-Sorted Decile Portfolios

This table reports summary statistics for decile portfolios formed each month by sorting stocks on their maximum daily return (*MAX*) of the previous month. Decile portfolio 1 (P1) always contains stocks with the lowest lagged *MAX* values and decile portfolio 10 (P10) always contains those with the highest. Panel A shows the average number of firms in each decile portfolio and their average share of total market capitalization. Panel B reports the median values of *MAX*, natural logarithm of market capitalization (*SIZE*), stock price (*PRICE*), beta (*BETA*), book-to-market ratio (*BM*), Amihud illiquidity (*ILLIQ*), and idiosyncratic volatility (*IVOL*), averaged over the whole sample period. All statistics in this table are based on the full sample.

	Decile portfolios									
	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**
Panel A										
Firms	38.89	38.79	38.68	38.59	38.51	38.37	38.26	38.20	38.05	37.98
Mkt. share [%]	18.66	19.24	15.58	12.57	10.36	8.06	5.66	4.68	3.31	1.76
Panel B										
MAX [%]	1.70	2.39	2.89	3.37	3.90	4.51	5.30	6.41	8.32	14.03
SIZE	21.95	22.44	22.20	22.02	21.76	21.57	21.31	21.05	20.67	19.86
PRICE [**SEK**]	69.63	69.52	64.78	58.15	52.90	49.60	42.03	36.91	29.71	19.21
BETA	0.49	0.72	0.75	0.74	0.73	0.72	0.70	0.69	0.67	0.60
BM	0.85	0.67	0.63	0.62	0.59	0.57	0.55	0.56	0.57	0.54
ILLIQ $\times 10^8$	0.41	0.29	0.47	0.45	0.72	0.85	1.37	2.10	3.86	13.45
IVOL [%]	1.06	1.30	1.41	1.53	1.65	1.76	1.91	2.04	2.31	2.98

Table III summarizes *MAX* decile portfolio characteristics. Portfolios display systematic variation across the *MAX* distribution, with P10 (highest *MAX*) concentrating in smaller, more illiquid, and more volatile stocks compared to P1 (lowest *MAX*).

Each portfolio contains approximately 38 firms on average, but both the share of total market capitalization and *SIZE* decline steadily, from 18.66% and 21.95 in P1 to 1.76% and 19.86 in P10. Other firm characteristics also vary systematically across the *MAX* distribution: As *MAX* increases, average *PRICE* falls sharply, from 69.63 SEK in P1 to 19.21 SEK in P10, while *ILLIQ* and *IVOL* rise from 0.41 and 1.06 to 13.45 and 2.98, respectively. This reflects the well-documented concentration of extreme daily returns among small, illiquid, and volatile stocks (Bali et al., 2011). *BM* declines from 0.85 in P1 to 0.54 in P10 and *BETA* also gradually declines from 0.75 in P3 to 0.60 in P10.

To examine whether return differences across *MAX* portfolios persist after controlling for common risk factors, we estimate Fama–French Carhart four-factor regressions for the portfolio excess return $(R_{P,t} - R_{f,t})$ in month t. In the following regression, portfolio P's abnormal return (α_P) estimates the excess return that cannot be explained by its exposure to the Swedish market risk premium $(R_{m,t} - R_{f,t})$, size factor (SMB_t), value factor (HML_t), and momentum factor (MOM_t) in month t:

$$(R_{P,t} - R_{f,t}) = \alpha_P + \beta_P(R_{m,t} - R_{f,t}) + s_P SMB_t + h_P HML_t + m_P MOM_t + \varepsilon_{P,t} \quad (1)$$

We run regression (1) for each *MAX* decile portfolio and for a long–short portfolio, denoted LS, that is formed each month as the excess return difference between the lowest and highest *MAX* decile portfolios (P1–P10). A positive and statistically significant (α_{P1-P10}) indicates that the excess return spread between low- and high-*MAX* stocks cannot be explained by exposure to risk factors and thus indicates a present MAX effect. All regressions use Newey-West adjusted t-statistics, correcting for heteroskedasticity and autocorrelation (Newey and West, 1987).

Table IV

Fama–French Carhart Four-Factor Loadings for MAX-Sorted Portfolios

This table presents Fama–French Carhart four-factor regressions for portfolios sorted on *MAX*. Stocks are assigned each month to decile portfolios based on their prior-month *MAX* values, forming portfolios from P1 (lowest *MAX*) to P10 (highest *MAX*). Panel A reports the regression intercepts and factor loadings for equally weighted portfolios, and Panel B reports the corresponding estimates for value-weighted portfolios. For each portfolio, the table lists coefficients from regressions on the market factor (*MKT*), size factor (*SMB*), value factor (*HML*), and momentum factor (*MOM*), together with Newey-West adjusted t-statistics shown in brackets. The final row in each panel provides estimates for a long–short portfolio constructed as the difference in excess returns between the lowest and highest *MAX* decile portfolios. The regressions are estimated using monthly portfolio returns in the full sample.

Portfolio	α	MKT	SMB	HML	MOM
Panel A, equally weighted portfolios					
P1	0.006 [4.18]	0.718 [19.03]	28.584 [6.06]	7.020 [1.35]	2.732 [0.53]
P2	0.005 [3.68]	0.864 [28.51]	29.883 [6.65]	14.477 [2.56]	-2.037 [-0.44]
P3	0.004 [2.89]	0.936 [28.77]	37.694 [8.12]	3.277 [0.47]	6.242 [1.27]
P4	0.002 [1.98]	0.972 [46.70]	37.547 [10.01]	3.825 [0.83]	4.276 [1.13]
P5	0.001 [0.58]	0.982 [35.82]	39.446 [8.47]	-8.347 [-1.52]	3.545 [1.06]
P6	0.004 [3.18]	0.948 [31.01]	39.475 [8.08]	-7.016 [-1.07]	-5.972 [-1.23]
P7	0.002 [1.31]	1.025 [24.97]	52.350 [10.36]	-7.919 [-1.07]	-5.606 [-1.05]
P8	-0.001 [-0.89]	0.934 [23.96]	53.749 [9.62]	-10.491 [-1.52]	-0.429 [-0.08]
P9	-0.001 [-0.74]	0.924 [20.75]	54.325 [9.85]	-19.013 [-3.19]	-14.304 [-2.34]
P10	-0.005 [-1.96]	0.839 [13.54]	82.237 [10.64]	-16.168 [-2.24]	-15.143 [-1.41]
LS	0.011 [3.91]	-0.121 [-1.72]	-53.653 [-5.28]	23.189 [3.49]	17.875 [1.37]
Panel B, value-weighted portfolios					
P1	0.004 [2.36]	0.674 [14.83]	-0.118 [-0.03]	27.406 [4.15]	1.976 [0.45]
P2	0.009 [4.87]	0.759 [13.28]	-11.135 [-1.72]	5.206 [0.45]	-10.561 [-1.89]
P3	0.003 [1.64]	0.927 [19.99]	-0.256 [-0.04]	2.343 [0.29]	-1.002 [-0.18]
P4	0.001 [0.48]	0.934 [28.13]	-0.457 [-0.07]	2.922 [0.41]	1.913 [0.33]
P5	-0.002 [-0.95]	0.966 [20.63]	-7.921 [-1.21]	-4.703 [-0.67]	-9.145 [-1.35]
P6	-0.002 [-1.10]	0.973 [14.11]	2.463 [0.39]	-2.350 [-0.25]	2.476 [0.37]
P7	-0.003 [-1.04]	1.047 [20.10]	0.557 [0.06]	-10.915 [-1.07]	-14.196 [-1.85]
P8	-0.004 [-1.47]	0.944 [17.82]	9.398 [1.10]	-26.144 [-2.83]	-9.173 [-0.79]
P9	-0.002 [-0.55]	1.014 [17.64]	0.475 [0.07]	-24.722 [-2.22]	-20.877 [-1.82]
P10	0.002 [0.53]	1.085 [7.87]	66.552 [4.94]	-30.919 [-1.48]	-19.294 [-1.35]
LS	0.002 [0.43]	-0.411 [-2.74]	-66.671 [-4.46]	58.325 [2.43]	21.271 [1.29]

Table IV reports the Fama–French Carhart four-factor regressions for portfolios sorted on *MAX*. Panel A shows that the factor loadings vary systematically across the *MAX* distribution for equally weighted portfolios. Since smaller stocks receive relatively larger weights under this scheme, all portfolios load positively on *SMB*, and the intensity of this loading increases from 28.584 (t-statistic=6.06) in P1 to 82.237 (t-statistic=10.64) in P10. *HML* loadings decline from 7.020 (t-statistic=1.35) in P1 to -16.168 (t-statistic=-2.24) in P10, indicating that high-*MAX* portfolios are tilted toward growth stocks. *MOM* coefficients fluctuate across decile portfolios and are generally imprecisely estimated.

Panel B presents the value-weighted results. The negative *HML* loadings in the high-*MAX* portfolios remain, reflecting growth characteristics, but the size pattern largely disappears when larger firms receive relatively greater weight. Nonetheless, P10 continues to load positively on *SMB*, 66.552 (t-statistic=4.94), reaffirming the concentration of MAX among smaller firms.

The regression intercepts decline monotonically across *MAX* decile portfolios in the equally weighted portfolios, ranging from 0.006 (t-statistic=4.18) in P1 to -0.005 (t-statistic=-1.96) in P10. Under value weighting, P1 and P2 have the only significant intercepts with 0.004 (t-statistic=2.36) and 0.009 (t-statistic=4.87), respectively.

Overall, high-*MAX* portfolios share characteristics with small growth stocks, and the strongest evidence of a return differential appears in the equally weighted specification. To provide a visual complement to these regression results, Figure 2 plots the corresponding portfolio alphas and their confidence intervals.

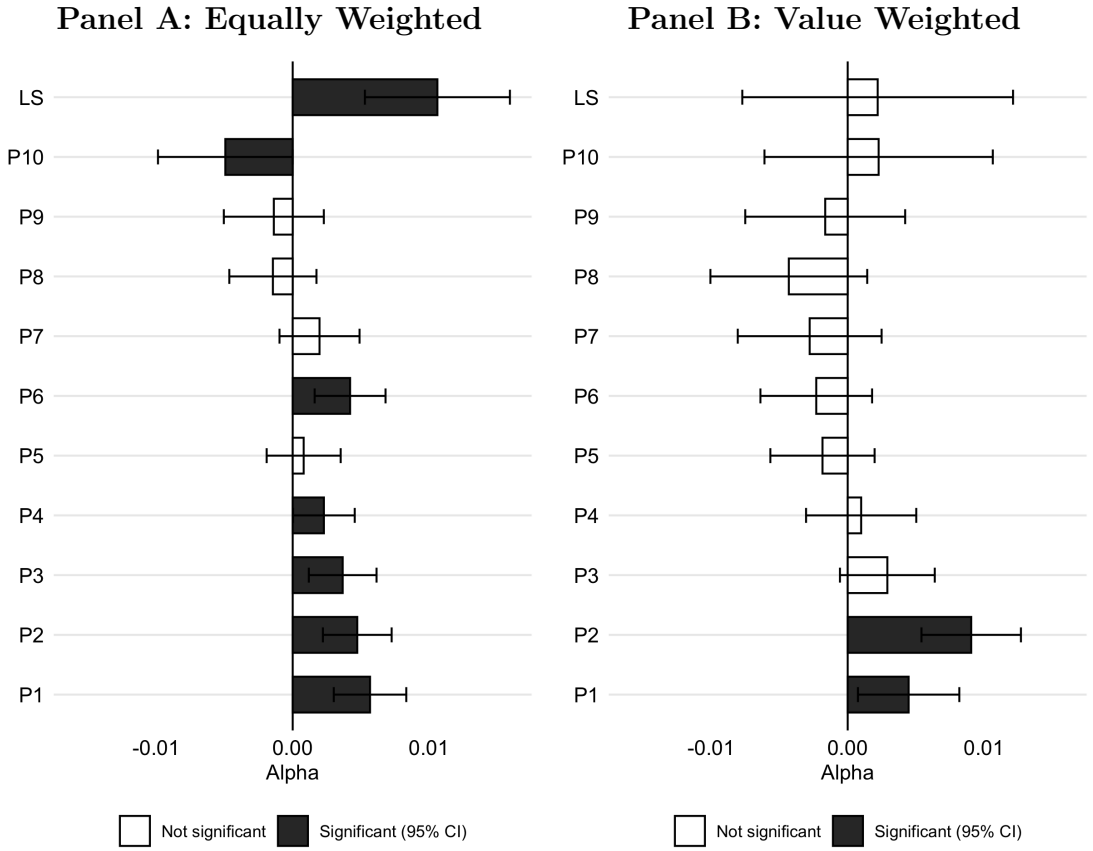


Figure 2. Fama–French Carhart Four-Factor Alphas for Portfolios Sorted by *MAX* (Decile Portfolios). This figure reports monthly Fama–French Carhart four-factor alphas for portfolios formed each month on their prior-month *MAX* values in the full sample. Panel A displays results for equally weighted portfolios, while Panel B presents the corresponding results for value-weighted portfolios. Within each panel, portfolios P1 through P10 are plotted from bottom to top, where P1 always contains stocks with the lowest *MAX* values and P10 always contains those with the highest. At the top of each panel, the long–short portfolio is shown, constructed as the difference in excess returns between P1 and P10. Bars represent point estimates of monthly alphas, and horizontal lines denote 95% confidence intervals based on Newey-West adjusted standard errors. Dark bars indicate estimates that are statistically significant at the 5% level, while unfilled bars indicate alphas that cannot be distinguished from zero.

The visual summary in Figure 2 of the Fama–French Carhart alphas reported in Table IV highlights how the results differ across weighting schemes. For the equally weighted portfolios, alphas decline steadily across the *MAX* portfolios, and several low-*MAX* portfolios have confidence intervals that exclude zero. The long–short strategy (P1–P10) is also positive and statistically significant, reinforcing the return difference identified by Bali et al. (2011), where stocks with low past extreme returns outperform those with high extremes after adjusting for risk factors.

In contrast, the value-weighted results display little evidence of risk-adjusted outperformance. Most portfolios have confidence intervals that include zero, and the long–short strategy is consequently statistically insignificant. This aligns with the findings of Mojtahedi et al. (2025), who find that the MAX effect in Sweden weakens once the influence of small firms is reduced. The comparison across weighting methods indicates that the MAX effect in Sweden is concentrated among small stocks,

whose impact is diluted when portfolios are weighted by market capitalization.

Having established the MAX effect at the equally weighted portfolio level, we turn to explore whether MAX is a significant determinant of returns at the firm level.

A.2 Firm-Level Analysis

We employ Fama–MacBeth cross-sectional regressions, averaging the estimated coefficients across the entire sample period. In the following regression, $R_{i,t+1}$ denotes the return of firm i in month $t+1$, which is regressed on its $MAX_{i,t}$, $SIZE_{i,t}$, $BM_{i,t}$, $RET12_2_{i,t}$, $REV_{i,t}$, $ILLIQ_{i,t}$, and $BETA_{i,t}$ in month t, all according to definitions in Section III:

$$\begin{aligned} R_{i,t+1} = \alpha_t + \beta_1 MAX_{i,t} + \beta_4 SIZE_{i,t} + \beta_5 BM_{i,t} + \beta_6 RET12_2_{i,t} \\ + \beta_7 REV_{i,t} + \beta_8 ILLIQ_{i,t} + \beta_9 BETA_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{2}$$

For this regression, a negative and statistically significant coefficient on MAX ($\beta_1 < 0$) indicates that stocks experiencing extreme daily returns in the past month predict lower subsequent returns, consistent with the MAX effect.

Table V

Baseline Fama–MacBeth Cross-Sectional Regressions

This table presents the results from Fama–MacBeth cross-sectional regressions evaluating the ability of firm-level characteristics to predict next-month stock returns. All but the last row report univariate regressions, where each variable is considered in isolation, while the last row shows the results from a full multivariate specification including all predictors together. Each coefficient is the time-series average of monthly cross-sectional slope estimates, with the corresponding Newey-West adjusted t-statistics shown under the coefficients in brackets. The regressions include the following firm characteristics as explanatory variables: *MAX*, beta (*BETA*), natural logarithm of market capitalization (*SIZE*), book-to-market ratio (*BM*), momentum (*RET12_2*), one-month reversal (*REV*), and Amihud illiquidity (*ILLIQ*). The explanatory variables are all lagged one month relative to the return they aim to predict. The regressions are estimated on a monthly basis using the full sample.

MAX	BETA	SIZE	BM	RET12_2	REV	ILLIQ
-0.1000						
[−4.49]						
	0.0013					
	[0.81]					
		0.0010				
		[2.44]				
			-0.0009			
			[−3.08]			
				0.0172		
				[6.95]		
					0.0279	
					[2.81]	
						-111.8828
						[−0.49]
-0.1101	0.0026	-0.0005	-0.0005	0.0135	0.0245	1104.8740
[−4.43]	[1.66]	[−0.99]	[−1.54]	[5.46]	[2.78]	[1.11]

Table V reports the time-series averages of monthly Fama–MacBeth cross-sectional regression coefficients of next-month returns. Each characteristic is examined both in isolation and in a full regression model in which all predictive variables are included.

In the univariate regressions, *MAX* enters with a negative coefficient of -0.1000 (t-statistic=-4.49), and the estimate remains negative in the full model at -0.1101 (t-statistic=-4.43). Among the control variables, *RET12_2* exhibits economically large and precisely estimated coefficients, 0.0172 (t-statistic=6.95) in the univariate model and 0.0135 (t-statistic=5.46) in the full model. *REV* also loads positively in both specifications, 0.0279 (t-statistic=2.81) and 0.0245 (t-statistic=2.78), indicating short horizon continuation in monthly returns. *SIZE* shows a positive coefficient in the univariate regression of 0.0010 (t-statistic=2.44), but becomes negative and statistically insignificant in the full model at -0.0005 (t-statistic=-0.99). *BM* enters negatively in both the univariate and full model with -0.0009 (t-statistic=-3.08) and -0.0005 (t-statistic=-1.54), respectively. *BETA* and *ILLIQ* lack statistical sig-

nificance in both the univariate and full specification. Taken together, our results suggest that *MAX*, momentum, and short-horizon return continuation are the characteristics most closely related to next-month returns in our sample. Traditional predictors such as size, value, beta, and illiquidity display limited or unstable explanatory power.

Our firm-level analysis documents a statistically significant MAX effect in Sweden between 2011 and 2024, with a full model coefficient estimate of -0.1101 (t-statistic=-4.43). This contrasts with Mojtahedi et al. (2025), who find no statistically significant firm-level relationship for the 1994 to 2019 period in Sweden, though they do document the effect in equally weighted portfolios. For comparison, Bali et al. (2011) report a coefficient of -0.0637 (t-statistic=-6.16) in a corresponding Fama–MacBeth regression for the US market over July 1962 to December 2005. Our coefficient is larger in absolute magnitude, though direct comparison is complicated by differences in sample periods, markets, and estimation windows.

The discrepancy in magnitude and statistical significance across these studies is consistent with prior evidence that the MAX effect is not constant over time and across markets. Bali et al. (2011) demonstrate that the return spread associated with *MAX* changes materially when their US sample is split into subperiods, indicating temporal variation in the anomaly's strength. Sample-specific conditions, evolving market composition, and differences in estimation windows can lead to heterogeneous results across studies. We therefore view our evidence as complementary to prior Swedish research rather than contradictory as we document that the MAX effect is present at the firm-level and statistically significant between 2011 and 2024.

B. The MAX Effect Across Attention States

With evidence of a the MAX effect in Swedish equities, this section examines whether the effect varies with firm-specific abnormal attention. In the final two stages of the four-stage approach, we first run four-factor regressions on double-sorted portfolios, then estimate a firm-level predictive model adding ATT and its interaction with MAX ($ATT \times MAX$) to Equation (2). The portfolio-level results show a consistent pattern: the MAX effect appears in low and moderate attention states but is absent in high-attention states. At the firm level, the interaction term is positive but statistically insignificant, providing no direct evidence of moderation in cross-sectional regressions. To explore whether this insignificance reflects delayed rather than eliminated reversals, we additionally examine the $MAX \times ATT$ interaction over extended return horizons, offering a direction for future research on the timing of attention-related corrections.

B.1 Double-Sorted Portfolio Analysis

At the end of each month, all stocks are first sorted into five quintiles based on their ATT from the previous month. These ATT quintiles are rebalanced monthly so that Q1 always contains the stocks with the lowest ATT values in the previous month, while Q5 always contains those with the highest. Within each ATT quintile, stocks are then ranked on their prior-month MAX and allocated into ten MAX decile portfolios, from portfolio 1 (lowest MAX) to portfolio 10 (highest MAX).

Table VI

Summary Statistics of *ATT* Quintiles

This table presents summary statistics for quintile portfolios formed each month by sorting stocks on standardized abnormal attention (*ATT*). Quintile 1 (Q1) always consists of stocks with the lowest abnormal attention in the previous month and quintile 5 (Q5) always consists of those with the highest. Panel A shows the average number of firms in each quintile and their average share of total market capitalization. Panel B reports the median values of *MAX*, natural logarithm of market capitalization (*SIZE*), stock price (*PRICE*), beta (*BETA*), book-to-market ratio (*BM*), Amihud illiquidity (*ILLIQ*), and idiosyncratic volatility (*IVOL*), averaged over the whole sample period. All statistics in this table are based on the GSVI-filtered sample.

	Quintile portfolios				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**
Panel A					
Firms	51.72	51.50	51.92	51.56	52.09
Mkt. share [%]	18.17	17.87	20.00	20.77	18.36
Panel B					
MAX [%]	3.68	3.80	3.77	3.85	4.33
SIZE	21.67	21.74	21.91	21.98	21.82
PRICE [SEK]	52.36	51.67	57.34	59.44	55.94
BETA	0.68	0.68	0.70	0.73	0.70
BM	0.66	0.68	0.60	0.61	0.57
ILLIQ $\times 10^8$	0.60	0.55	0.44	0.36	0.39
IVOL [%]	1.52	1.54	1.52	1.55	1.73

Table VI presents summary statistics for quintile portfolios sorted on *ATT*. Panel A reports portfolio characteristic averages, whereas Panel B reports medians of within-portfolio firm characteristics averaged over the sample period. Each quintile contains roughly 52 firms, and market-capitalization shares are evenly distributed at around 18-21% across quintiles, indicating that abnormal attention is not mechanically related to *SIZE*. Cross-sectional differences across the attention portfolios are modest compared to the single-sorted *MAX* portfolios. Firms in the highest *ATT* quintile exhibit slightly higher *MAX* and *IVOL*, 4.33% and 1.73 in Q5 compared to 3.68% and 1.52 in Q1, consistent with elevated search activity coinciding with salient price movements or heightened uncertainty. *ILLIQ* and *BM* decline gradually from Q1 to Q5, from 0.60 and 0.66 to 0.39 and 0.57, while *BETA* and *PRICE* show no systematic patterns. The limited variation across characteristics suggests that abnormal attention reflects a distinct dimension of investor focus rather than a disguised size or value effect.

We next examine whether the MAX effect varies with *ATT*. Within each *ATT* quintile, we form long–short *MAX* portfolios and estimate their alphas using the Fama–French Carhart four-factor model to assess how the risk-adjusted *MAX* return spread differs across attention levels.

Table VII

Fama–French Carhart Four-Factor Regressions for MAX Long–Short Portfolios by *ATT* Quintile

This table reports Fama–French Carhart four-factor regressions for double-sorted long–short portfolios. At the end of every month, stocks are first sorted into five quintiles based on their lagged standardized abnormal attention (ATT), where Q1 contains the stocks with the lowest values and Q5 contains those with the highest. Within each ATT quintile, stocks are further sorted into decile portfolios based on their prior-month MAX values, and a MAX long–short portfolio is formed by taking a long position in the lowest MAX decile portfolio and a short position in the highest MAX decile portfolio. The table presents the time-series regression intercepts and factor loadings from estimating the Fama–French Carhart four-factor model on these long–short excess returns. Panel A reports the regression intercepts and factor loadings for equally weighted portfolios, and Panel B reports the corresponding estimates for value-weighted portfolios. For each long–short portfolio, the table lists coefficients from regressions on the market factor (MKT), size factor (SMB), value factor (HML), and momentum factor (MOM), together with Newey-West t-statistics shown in brackets. The regressions are estimated using monthly portfolio returns in the full sample.

Portfolio	α	MKT	SMB	HML	MOM
Panel A, equally weighted long–short portfolios					
Q1	0.012 [2.41]	0.007 [0.08]	-54.944 [-3.91]	-15.798 [-0.95]	25.226 [1.46]
Q2	0.004 [0.63]	-0.344 [-2.91]	-39.805 [-2.13]	19.703 [1.06]	23.082 [1.56]
Q3	0.011 [2.23]	-0.072 [-0.75]	-8.673 [-0.58]	38.419 [1.79]	38.998 [2.66]
Q4	-0.006 [-0.74]	-0.177 [-1.25]	-68.196 [-3.58]	34.129 [1.52]	44.911 [2.80]
Q5	0.002 [0.21]	-0.289 [-2.21]	-84.061 [-4.13]	17.655 [0.71]	21.725 [1.02]
Panel B, value-weighted long–short portfolios					
Q1	0.018 [3.37]	-0.272 [-2.14]	-38.339 [-2.54]	-45.122 [-1.68]	16.387 [1.00]
Q2	-0.003 [-0.40]	-0.216 [-1.05]	-29.168 [-1.07]	46.257 [1.54]	18.947 [1.09]
Q3	0.010 [1.47]	-0.188 [-1.57]	10.043 [0.50]	53.576 [1.51]	51.553 [2.03]
Q4	-0.012 [-0.92]	-0.312 [-1.87]	-64.287 [-2.71]	47.299 [1.63]	58.362 [2.52]
Q5	-0.013 [-1.38]	-0.171 [-0.67]	-110.235 [-3.78]	46.523 [1.48]	37.563 [1.88]

Table VII reports the regression results for the abnormal-attention sorted long–short MAX portfolios. In Panel A, the equally weighted results show large and statistically significant negative SMB loadings across all attention groups, ranging from -54.944 (t-statistic=-3.91) in Q1 to -84.061 (t-statistic=-4.13) in Q5. This pattern reflects the intrinsic size tilt of the long–short MAX portfolios: the low-MAX long leg consists mainly of larger firms, whereas the high-MAX short leg contains smaller firms (see Table III). Consequently, the long–short spread naturally loads negatively on SMB. HML estimates are generally imprecise across all attention groups. In Q1, the HML loading is -15.798 (t-statistic=-0.95), suggesting no statistically meaningful tilt toward value or growth when abnormal attention is low. As attention increases, the coefficients turn positive, but remain statistically indistinguishable from zero throughout. All long–short portfolios have positive exposures on MOM.

Panel B shows similar patterns under value weighting. SMB loadings remain negative and statistically significant in most cases, ranging from -38.339 (t-statistic=-2.54) in Q1 to -110.235 (t-statistic=-3.78) in Q5, again reflecting the firm-size differences in the long- and short legs. HML coefficients are negative in Q1 at -45.122 (t-statistic=-1.68), but become positive in higher attention groups, such as 46.523 (t-statistic=1.48) in Q5. MOM loadings remain positive, though their statistical

significance varies across quintiles.

The key finding concerns variation in alphas across attention levels. Under equal weighting, positive and statistically significant alphas arise in Q1 and Q3, 0.012 (t-statistic=2.41) and 0.011 (t-statistic=2.23), respectively, while the remaining quintiles yield alpha estimates closer to zero without statistical significance. The corresponding value-weighted results show insignificant alphas for all quintiles except for Q1 where the alpha remains positive and significant at 0.018 (t-statistic=3.37). These results indicate that the *MAX* long–short strategy generates significant abnormal returns primarily when abnormal attention is low (Q1) or moderate (Q3, equally weighted only). Figure 3 provides a visual complement to these results by illustrating how the estimated alphas vary across *ATT* quintiles.

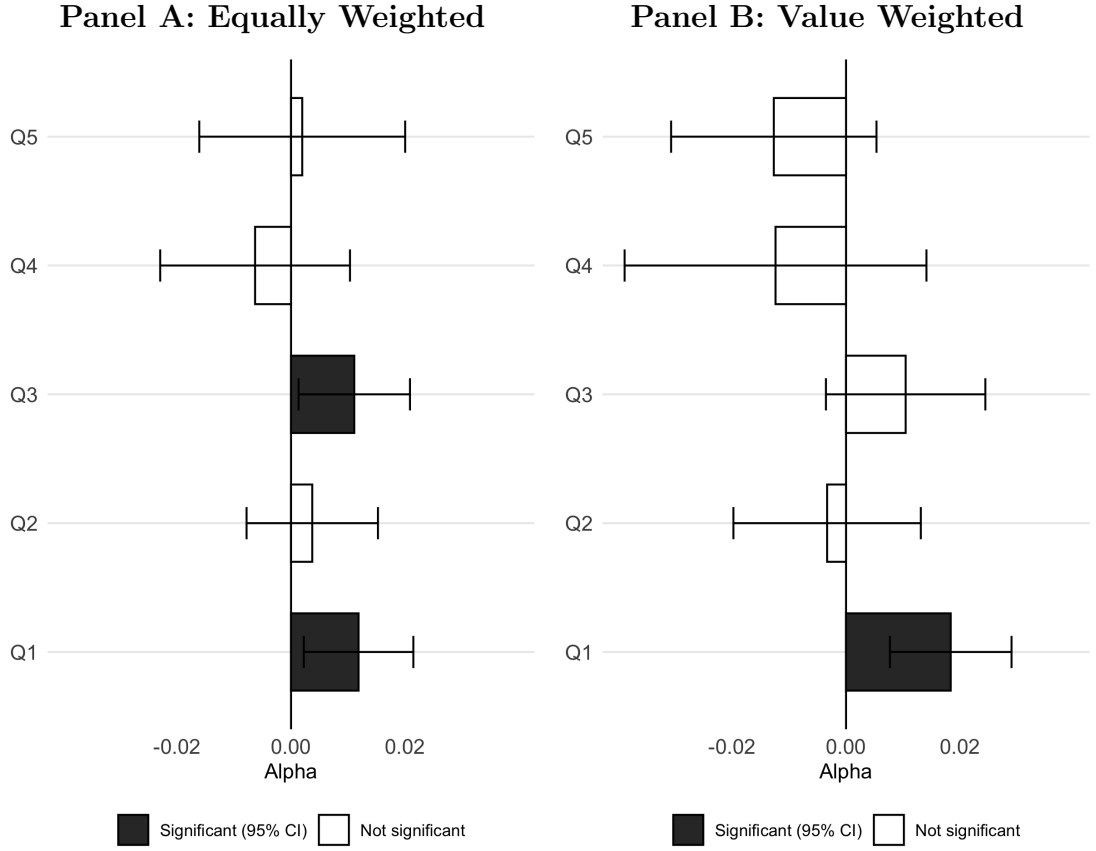


Figure 3. Fama–French Carhart Long–Short *MAX* Portfolio Alphas by *ATT* quintile. This figure presents alphas from monthly Fama–French Carhart four-factor regressions for *MAX* long–short portfolios formed within *ATT* quintiles using the GSVI-filtered sample. Panel A reports equally weighted portfolio results, and Panel B shows value-weighted portfolio results. At each month-end, stocks are sorted into five quintiles based on lagged standardized abnormal attention (Q1 lowest, Q5 highest). Within each quintile, stocks are further sorted into decile portfolios based on prior month *MAX*, and a long–short *MAX* portfolio is constructed by going long on the lowest *MAX* decile portfolio and short on the highest *MAX* decile portfolio. Bars plot the estimated monthly alphas, with horizontal lines showing 95% Newey-West confidence intervals. Dark bars indicate significance at the 5% level, while unfilled bars denote estimates not statistically different from zero.

Conditioning the *MAX* portfolios on abnormal attention reveals a pronounced and economically meaningful pattern that unconditional sorts fail to capture. Figure 3 demonstrates that the MAX effect is present in low and moderate attention states, but is consistently absent when attention is high. In the lowest *ATT* quintile (Q1), the long–short portfolio produces statistically significant alphas under both weighting schemes, with 0.012 (t-statistic=2.41) for equal weighting and 0.018 (t-statistic=3.37) for value weighting. For all other *ATT* quintiles the alphas are materially smaller and, with the exception of a statistically significant effect in Q3 under equal weighting, none differ significantly from zero. In the highest *ATT* quintile the alphas are near zero and statistically indistinguishable from zero under both weighting schemes, indicating that economically meaningful return differences occur when abnormal attention is low or moderate, and do not appear at all when attention is high.

This attention-based heterogeneity provides insight into the unconditional results from Section IV.A.1, where the MAX effect appeared only under equal weighting. The unconditional results suggest a small-firm phenomenon, in which extreme return spikes occur predominantly among smaller stocks, and value weighting dampens their influence. However, Figure 3 reveals that the weak unconditional value-weighted result arises not from the absence of the effect among larger firms, but from pooling stocks across heterogeneous attention states. When *MAX* events occurring during all attention states are aggregated within the same portfolio, the strong reversals in lower-attention states are offset by the absence of reversals in high-attention states, which eliminates the unconditional value-weighted effect.

The attention-conditional results additionally clarify that the MAX effect is not confined to small stocks. While the unconditional value-weighted alpha is negligible and insignificant, 0.002, (t-statistic=0.43), consistent with a small-firm interpretation, the Q1 value-weighted alpha is larger and highly significant at 0.018 (t-statistic=3.37). This cannot be attributed to firm size, as *ATT* is largely independent of *SIZE* given the correlation between *ATT* and *SIZE* is only 0.02 (see Table II), and the *ATT* quintiles exhibit similar size distributions (see Table VI). The low *ATT* quintile therefore includes firms across the size spectrum, indicating that the MAX effect operates among both small and large firms when attention is low rather than being mechanically driven by firm size.

The source of the long–short alphas can be traced to the return patterns within each *ATT* quintile. Significant long–short spreads arise only when the low-*MAX* decile portfolio (P1) earns positive alphas while the high-*MAX* decile portfolio (P10) earns negative alphas, a pattern observed in Q1 under both weighting schemes and in Q3 under equal weighting (see Table A.2). In higher *ATT* quintiles (Q4 and Q5), P1 alphas remain generally positive, but P10 alphas turn positive as well, eliminating the return spread. This indicates that high abnormal attention is associated with absent next-month reversals among high-*MAX* stocks.

The economic significance of conditioning on attention is material. The unconditional equally weighted long–short monthly alpha of 1.1% (see Table IV) translates to approximately 13.2% in annual terms, while the unconditional value-weighted monthly alpha of 0.2% corresponds to an insignificant annual 2.4%. Conditioning on attention increases these magnitudes in low-attention states. The Q1 value-

weighted monthly alpha of 1.8% translates to an annual alpha of approximately 21.6%, while the equally weighted monthly alpha of 1.2% translates to an annual alpha of 14.4%. The value-weighted comparison is particularly striking, since conditioning on attention increases the annualized alpha from an insignificant 2.4% to a highly significant 21.6% in Q1. This demonstrates that attention-based conditioning exposes economically material return spreads that remain hidden when portfolios aggregate across heterogeneous attention states.

However, practical implementation faces significant challenges. Each month, constructing ATT quintiles across hundreds of firms requires substantial operational effort. Rebalancing the resulting trades in predominantly small and illiquid stocks would then generate significant transaction and price impact costs that are likely to erode returns, particularly at institutional scale.

Overall, the portfolio-level results show that the MAX effect appears when abnormal firm-specific attention is low or moderate, and is consistently absent when attention is high. This raises the question of whether a similar pattern holds in the cross-section of individual stocks, which we now examine through firm-level regressions.

B.2 Firm-Level Analysis

To examine whether abnormal attention moderates the MAX effect at the firm level, we extend Equation (2) by adding $ATT_{i,t}$ and its interaction with $MAX_{i,t}$. The specification follows Equation (2) in all controls and variable definitions. In this setting, $ATT_{i,t}$ captures the direct relation between abnormal attention and next month returns, while the interaction term $MAX_{i,t} \times ATT_{i,t}$ tests whether the predictive power of MAX is moderated by the level of abnormal attention for firm i in month t.

$$\begin{aligned} R_{i,t+1} = \alpha_t + \beta_1 MAX_{i,t} + \beta_2 ATT_{i,t} + \beta_3 (MAX_{i,t} \times ATT_{i,t}) + \beta_4 SIZE_{i,t} \\ + \beta_5 BM_{i,t} + \beta_6 RET12_2_{i,t} + \beta_7 REV_{i,t} + \beta_8 ILLIQ_{i,t} + \beta_9 BETA_{i,t} + \varepsilon_{i,t+1} \end{aligned} \tag{3}$$

A positive interaction coefficient indicates that the negative relation between MAX and subsequent returns weakens when abnormal attention is high, consistent with the portfolio-level findings. Conversely, a negative coefficient would indicate a stronger MAX effect in high-attention states.

Table VIII

Fama–MacBeth Cross-Sectional Regressions with MAX×ATT Interaction

This table presents the results from Fama–MacBeth cross-sectional regressions evaluating the ability of firm-level characteristics to predict next-month stock returns. All but the last row report univariate regressions, where each variable is considered in isolation, while the last row shows the results from a full multivariate specification including all predictors together. Each coefficient is the time-series average of monthly cross-sectional slope estimates, with the corresponding Newey-West adjusted t-statistics shown under the coefficients in brackets. The regressions include the following firm characteristics as predictors: *MAX* (the maximum daily return within the previous month), standardized abnormal attention (*ATT*), defined as the firm's Google search volume in month t relative to its own historical mean and volatility, their interaction term *MAX×ATT*, beta (*BETA*), natural logarithm of market capitalization (*SIZE*), book-to-market ratio (*BM*), momentum (*RET12_2*), one-month reversal (*REV*), and Amihud illiquidity (*ILLIQ*). The explanatory variables are all lagged one month relative to the return they aim to predict. The regressions are estimated on a monthly basis using the GSVI-filtered sample.

MAX	ATT	MAX×ATT	BETA	SIZE	BM	RET12_2	REV	ILLIQ
-0.0698								
[−2.66]								
	0.0006							
	[0.87]							
			0.0012					
			[0.71]					
				0.0002				
				[0.57]				
					-0.0009			
					[−2.82]			
						0.0124		
						[4.23]		
							0.0081	
							[0.77]	
								603.1270
								[1.13]
-0.1101	-0.0001	0.0141	0.0032	-0.0008	-0.0012	0.0105	0.0083	-1326.2304
[−3.76]	[−0.11]	[0.64]	[1.95]	[−1.65]	[−3.07]	[4.24]	[0.93]	[−0.93]

Table VIII presents the Fama–MacBeth cross-sectional regression results, evaluating whether abnormal attention moderates the MAX effect at the firm level. The upper rows show univariate regressions where each variable is examined individually, and the bottom row reports the full specification including all predictors jointly. In the full model, *RET12_2* continues to load positively and significantly at 0.0105 (t-statistic=4.24), and *BM* remains negatively related to returns at -0.0012 (t-statistic=-3.07). *SIZE*, *REV*, and *ILLIQ* are statistically weak, consistent with the findings in Section IV.A.2, while *BETA* is positive and just falls short of significance (t-statistic=1.95). The predictions of the control variables thus remain similar despite controlling for abnormal attention and its interaction with *MAX*.

Turning to the core variables, *MAX* remains negative and statistically significant at -0.1101 (t-statistic=-3.76), reinforcing the presence of a MAX effect in line with

prior findings. ATT itself is small and insignificant at -0.0001 (t-statistic=-0.11), suggesting that abnormal attention does not predict next-month returns directly. The interaction term $MAX{\times}ATT$ enters positively at 0.0141 (t-statistic=0.64) but is statistically insignificant, providing no direct evidence that the MAX effect varies with ATT at the one-month horizon.

The insignificant interaction at the one-month horizon contrasts with the portfolio-level evidence, which shows that the MAX effect appears in low and moderate attention states but is absent when attention is high. This divergence reflects a fundamental difference in measurement. Portfolio sorts condition on distinct attention states and reveal that one-month reversals vary across these states. Firm-level regressions impose a linear interaction term that averages over the entire attention distribution, limiting power to detect effects concentrated in extreme quintiles.

Beyond this methodological difference, theoretical mechanisms suggest that attention may influence the timing of reversals rather than their elimination. Da et al. (2011) document that attention-driven buying pressure can temporarily elevate prices before reversals emerge over longer horizons. To examine whether similar patterns appear in our data, we test the $MAX{\times}ATT$ relationship over extended return windows. If such delayed reversals are present, the interaction term should turn negative at longer horizons. These results can provide indicative evidence to guide future research on underlying mechanisms.

We estimate monthly Fama–MacBeth regressions where the dependent variable is the cumulative return over months $t+2$ to $t+k$, with k ranging from 3 to 12 months. The specification includes $MAX_{i,t}$, $ATT_{i,t}$, their interaction $MAX_{i,t} \times ATT_{i,t}$, and the same control variables as in Equation (3):

$$\begin{aligned} R_{i,t+2:t+k} = \alpha_t &+ \beta_1 MAX_{i,t} + \beta_2 ATT_{i,t} + \beta_3\big(MAX_{i,t} \times ATT_{i,t}\big) \\ &+ \beta_4 SIZE_{i,t} + \beta_5 BM_{i,t} + \beta_6 RET12_2_{i,t} + \beta_7 REV_{i,t} \\ &+ \beta_8 ILLIQ_{i,t} + \beta_9 BETA_{i,t} + \varepsilon_{i,t+2:t+k}. \end{aligned} \tag{4}$$

Figure 4 plots the estimated $MAX{\times}ATT$ coefficients across the four cumulative return horizons, with full regression results reported in Table A.3.

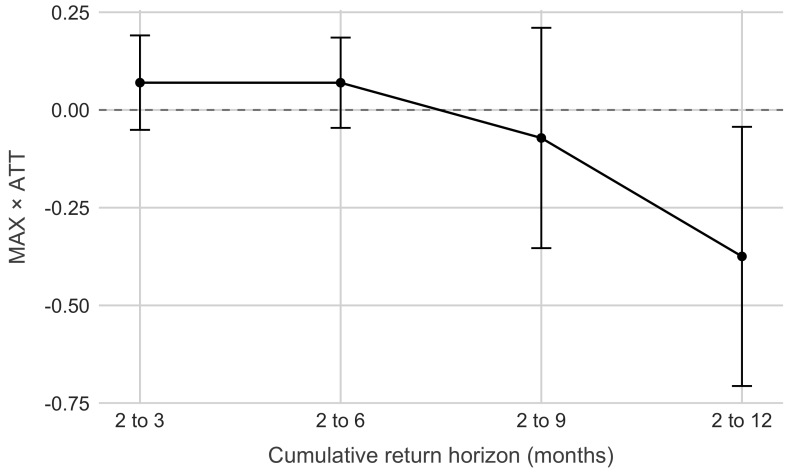


Figure 4. Fama–MacBeth *MAX×ATT* Coefficients Across Cumulative Return Horizons. This figure plots the estimated coefficients on the interaction between MAX and ATT from monthly Fama–MacBeth cross-sectional regressions of cumulative returns using the GSVI-filtered sample. The dependent variable is the cumulative return over four horizons, from months $t+2$ to $t+3$, $t+2$ to $t+6$, $t+2$ to $t+9$, and $t+2$ to $t+12$, measured after the month t in which MAX and ATT are defined. MAX is the largest daily return in month t, and ATT is the standardized abnormal in month t. Point estimates represent the coefficients on $MAX \times ATT$, and vertical bars show 95% Newey-West adjusted confidence intervals. Negative coefficients indicate stronger long-run reversals for high-attention MAX events.

Figure 4 shows that the interaction coefficient is close to zero at the 2- to 3-month horizon but turns significantly negative at longer windows, reaching -0.3747 (t-statistic=-2.22) over months 2 to 12 (see Table A.3). This pattern suggests that high-attention MAX events are followed by stronger cumulative reversals over extended periods, consistent with temporary price pressure documented by Da et al. (2011).

However, this evidence is merely suggestive. Our contemporaneous measurement of MAX and ATT prevents us from establishing causality or isolating mechanisms. Distinguishing between price pressure, enhanced monitoring, and confounding factors requires higher-frequency data that can separate the temporal sequence of attention and MAX events, as well as direct controls for news flow and ownership composition. Given that significant patterns emerge over longer horizons in our data, exploring the dynamics of long-term reversals could provide insight into which mechanisms attention captures and represents an important direction for future research.

Regardless of these future research directions, this paper's core findings remain at the portfolio level: stocks with high prior-month extreme daily returns significantly underperform when firm-specific attention is abnormally low or moderate, while this effect disappears entirely when attention is abnormally high. At the firm level, the one-month $MAX{\times}ATT$ interaction shows no significant moderation effect.

V. Robustness

The empirical results demonstrate that the MAX effect in Sweden is present, yet absent in higher attention states. To ensure that these findings are not driven by specific measurement choices, we perform a series of robustness tests. These address three practical concerns: First, *MAX* may be overly influenced by a single extreme daily return, so we evaluate a broader *MAX* definition. Second, periods of unusual market conditions may distort our results, so we re-estimate our specifications excluding the COVID-19 shock. Third, since Google Trends data may contain noise or reflect non-financial interest, we validate the attention measure using both randomization and targeted sample adjustments.

A. Redefining MAX

Following Bali et al. (2011), we redefine our *MAX* variable to the average of the five highest daily returns in a month (*MAX5*) to reduce the influence of one day's extreme movement and capture broader tail behavior within the month.

Table IX

Fama–MacBeth Cross-Sectional Regressions Using *MAX5*

This table displays the results from Fama–MacBeth cross-sectional regressions using the revised *MAX5* measure, defined as the average of the five highest daily returns in a month. All rows except the last present univariate regressions for each variable separately, while the final row reports the full multivariate model with all predictors. Each coefficient is the time-series average of monthly cross-sectional slope estimates, with the corresponding Newey-West adjusted t-statistics shown under the coefficients in brackets. The regressions include the following firm characteristics as explanatory variables: *MAX5*, beta (*BETA*), natural logarithm of market capitalization (*SIZE*), book-to-market ratio (*BM*), momentum (*RET12_2*), one-month reversal (*REV*), and Amihud illiquidity (*ILLIQ*). The explanatory variables are all lagged one month relative to the return they aim to predict. The regressions are estimated on a monthly basis using the full sample.

MAX5	BETA	SIZE	BM	RET12_2	REV	ILLIQ
-0.2527						
[−4.95]						
	0.0013					
	[0.81]					
		0.0010				
		[2.44]				
			-0.0009			
			[−3.08]			
				0.0172		
				[6.95]		
					0.0279	
					[2.81]	
						-111.8828
						[−0.49]
-0.3690	0.0035	-0.0010	-0.0007	0.0135	0.0407	1223.0337
[−5.62]	[2.24]	[−2.05]	[−2.42]	[5.54]	[3.91]	[1.21]

After replacing *MAX* with *MAX5* and rerunning the same Fama–MacBeth cross-sectional regressions as in Section IV.A.2, the results remain strongly negative and significant for the *MAX5* variable at -0.3690 (t-statistic=-5.62) in the full model (see Table IX). This coefficient is larger in absolute magnitude than the baseline *MAX* coefficient of -0.1101, consistent with *MAX5* capturing a broader measure of extreme return behavior rather than isolated single-day spikes. The finding confirms that the return predictability is not driven by a single extreme daily jump, but by periods in which several very large daily returns occur within the same month.

At the portfolio level, the Fama–French Carhart four-factor regressions using *MAX5*-sorted portfolios (see Table A.4) yield results consistent with the baseline MAX analysis in Section IV.A.1. The long–short strategy generates a statistically significant alpha of 0.011 (t-statistic=3.60) under equal weighting, while the value-weighted alpha of 0.003 (t-statistic=0.57) remains statistically insignificant. As with the baseline *MAX* portfolios, this pattern indicates that the effect is more pronounced among smaller stocks whose influence is diluted under value weighting.

These results align with the robustness tests of Bali et al. (2011), who similarly replace *MAX* with multi-day extreme-return measures and continue to find that stocks with frequent large jumps subsequently earn lower returns. The consistency of our findings across *MAX* and *MAX5* specifications strengthens the evidence that extreme positive returns predict lower subsequent performance in the Swedish equity market, regardless of whether extremes are measured by the single largest daily return or the average of the five largest returns within a month.

B. Excluding COVID Period (2020)

Next, we test whether our results are robust to excluding periods characterized by extreme market uncertainty. We re-estimate our specifications from Section IV.B.1 using the same GSVI-filtered sample but exclude observations from 2020, since these coincide with the spike in average *MAX* documented in Figure A.2. This allows us to verify that the strong jump in average *MAX* during the pandemic shock does not disproportionately drive our findings and that the relation between *MAX* and future returns continues to hold in more typical market environments.

Table X

Four-Factor Regressions for Attention-Sorted *MAX* Long–Short Portfolios Excluding 2020

This table reports Fama–French Carhart four-factor regressions for double-sorted long–short portfolios after excluding 2020. At the end of every month, stocks are first sorted into five quintiles based on their lagged standardized abnormal attention (ATT), with Q1 always containing the stocks with the lowest prior-month abnormal attention and Q5 those with the highest. Within each ATT quintile, stocks are further sorted into deciles based on their prior-month MAX values, and a long–short portfolio is formed by taking a long position in the lowest MAX decile portfolio and a short position in the highest MAX decile portfolio. The table presents the time-series regression intercepts and factor loadings from estimating the Fama–French Carhart four-factor model on these long–short excess returns. Panel A reports the regression intercepts and factor loadings for equally weighted portfolios, and Panel B reports the corresponding estimates for value-weighted portfolios. For each long–short portfolio, the table lists coefficients from regressions on the market factor (MKT), size factor (SMB), value factor (HML), and momentum factor (MOM), together with Newey-West t-statistics shown in brackets. The regressions are estimated using monthly portfolio returns from the GSVI-filtered sample, with 2020 excluded.

Portfolio	α	MKT	SMB	HML	MOM
Panel A, equally weighted long–short portfolios					
Q1	0.013 [2.70]	-0.007 [-0.07]	-49.352 [-3.61]	-11.758 [-0.60]	23.473 [1.33]
Q2	0.003 [0.44]	-0.293 [-1.99]	-25.989 [-1.33]	21.452 [0.80]	27.324 [1.56]
Q3	0.012 [2.08]	-0.096 [-0.80]	-8.401 [-0.54]	54.274 [2.14]	39.767 [2.63]
Q4	-0.006 [-0.68]	-0.133 [-0.79]	-73.205 [-3.26]	52.485 [1.84]	39.369 [2.18]
Q5	0.002 [0.20]	-0.246 [-1.51]	-79.303 [-3.45]	7.970 [0.27]	22.173 [1.03]
Panel B, value-weighted long–short portfolios					
Q1	0.019 [3.10]	-0.197 [-1.19]	-42.762 [-2.28]	-18.910 [-0.61]	9.638 [0.47]
Q2	-0.002 [-0.26]	-0.399 [-1.82]	-24.527 [-0.90]	15.801 [0.48]	15.241 [0.84]
Q3	0.010 [1.40]	-0.193 [-1.34]	22.810 [1.16]	28.317 [0.80]	49.796 [1.91]
Q4	-0.012 [-0.85]	-0.435 [-2.06]	-80.490 [-2.88]	66.764 [1.99]	46.014 [1.74]
Q5	-0.013 [-1.33]	0.019 [0.06]	-105.403 [-3.28]	48.641 [1.31]	37.012 [1.87]

Table X reports regression results for the abnormal-attention-sorted long–short MAX portfolios in our GSVI-filtered sample, excluding 2020. The Q1 long–short alphas for both equally and value-weighted portfolios remain similar in magnitude and significance to the full GSVI-filtered sample results, indicating that the return spread in low-attention environments is robust to the exclusion of pandemic-induced extremes. The equally weighted Q3 long–short portfolio also remains positive and significant. In contrast, long–short alphas for the higher ATT quintiles (Q4 and Q5) statistically indistinguishable from zero. This pattern reinforces that the MAX effect appears in low and moderate attention states and disappears entirely in higher-attention states.

We also report firm-level results for this sample, corresponding to the specification in Section IV.B.2. These results remain highly consistent with those obtained in the full GSVI-filtered sample (see Table A.5).

C. Attention Measure Validation

Finally, to verify that our attention measure captures investor attention rather than unrelated search behavior, we conduct three additional validation tests. First, we increase the minimum Google Trends data requirement from 15 to 100 observations to ensure that our findings are not driven by sparse search activity. Second, we implement a Monte Carlo randomization procedure to assess whether our measure reflects economically meaningful variation rather than patterns arising by chance. In each of one hundred iterations, firms are randomly assigned another firm's GSVI history from a similar period, preserving the temporal structure of search data while breaking the link to the underlying firm. This procedure generates a distribution of placebo estimates against which we benchmark our true results. Third, we exclude firms whose search histories are prone to capturing general web traffic rather than financial attention, such as firms whose retail websites share the same name as the company.

Table XI

Fama–French Carhart *MAX* Long–Short Alphas Across Attention States: Robustness Tests

This table reports Fama–French Carhart four-factor alphas and Newey-West t-statistics for long–short portfolios sorted by *MAX* within *ATT* quintiles. The results reflect three robustness checks on the attention measure. Panel A increases the Google Trends data requirement to avoid sparse-signal effects. Panel B randomizes search histories to test whether results arise by chance. Panel C excludes consumer-facing firms to ensure the attention proxy captures investor focus rather than general brand interest. Portfolios are constructed separately using equal-weighted and value-weighted structures. Each month, stocks are first sorted into quintiles based on their standardized abnormal attention (*ATT*) from the previous month. Within each *ATT* quintile, stocks are further sorted into decile portfolios based on their prior-month *MAX* values, and a long–short portfolio is formed by taking a long position in the lowest *MAX* decile portfolio and a short position in the highest MAX decile portfolio. Alphas are estimated as the intercepts from four-factor regressions of portfolio excess returns. The regressions are estimated using monthly portfolio returns in the GSVI-filtered sample.

	Panel A *Data Requirement*		**Panel B** *Randomized Trends*		**Panel C** *No Consumer Firms*	
Portfolio	EW Alpha	VW Alpha	EW Alpha	VW Alpha	EW Alpha	VW Alpha
Q1	0.016 [3.35]	0.023 [2.96]	0.006 [0.89]	0.005 [0.72]	0.014 [2.12]	0.016 [2.62]
Q2	0.011 [1.72]	0.012 [1.22]	0.005 [0.82]	0.005 [0.76]	0.004 [0.58]	-0.009 [-0.72]
Q3	0.018 [2.68]	0.008 [0.83]	0.006 [0.92]	0.005 [0.63]	0.014 [2.42]	0.019 [2.88]
Q4	0.000 [0.01]	0.006 [0.48]	0.006 [0.90]	0.005 [0.69]	0.000 [0.02]	-0.003 [-0.32]
Q5	0.001 [0.06]	-0.002 [-0.14]	0.006 [0.81]	0.005 [0.61]	0.005 [0.41]	-0.003 [-0.23]

Table XI reports Fama–French Carhart four-factor alphas for long–short portfolios sorted by MAX within *ATT* quintiles across three robustness checks. Panel A shows that the results are not driven by sparse Google Trends coverage. Significant long–short performance remains in the lowest *ATT* quintile under both weighting schemes and in the third quintile under equal weighting, with magnitudes comparable to or larger than in the baseline specification. This indicates that the MAX effect continues to appear in low and moderate attention environments and that these returns are robust to stricter data requirements.

Panel B presents a Monte Carlo randomization test in which each firm is reassigned a search history from a similar period. Once the link between firms and their own attention histories is removed, abnormal returns disappear and no systematic pattern emerges across quintiles. This confirms that the documented return patterns reflect meaningful investor attention rather than coincidental search variation.

Panel C reports the results after excluding consumer-facing firms whose search activity may reflect general product or brand interest rather than investor focus. The overall pattern remains intact: the MAX effect appears in low and moderate attention states and is absent when attention is high. In this refined sample, the strongest alpha shifts from Q1 to Q3, suggesting that consumer-related searches previously added noise and that the MAX effect may peak at moderate attention levels when attention is more precisely measured. We do not interpret this as evidence that any single attention quintile produces the strongest MAX effect. Instead, the consistent conclusion across all specifications is that high-attention environments (Q4 and Q5) exhibit no sign of a MAX effect.

VI. Conclusion

This paper examines the MAX effect in Swedish equities from 2011 to 2024 and whether it varies with the level of firm-specific attention. We combine portfolio-level tests with firm-level Fama–MacBeth regressions and proxy attention using standardized Google Search Volume Index.

We document two main findings. First, the MAX effect is present in Sweden during our sample period. Stocks with higher prior-month MAX earn lower risk-adjusted returns in equally weighted portfolios, and MAX significantly predicts lower subsequent stock returns. This firm-level evidence complements prior Swedish research, which found directionally similar but statistically insignificant results for earlier periods.

Second, the MAX effect varies systematically with firm-specific attention at the portfolio level. When we double-sort stocks on abnormal attention and MAX, the long–short return spread appears in low and moderate attention quintiles but is absent in high-attention states. This pattern clarifies why our unconditional tests show a MAX effect only in equally weighted portfolios. The weak unconditional value-weighted result does not reflect the absence of the effect among larger firms, but rather dilution from pooling heterogeneous attention states. At the firm level, however, the MAX-attention interaction does not significantly predict next-month returns. This divergence may reflect methodological differences, as portfolio sorts condition on discrete attention states while regressions impose linear interactions, or temporal dynamics where attention influences reversal timing across multiple months. Our contemporaneous measurement and lack of control variables for potential confounding factors prevent distinguishing between these explanations.

Our study has several limitations that restrict causal interpretation. Because MAX and attention are measured in the same month, we cannot determine whether attention moderates reversals or whether both variables respond to common factors such as firm-specific news or investor composition. The modest correlation between the two variables rules out a purely mechanical link but does not establish causal

direction. Additionally, Google search data are noisy and may capture non-financial interest, although robustness tests excluding consumer-facing firms and randomizing search histories support their interpretation as investor attention. Monthly aggregation prevents us from observing the timing of attention changes relative to MAX events, and our measure cannot distinguish between different sources of attention, such as news processing, speculative trading, or monitoring. These limitations mean we document when the MAX effect varies with attention, rather than why it does so or through which mechanism attention influences reversals.

For investors, our results highlight that MAX-related reversals occur in low- and moderate-attention periods with substantial abnormal returns. However, practical implementation poses significant challenges. The strategy requires monthly rebalancing across numerous positions in relatively illiquid small stocks, likely causing transaction costs and price impact to erode returns significantly, particularly at institutional scale. Our findings thus document a persistent behavioral pattern rather than providing a ready-made investment strategy.

For researchers, our evidence demonstrates the importance of conditioning behavioral anomalies on firm-specific attention. Attention-based heterogeneity helps explain varying empirical evidence on the MAX effect across markets, sample periods, and portfolio constructions, including why value-weighted tests show weaker results than equally weighted ones. Future research could employ higher-frequency attention data to examine intra-month dynamics and incorporate direct news controls to better distinguish attention-based from information-based mechanisms. While our one-month firm-level interaction is insignificant, we find the MAX-attention interaction is significantly negative over 2- to 12-month cumulative returns, suggesting attention may influence reversal timing and persistence. Establishing causality and identifying mechanisms will require higher-frequency data, non-contemporaneous measurement, and direct controls for news flow and ownership composition.

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Appendix

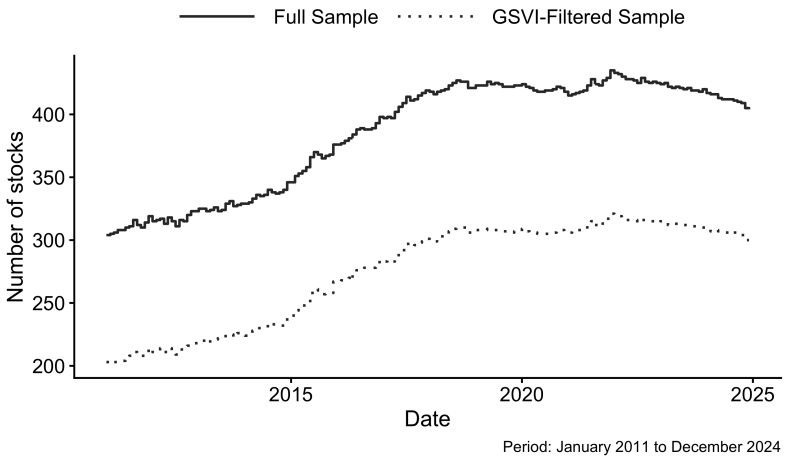


Figure A.1. Number of Firms in the Samples Over Time. This figure shows the number of stocks in the sample from January 2011 to December 2024. The solid line shows the number of stocks remaining after the initial data requirements, which include at least 24 months of observations and at least 10 daily closing prices. This defines our full sample. The dotted line shows the number of stocks remaining after additionally requiring at least 15 nonzero Google Search Volume Index observations over the sample period. This defines our GSVI-filtered sample.

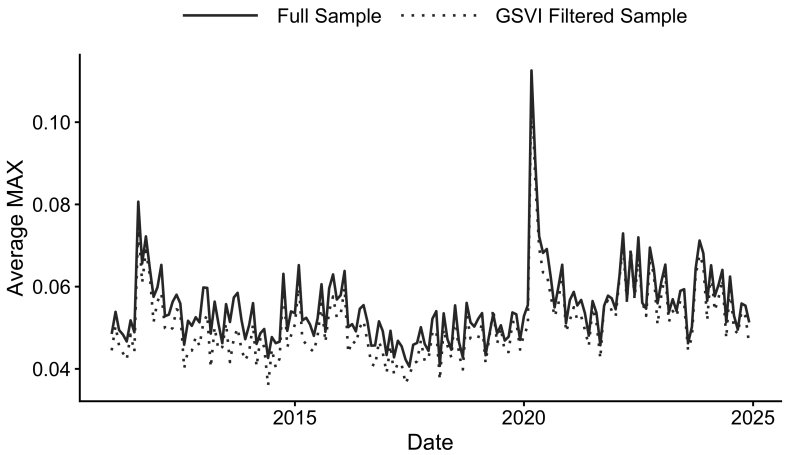


Figure A.2. Average *MAX* Over Time. This figure shows the monthly average of the maximum daily return (MAX) from January 2011 to December 2024. The solid line shows the full sample and the dotted line the GSVI-filtered sample. The y axis plots average MAX values, and the x axis represents time.

Table A.1

Correlation Matrix (Full Sample)

This table presents the contemporaneous correlations between *MAX*, standardized abnormal attention (*ATT*), beta (*BETA*), natural logarithm of market capitalization (*SIZE*), book-to-market ratio (*BM*), momentum (*RET12_2*), one-month reversal (*REV*), and Amihud illiquidity (*ILLIQ*), computed using the full sample.

	MAX	BETA	SIZE	BM	RET12_2	REV	ILLIQ
MAX	1.00	0.04	-0.29	-0.04	-0.09	0.21	0.21
BETA	0.04	1.00	0.24	-0.03	0.03	0.00	-0.08
SIZE	-0.29	0.24	1.00	-0.23	0.11	0.06	-0.26
BM	-0.04	-0.03	-0.23	1.00	-0.10	-0.04	0.04
RET12_2	-0.09	0.03	0.11	-0.10	1.00	0.05	-0.09
REV	0.21	0.00	0.06	-0.04	0.05	1.00	-0.04
ILLIQ	0.21	-0.08	-0.26	0.04	-0.09	-0.04	1.00

Table A.2

Fama–French Carhart Alphas for MAX Decile Portfolios within *ATT* Quintiles

This table presents Fama–French Carhart four-factor alphas and Newey-West adjusted t-statistics for portfolios sorted by MAX decile within each ATT quintile. At the end of every month, stocks are first sorted into five quintiles based on their lagged standardized abnormal attention (ATT), with Q1 always containing the stocks with the lowest prior-month abnormal attention and Q5 those with the highest. Within each ATT quintile, stocks are further sorted into decile portfolios based on their prior month MAX values, and a long–short portfolio (LS) is formed by taking a long position in the lowest MAX decile portfolio and a short position in the highest MAX decile portfolio. Panel A reports alphas for equally weighted portfolios, and Panel B reports alphas for value-weighted portfolios. The regressions are estimated using monthly portfolio excess returns over the full sample period.

	Q1	**Q2**	**Q3**	**Q4**	**Q5**
Panel A: equally weighted portfolios					
P1	0.007 [2.40]	0.010 [3.06]	0.007 [2.08]	0.005 [1.80]	0.005 [2.19]
P2	0.004 [1.62]	0.003 [1.11]	0.005 [2.11]	0.005 [1.79]	0.005 [2.32]
P3	0.005 [1.79]	0.005 [2.17]	0.003 [0.89]	0.001 [0.31]	0.005 [1.81]
P4	0.001 [0.43]	0.000 [0.15]	0.007 [2.28]	-0.002 [-0.65]	0.002 [0.73]
P5	0.005 [1.29]	0.010 [2.91]	0.001 [0.42]	0.005 [1.46]	0.001 [0.31]
P6	0.001 [0.25]	0.003 [0.93]	0.005 [1.61]	0.002 [0.40]	0.006 [1.78]
P7	0.001 [0.38]	0.003 [0.83]	0.000 [0.06]	0.008 [2.54]	-0.003 [-0.59]
P8	-0.007 [-1.33]	0.000 [0.04]	0.003 [0.63]	-0.001 [-0.24]	-0.006 [-1.24]
P9	-0.004 [-0.99]	-0.001 [-0.18]	0.002 [0.38]	0.002 [0.51]	0.000 [0.05]
P10	-0.006 [-1.50]	0.003 [0.51]	-0.007 [-1.60]	0.009 [1.19]	0.003 [0.27]
LS	0.012 [2.41]	0.004 [0.63]	0.011 [2.23]	-0.006 [-0.74]	0.002 [0.21]
Panel B: value-weighted portfolios					
P1	0.010 [2.78]	0.007 [1.76]	0.006 [1.26]	0.012 [4.70]	0.005 [1.77]
P2	0.005 [1.34]	0.008 [2.13]	0.003 [1.02]	0.005 [1.41]	0.007 [2.16]
P3	0.008 [1.52]	0.005 [1.78]	0.001 [0.17]	0.003 [0.79]	0.006 [1.34]
P4	-0.001 [-0.21]	0.000 [0.03]	0.006 [1.93]	0.001 [0.14]	0.001 [0.25]
P5	0.003 [0.82]	0.005 [1.30]	-0.000 [-0.07]	0.003 [0.92]	-0.004 [-1.18]
P6	-0.001 [-0.32]	0.001 [0.30]	-0.004 [-1.23]	-0.003 [-0.87]	0.002 [0.51]
P7	-0.001 [-0.16]	0.006 [1.28]	-0.002 [-0.53]	0.009 [2.44]	0.001 [0.17]
P8	-0.013 [-2.53]	-0.005 [-0.76]	-0.005 [-0.85]	-0.000 [-0.04]	-0.008 [-1.45]
P9	-0.009 [-1.76]	-0.005 [-0.82]	0.004 [0.59]	-0.006 [-1.13]	0.001 [0.13]
P10	-0.010 [-1.91]	0.007 [0.94]	-0.007 [-1.14]	0.023 [1.73]	0.017 [1.85]
LS	0.018 [3.37]	-0.003 [-0.40]	0.010 [1.47]	-0.012 [-0.92]	-0.013 [-1.38]

Table A.3

Fama–MacBeth Cross-Sectional Cumulative Return Regressions (Conditional on Abnormal Attention)

This table reports monthly Fama–MacBeth cross-sectional regressions of cumulative returns on *MAX*, abnormal firm-specific attention (*ATT*), and their interaction (*MAX*×*ATT*). The dependent variable is the cumulative return over four horizons, from months $t+2$ to $t+3$, $t+2$ to $t+6$, $t+2$ to $t+9$, and $t+2$ to $t+12$, measured after the month t in which *MAX* and *ATT* are defined. *MAX* is the largest daily return in month t, and *ATT* is the standardized abnormal Google Search Volume Index in month t. Control variables include beta (*BETA*), natural logarithm of market capitalization (*SIZE*), book-to-market ratio (*BM*), momentum (*RET12_2*), one-month reversal (*REV*), and Amihud illiquidity (*ILLIQ*). Values in brackets report Newey-West adjusted t-statistics. The regressions are estimated over the full sample period, using the GSVI-filtered sample.

	Cumulative returns			
Variable	Months 2 to 3	Months 2 to 6	Months 2 to 9	Months 2 to 12
MAX	-0.1777 [-2.53]	-0.1180 [-1.13]	-0.4984 [-3.07]	-0.3070 [-1.20]
ATT	-0.0010 [-0.39]	0.0033 [1.26]	0.0090 [1.73]	0.0170 [3.21]
MAX×ATT	0.0699 [1.13]	0.0696 [1.18]	-0.0717 [-0.50]	-0.3747 [-2.22]
BETA	0.0017 [0.79]	-0.0062 [-0.94]	0.0111 [1.45]	0.0123 [0.91]
SIZE	-0.0006 [-0.72]	-0.0011 [-0.87]	-0.0086 [-4.05]	-0.0131 [-3.28]
BM	-0.0013 [-1.62]	-0.0041 [-3.44]	-0.0090 [-7.02]	-0.0144 [-8.59]
RET12_2	0.0130 [1.16]	0.0526 [6.66]	0.0853 [6.81]	0.0803 [4.75]
REV	0.1227 [2.68]	0.1373 [2.93]	0.2956 [5.33]	0.2403 [2.55]
ILLIQ	-2631.5102 [-0.95]	-8836.0441 [-4.87]	-15155.0145 [-5.83]	-15175.7802 [-3.61]

Table A.4
Fama–French Carhart Four-Factor Loadings for MAX5-Sorted Portfolios

This table presents Fama–French Carhart four-factor regressions for portfolios sorted on the revised measure, *MAX5*, defined as the average of the five highest daily returns in a month. Stocks are assigned each month to decile portfolios based on their prior-month *MAX5* values, forming portfolios from P1 (lowest *MAX5*) to P10 (highest *MAX5*). Panel A reports the regression intercepts and factor loadings for equally weighted portfolios, and Panel B reports the corresponding estimates for value-weighted portfolios. For each portfolio, the table lists coefficients from regressions on the market factor (*MKT*), size factor (*SMB*), value factor (*HML*), and momentum factor (*MOM*), together with Newey-West t-statistics shown in brackets. The final row in each panel provides estimates for a long–short portfolio constructed as the difference in excess returns between the lowest and highest *MAX5* decile portfolios. The regressions are estimated using monthly portfolio returns in the full sample.

Portfolio	α	MKT	SMB	HML	MOM
Panel A, equally weighted portfolios					
P1	0.008 [5.31]	0.691 [16.94]	32.282 [6.07]	5.000 [0.84]	-5.097 [-0.86]
P2	0.004 [3.26]	0.848 [26.36]	28.153 [6.55]	13.711 [2.58]	6.605 [1.69]
P3	0.003 [2.76]	0.929 [28.08]	36.474 [9.27]	7.542 [1.55]	3.520 [0.86]
P4	0.005 [3.73]	0.988 [38.43]	34.921 [7.73]	0.234 [0.04]	1.176 [0.28]
P5	0.003 [2.09]	0.916 [40.51]	41.097 [9.97]	-6.356 [-1.13]	0.245 [0.06]
P6	0.001 [0.90]	0.968 [28.56]	42.501 [7.61]	-4.388 [-0.60]	1.526 [0.26]
P7	0.000 [0.21]	1.009 [31.44]	45.510 [10.11]	-14.526 [-2.14]	-5.065 [-0.99]
P8	-0.000 [-0.35]	1.010 [31.04]	55.243 [10.09]	-12.374 [-1.97]	-5.357 [-0.75]
P9	-0.004 [-2.57]	0.962 [21.14]	57.364 [9.37]	-10.318 [-1.33]	1.696 [0.24]
P10	-0.004 [-1.19]	0.821 [12.37]	81.629 [10.11]	-18.647 [-2.65]	-25.911 [-2.32]
LS	0.011 [3.60]	-0.129 [-1.55]	-49.347 [-4.47]	23.646 [2.92]	20.813 [1.49]
Panel B, value-weighted portfolios					
P1	0.009 [6.66]	0.629 [12.89]	4.610 [0.69]	17.059 [2.51]	-4.292 [-0.92]
P2	0.006 [3.03]	0.765 [11.66]	-7.498 [-1.10]	7.175 [0.71]	-1.947 [-0.40]
P3	0.003 [1.60]	0.888 [35.96]	-8.596 [-1.59]	4.347 [0.78]	-2.918 [-0.63]
P4	0.003 [1.60]	0.947 [25.75]	7.934 [1.49]	-1.222 [-0.15]	-0.054 [-0.01]
P5	-0.001 [-0.76]	0.938 [28.61]	0.160 [0.02]	8.796 [1.49]	-2.714 [-0.52]
P6	-0.005 [-2.32]	1.048 [23.41]	-3.391 [-0.47]	-8.070 [-0.91]	-7.486 [-1.27]
P7	-0.004 [-1.78]	1.077 [21.68]	-15.785 [-1.92]	-3.847 [-0.40]	-9.411 [-1.35]
P8	-0.005 [-2.45]	1.007 [17.13]	9.917 [1.48]	-14.508 [-1.49]	-10.008 [-0.99]
P9	-0.006 [-1.68]	1.112 [19.43]	21.714 [2.34]	-22.113 [-1.94]	-7.589 [-0.56]
P10	0.006 [1.32]	1.022 [7.49]	79.116 [5.29]	-51.948 [-2.58]	-41.794 [-2.90]
LS	0.003 [0.57]	-0.393 [-2.46]	-74.505 [-4.11]	69.006 [3.10]	37.501 [2.22]

Table A.5

Fama–MacBeth Cross-Sectional Regressions with MAX×ATT Interaction (Excluding 2020)

This table presents the results from Fama–MacBeth cross-sectional regressions evaluating the ability of firm-level characteristics to predict next-month stock returns when excluding 2020. All but the last row report univariate regressions, where each variable is considered in isolation, while the last row shows the results from a full multivariate specification including all predictors together. Each coefficient is the time-series average of monthly cross-sectional slope estimates, with the corresponding Newey-West adjusted t-statistics shown under the coefficients in brackets. The regressions include the following firm characteristics as predictors: *MAX*, standardized abnormal attention (*ATT*), defined as the firm's Google search volume in month t relative to its own historical mean and volatility, their interaction term *MAX×ATT*, beta (*BETA*), natural logarithm of market capitalization (*SIZE*), book-to-market ratio (*BM*), momentum (*RET12_2*), one-month reversal (*REV*), and Amihud illiquidity (*ILLIQ*). The explanatory variables are all lagged one month relative to the return they aim to predict. The regressions are estimated on a monthly basis using the GSVI-filtered sample, excluding 2020.

MAX	ATT	MAX×ATT	BETA	SIZE	BM	RET12_2	REV	ILLIQ
-0.0720								
[−2.75]								
	0.0006							
	[0.73]							
			0.0001					
			[0.08]					
				0.0003				
				[0.75]				
					-0.0007			
					[−2.12]			
						0.0107		
						[3.63]		
							0.0096	
							[0.87]	
								606.3588
								[1.14]
-0.1193	-0.0002	0.0161	0.0022	-0.0006	-0.0010	0.0089	0.0112	-114.0594
[−3.99]	[−0.27]	[0.73]	[1.47]	[−1.36]	[−2.63]	[3.57]	[1.18]	[−0.08]

AI Recognition

We have made use of the AI tools ChatGPT and Grammarly for assistance with grammar, R coding, and LaTeX formatting. However, all analyses, interpretations, and conclusions are entirely our own.