An Alternative Behavioral Explanation for the MAX Effect

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Abstract: Stocks with high maximum daily returns in the previous month (MAX) yield low future returns. We examine the underlying sources of this MAX effect and present three empirical arguments that question the common presumption that investors with lottery preferences cause an overvaluation of high-MAX stocks. First, high-MAX stocks are comparably unattractive for investors with cumulative prospect theory preferences. Second, we find no price pressure from lottery investors after high-MAX observations but immediate price reversals. Hence, the MAX return itself seems to be the source of the overvaluation. Third, the MAX effect reverses if the MAX return can be linked to an earnings announcement. These findings are perfectly in line with a behavioral phenomenon called strength-weight bias: Investors usually overreact towards extreme high-strength news such that high-MAX stocks tend to be overvalued. However, they underreact if the MAX return is accompanied by reliable high-weight news such as earnings announcements.

Keywords: MAX effect, lottery preferences, strength-weight bias, cross-sectional return predictability.

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1. Introduction

Bali et al. (2011) show that stocks with high maximum daily returns (MAX) in the previous month yield low subsequent returns. As they cannot reconcile this return predictability with risk-based explanations, they propose that behavioral biases lead to an overvaluation of high-MAX stocks. They argue that investors following cumulative prospect theory (CPT; Tversky and Kahneman, 1992) have a preference for lottery-like payoffs and therefore increase the prices of high-MAX stocks beyond their fundamental value. While we support a behavioral mechanism for the MAX effect, we present empirical evidence that the return patterns might rather be due to judgment biases in information processing than evaluation biases underlying cumulative prospect theory.[1]

Following the seminal findings of Bali et al. (2011), empirical evidence largely points at a behavioral driving force of the MAX effect. For example, Lin and Liu (2017) show that the MAX effect only exists among those stocks that are attractive for private investors who are presumably most affected by behavioral biases. Similarly, Kumar (2009), Han and Kumar (2013), and Bali et al. (2017) provide evidence that particularly retail investors like to trade high-MAX stocks. Fong and Toh (2014) show that the MAX effect is stronger in periods of high investor sentiment. Further supporting a behavioral driving force, Cheon and Lee (2017) link the MAX effect to overconfident investors since it is stronger in countries with higher levels of individualism.[2] Since overconfidence affects individuals' information processing (Peng and Xiong, 2006; Glaser et al., 2013), these findings point at the relevance of judgment biases rather than evaluation biases. In conclusion, while the overall research provides a clear link between the MAX effect and investors who are most affected by behavioral biases, the identification of the specific behavioral mechanism proves difficult.

On the one hand, lottery preferences are a natural candidate to explain the anomaly since Barberis and Huang (2008) theoretically show that lottery-like stocks can become overvalued if investors have CPT-preferences. This idea builds on the well-established evaluation bias that individuals tend to overweight low probabilities for extreme outcomes (Tversky and Kahneman, 1992). On the other hand, psychological studies also clearly point

[1] While judgment biases affect how individuals process information to form beliefs and thereby the input of a decision problem, evaluation biases affect how beliefs are subsequently evaluated by individuals and turned into actual decisions.

[2] Additional support for the international validity of the MAX effect is provided by Annaert et al. (2013), Walkshäusl (2014), Zhong and Gray (2016) and Nartea et al. (2017).

out that individuals are often prone to judgment biases such as base rate neglect which can imply an overreaction towards new information (Kahneman and Tversky, 1973; Odean, 1998; and Daniel et al., 1998). Griffin and Tversky (1992) show that people particularly tend to overreact if they receive high-strength news, that is, extreme information. Hence, psychological evidence suggests that investors might overreact towards the strong positive news that generate the maximum daily return. Thus, overreaction resulting from investors' judgment biases could also be the reason for the overvaluation and low subsequent returns of high-MAX stocks.

Both explanatory approaches rely on psychologically well-founded theories and predict a MAX effect that becomes stronger if more investors with presumably biased behavior enter the market. So far, neither theoretical nor empirical arguments allow to differentiate between the two mechanisms. However, this distinction is highly relevant because the two competing hypotheses have different empirical implications. The aim of this paper is to examine these empirical predictions in order to decide which of the two behavioral mechanisms explains the negative subsequent returns of high-MAX stocks more convincingly.

First, a lottery-explanation implies that investors judge upon a stock's attractiveness based on historical return patterns. Based on the psychological evidence by Tversky and Kahneman (1992), Barberis et al. (2016) introduce a TK-measure that equals the CPT-value of realized past returns. They argue that TK-values reflect how appealing a stock is for investors who are prone to the evaluation biases underlying cumulative prospect theory. They also present empirical evidence that stocks with high TK-values calculated for monthly returns of the preceding five years indeed tend to be overvalued. We apply the proposed TK-calculation procedure using daily returns of the previous month since lottery-based MAX explanations argue that investors use this time horizon to judge on a stock's attractiveness as well. Our empirical analyses show that these short-term TK-values do not capture the predictability of MAX and that they are even comparably low for high-MAX stocks. This implies that high-MAX stocks are even considered unattractive by CPT-investors who evaluate the daily returns of the previous month. Consequently, the findings question a CPT-based explanation for the MAX effect.

Second, we show that stocks with high-MAX values start to underperform immediately after the realization of MAX. This means that we cannot identify any subsequent buying pressure from investors who have observed the potentially attractive MAX return.

Consequently, the overvaluation seems to originate at the realization date of MAX. This indicates that the MAX return itself is the overvaluation source which is more in line with the overreaction hypothesis than a preference-based line of argument.

Third, psychological research provides clear-cut predictions in which situations over- or underreaction are more prevalent. Griffin and Tversky (1992) show that individuals generally tend to overreact towards extreme information. However, people usually underreact if the information is high in weight, that is, if the information is very reliable and valid.[3] This strength-weight judgment bias implies that investors in general should overreact towards extreme positive news, while they should not do so if the positive information has high reliability. Since high MAX returns are presumably the consequence of extreme positive information, these arguments perfectly predict an overvaluation of high-MAX stocks. However, the strength-weight bias predicts no overreaction if news is reliable. In line with previous literature, we consider earnings announcements a comparably reliable information source (Liang, 2003) and show that high-MAX stocks indeed subsequently outperform if the MAX return coincides with an earnings announcement. While this empirical finding is fully in line with psychological evidence on over- and underreaction, preference-based MAX-explanations do not predict such an information dependence.

To sum up these three aspects, judgment biases seem to play an important role in understanding the MAX effect. Moreover, one specific well-known bias of information processing is sufficient to reconcile all the presented empirical findings. Of course, evaluation biases might still affect investor behavior around MAX returns. However, on a standalone basis, they are not able to explain the empirical findings since evaluation biases do not influence the processing of different information types, but only the evaluation of given risky alternatives. We also discuss how combinations of various biases can explain our empirical findings. However, these approaches are by construction more complicated, require more restrictive assumptions, and thus provide less convincing explanations for the MAX effect's origin in comparison to simple patterns of over- and underreaction.

In Section 2, we introduce the data. In Section 3, we present three empirical analyses aimed at distinguishing between judgment and evaluation biases as possible explanations

[3]These information-dependent patterns of over- and underreaction have also been applied in various behavioral finance models, see for example Daniel et al. (1998), Barberis et al. (1998), Hong and Stein (1999), and Brav and Heaton (2002). Empirical support for a strength-weight bias is provided in event studies by Pritamani and Singal (2001), Chan (2003), Tetlock (2010), and Savor (2012).

for the MAX effect. In Section 4, we discuss the empirical implications and critically contrast the two opposing approaches. Based on this, we conclude in Section 5 that our analyses favor judgment over evaluation biases as the driving force of the MAX effect.

2. Data and Summary Statistics

2.1. Data Sources and Variable Construction

Our analyses are based on a monthly sample of common ordinary US stocks traded on NYSE, AMEX, or NASDAQ. Data on returns, trading volume, and market capitalization is obtained from the Center of Research in Security Prices (CRSP). Based on CRSP data, MAX is the maximum daily return of the previous month. IVOL denotes the idiosyncratic return volatility of the previous month, that is, the volatility of residuals from a regression of stock excess returns on the Fama-French-factors (Ang et al., 2006).[4] The market beta, BETA, is estimated using daily returns of the previous year. MV is the market value of equity at the end of the last month. The Amihud (2002) illiquidity measure ILLIQ is calculated as the ratio of absolute daily return and daily dollar trading volume averaged over the previous year. REV denotes short term reversal and equals the stock return of the previous month; momentum MOM is calculated as the return of the previous year excluding the previous month. Further, we estimate the cumulative prospect theory value TK as introduced by Barberis et al. (2016) based on daily returns of the previous month. Barberis et al. (2016) estimate TK-values based on monthly returns of the preceding five years and argue that TK reflects the stock's attractiveness in the view of CPT-investors.[5]

Accounting data is retrieved from annual COMPUSTAT files to calculate the book-to-market-ratio.[6] The book value of equity is calculated in line with Fama and French (1993) such that we use annual balance sheet data at the earliest at the end of June of the following

[4]Risk factors and risk-free rate data come from Kenneth R. French's homepage `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

[5]As the MAX return is determined using daily returns within one month, we transfer this evaluation period to our TK estimation. Apart from changing the time horizon, the estimation procedure strictly follows Barberis et al. (2016): Daily returns in excess of the value-weighted market return are evaluated via a value function with diminishing value sensitivity parameter $\alpha = 0.88$ and loss aversion parameter $\lambda = 2.25$. The probability weighting parameters are $\gamma = 0.61$ and $\delta = 0.69$ for gain and loss domain, respectively. This parametrization is in line with experimental evidence in Tversky and Kahneman (1992).

[6]Both CRSP and COMPUSTAT data were provided by Wharton Research Data Services.

year. Firms with negative book values are excluded from our sample. The book-to-market-ratio BM is then calculated as book value of equity divided by the most recent market value of equity. In addition, we use quarterly COMPUSTAT data to retrieve quarterly earnings announcement report dates. We restrict our sample to those firms with at least two report dates available in the previous year.

We include any stock observation if it meets the described requirements and if all introduced variables are available at the end of a month. This procedure yields a total of 1,872,475 stock-month-observations from January 1972 to December 2016. Our sample period starts in 1972 since quarterly earnings announcement data is not sufficiently available for earlier periods.[7]

2.2. Summary Statistics

In Table 1, we provide pooled summary statistics and correlation coefficients for the introduced variables. Most notably, the correlation between MAX and IVOL is 90.38%. This high correlation is in line with previous literature (see for example Bali et al., 2014 and Hou and Loh, 2016). Seminal evidence by Ang et al. (2006) and Bali et al. (2011) shows that both MAX and IVOL negatively predict subsequent returns on a stand-alone basis, respectively. Resulting from the strong empirical link between MAX and IVOL, the most prominent lottery-based explanation for MAX has also been proposed as the driving force of the return premiums associated with IVOL (Bali et al., 2011). For example, Hou and Loh (2016) conduct a horse race among different explanatory approaches for the IVOL puzzle and find that MAX explains the highest fraction of the IVOL puzzle.

Due to the very strong multicollinearity in regression analyses, it is however unclear whether MAX is the true source of return predictability such that it subsumes the IVOL puzzle or vice versa. For example, Bali et al. (2011) and Barberis et al. (2016) provide evidence that the predictability of IVOL vanishes if MAX is controlled for while Bali et al. (2014) and Cosemans and Frehen (2017) present Fama-MacBeth-regressions with significant IVOL-coefficients while MAX is insignificant at the same time. Thus the specific empirical findings seem to be crucially dependent on the exact sample definition and the choice of additional control variables (also see Bali and Cakici, 2008). Since disentangling this

[7] Our Online Appendix shows very similar results if the sample period starts in 1927 for those analyses which do not require earnings announcement report dates.

Table 1. Summary Statistics
This table reports pooled summary statistics for the variables of interest. This includes sample mean, standard deviation, 0.1-quantile, median, 0.9-quantile, and correlation coefficients. MAX denotes the maximum daily return of the previous month. IVOL is the annualized idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors. MV denotes the market value of equity. BM is the book-to-market ratio. MOM is the return of months $t-12$ to $t-2$. Amihud (2002) illiquidity measure, ILLIQ, and market beta, BETA, are estimated based on daily returns of the previous year. TK is the prospect theory value based on daily returns of the previous month following the methodology of Barberis et al. (2016). REV is the return of month $t-1$. ILLIQ is stated in million; MAX, TK, and REV are stated in %. The sample covers January 1972 to December 2016 on a monthly basis.

	MAX	IVOL	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
mean	7.5339	0.4370	0.8097	19.0432	0.9545	13.7697	4.6772	-2.3290	1.2035
SD	9.1102	0.4089	0.6037	2.1090	4.8161	70.1764	37.4401	2.1775	17.1755
$q_{0.1}$	2.1106	0.1393	0.1150	16.4098	0.1648	-45.3101	0.0009	-4.9004	-14.7541
$q_{0.5}$	5.2632	0.3260	0.7594	18.9137	0.6077	5.5409	0.0991	-1.8761	0.1021
$q_{0.9}$	14.7059	0.8423	1.5869	21.8472	1.7331	70.4388	6.7915	-0.3787	16.6832
Correlation Coefficients									
MAX	1.0000								
IVOL	0.9038	1.0000							
BETA	0.0008	-0.0483	1.0000						
ln(MV)	-0.3043	-0.4407	0.3434	1.0000					
BM	0.0858	0.1109	-0.0224	-0.0980	1.0000				
MOM	-0.1043	-0.1309	0.0517	0.1321	-0.0694	1.0000			
ILLIQ	0.1892	0.2402	-0.0993	-0.1916	0.0502	-0.0343	1.0000		
TK	-0.0848	-0.4070	0.0143	0.3566	-0.0927	0.0799	-0.1159	1.0000	
REV	0.3105	0.1358	-0.0120	0.0494	-0.0392	0.0001	0.0164	0.6825	1.0000

sensitive dominance relation is beyond the scope of this paper, we rather consider MAX and IVOL as two different proxies for one broadly defined identical economic mechanism.

Following this view, given that MAX and IVOL are highly correlated, considering both variables in joint regression analyses merely implies very unstable coefficient estimates due to severe multicollinearity issues. In comparison to IVOL, MAX carries the advantage that it can be pinned down to one single day while IVOL requires an estimation horizon of one month. Moreover, the prevalent explanation for IVOL- and MAX-effect based on lottery preferences is better reflected by MAX, which resembles an intuitively obvious lottery payoff. As a consequence, we only consider MAX in the subsequent analyses. However, the Online Appendix shows that our line of argument is identically applicable if the empirical analyses use IVOL instead of MAX.[8]

[8] More specifically, these IVOL-based analyses also question whether the return predictability of IVOL is due to attractive historical return patterns. First, high-IVOL stocks are unattractive judged by their TK-values. Second, the low subsequent returns of high-IVOL stocks are particularly pronounced directly after high-volatility-days such that no preference-driven buying pressure can be identified. Third, the IVOL puzzle vanishes if the high IVOL is driven by earnings announcement days (also see analyses by DeLisle et al., 2016).

3. Empirical Analyses

3.1. Stock Attractiveness Based on MAX

According to cumulative prospect theory as introduced by Tversky and Kahneman (1992), individuals tend to overweight small probabilities for extreme outcomes. Consequently, stocks with potential lottery-like future payoffs might be overvalued as investors overestimate the small probability of a jackpot return (Barberis and Huang, 2008). If investors behave in line with cumulative prospect theory and judge on a stock's future return distribution based on past realized returns, high-MAX-stocks might thus be overvalued and yield low subsequent returns. This mechanism constitutes the most popular theoretical foundation to explain the return predictability associated with MAX (see Bali et al., 2011; Fong and Toh, 2014; and Lin and Liu, 2017 among others).

Table 2. Portfolio Sorts based on MAX
This table reports monthly quintile portfolio sorts based on the maximum daily return of the previous month MAX. The table provides equally-weighted subsequent FFC-adjusted returns α_{FFC} and the corresponding factor loadings. In addition, portfolio characteristics are provided. These variables are described in the caption of Table 1. The sample period is from January 1972 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. ILLIQ is stated in million; α_{FFC}, MAX, TK, and REV are stated in %.

	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	MAX	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
low	0.35	0.78	0.35	0.33	-0.06	2.17	0.64	19.93	0.86	15.25	1.24	-1.70	-2.06
2	0.33	0.96	0.53	0.31	-0.10	3.72	0.82	19.63	0.83	15.50	1.22	-1.91	-0.86
3	0.31	1.04	0.75	0.21	-0.16	5.30	0.91	19.10	0.87	16.71	2.07	-2.19	0.05
4	0.21	1.10	1.05	0.09	-0.26	7.71	0.95	18.49	0.97	16.19	4.10	-2.51	1.46
high	-0.24	1.09	1.39	0.03	-0.39	16.61	0.90	17.59	1.45	5.59	14.69	-2.79	7.57
5-1	-0.59	0.30	1.04	-0.31	-0.33	14.44	0.26	-2.34	0.60	-9.66	13.45	-1.09	9.63
t(5-1)	(-3.18)	(6.22)	(6.99)	(-1.67)	(-2.45)	(20.58)	(8.71)	(-29.65)	(5.40)	(-2.92)	(7.73)	(-10.40)	(20.41)

The empirical findings in Table 2 support the hypothesized negative relationship between MAX and subsequent returns. At the end of each month, stocks are allocated to quintile portfolios based on MAX. According to Table 2, high-MAX-stocks underperform low-MAX-stocks by 0.59% per month after accounting for the Fama-French-Carhart (FFC) factors.[9] However, Table 2 also shows that high-MAX stocks have substantially lower

[9]Untabulated results show that MAX is also a robust predictor of unadjusted subsequent returns: The quintile return spread has a similar magintude of 0.60% per month (t-statistic of 2.19). Moreover, our Online Appendix also provides similar findings if value-weighted portfolio sorts are applied instead of the equally-weighting methodology in Table 2. The same holds true if an extended sample period beginning in 1927 is considered.

TK-values compared to their low-MAX counterparts. Hence, if investors judge on a stock's attractiveness by evaluating historical returns with cumulative prospect theory preferences, they would rather prefer low-MAX stocks than high-MAX stocks. Thus, applying cumulative prospect theory in a stock market setting as proposed by Barberis et al. (2016) cannot explain the negative relationship between MAX and subsequent returns.

This finding is puzzling at first glance since high MAX-values are supposed to be attractive for CPT decision makers. First, a high-MAX observation is attractive per se because of an upward-sloping value function. Second, CPT decision makers overweight tail events such that a high positive return receives a disproportionately high decision weight. However, high-MAX stocks are also more volatile. Due to the CPT component of loss aversion, this higher amount of volatility strongly decreases the TK-values of high-MAX stocks which results in the patterns observed in Table 2. Untabulated analyses support this line of argument: If we estimate TK-values without loss aversion (that is, the loss aversion parameter is set to $\lambda = 1$), the TK-difference between top- and bottom-MAX-quintile switches its sign and becomes significantly positive (TK-difference of 1.33 with a t-statistic of 25.22).

Table 3. MAX in Fama-MacBeth-Regressions
This table reports Fama-MacBeth-regression estimates for the sample period from January 1972 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. The explanatory variables are described in the caption of Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	1.5434	4.3000	4.2620	3.8035	1.9588	3.6657
	(6.96)	(4.05)	(4.36)	(3.94)	(2.22)	(4.30)
MAX	-0.0595	-0.0807	-0.0750	-0.0835	-0.0772	-0.0300
	(-4.79)	(-8.22)	(-8.08)	(-9.10)	(-9.36)	(-4.53)
BETA		0.0611	0.0063	0.0487	-0.0753	-0.0231
		(0.35)	(0.04)	(0.30)	(-0.48)	(-0.15)
ln(MV)		-0.1498	-0.1589	-0.1356	-0.0564	-0.1163
		(-2.92)	(-3.38)	(-2.94)	(-1.36)	(-2.87)
BM		0.1525	0.2366	0.2232	0.1922	0.1724
		(3.02)	(4.59)	(4.40)	(3.91)	(3.61)
MOM			0.0076	0.0076	0.0082	0.0077
			(4.16)	(4.16)	(4.45)	(4.20)
ILLIQ				0.0187	0.0152	0.0187
				(5.74)	(4.72)	(5.51)
TK					-0.1946	0.2229
					(-4.56)	(5.54)
REV						-0.0693
						(-11.60)

Regression analyses following Fama and MacBeth (1973) in Table 3 support the portfolio sort findings. MAX negatively predicts subsequent returns and this effect is not subsumed by other known cross-sectional return determinants. More specifically, column (5) shows that the monthly TK-value cannot explain the MAX effect, too. The negative sign of the TK-coefficient is at least in line with an overvaluation of those stocks that are attractive to CPT-investors. However, this effect seems to be driven by short-term reversals as the TK-coefficient changes its sign if REV is included as additional control variable in column (6). Consequently, monthly TK-values seem to be no valid overvaluation measure as one would expect if CPT-investors evaluate a stock's attractiveness based on daily returns of the previous month. This suggests that CPT-investors rather trade on long-term historical return patterns such that only TK-measures based on longer time horizons consistently predict returns (Barberis et al., 2016).

Although simultaneously accounting for all CPT-components via the use of TK-values cannot explain the MAX effect, different specifications might do so. In the Online Appendix, we therefore follow robustness analyses of Barberis et al. (2016), calculate monthly TK-values based on different probability weighting parameters, and alternatively use TK-values without consideration of the loss aversion component. However, monthly TK-values do not capture the MAX effect in any of the specifications. Of course, this does not automatically rule out that the MAX effect is caused by investors who consider the observed historical return patterns attractive. For example, investors might judge on a stock exclusively based on the most prominent MAX observation and completely disregard other parts of the return distribution. Such a behavior would perfectly justify the use of MAX as a stock attractiveness measure. We merely argue that the most prominent evaluation model of cumulative prospect theory as proposed by Tversky and Kahneman (1992) and implemented by Barberis et al. (2016) is not the underlying driving force for the MAX effect since high-MAX stocks are even perceived as less attractive according to cumulative prospect theory (see Table 1). Thus, the presented findings are at least sufficient to conclude that preference-based explanations for the MAX effect require further critical investigation.

3.2. Timeline of the MAX Effect

The well established preference-based reasoning for the MAX effect basically goes along with the following timeline: First, a stock experiences a jackpot return denoted as MAX. Second, lottery investors observe this extremely positive return and buy the stock. In this second step the stock becomes overvalued. Third, the overvaluation is corrected which results in low subsequent returns of high-MAX stocks. The corresponding empirical analyses, however, only link the first and the third step, calling into question whether the second step actually exists. As a consequence, so far, we do not know when exactly and thus why exactly the overvaluation emerges. It might arise due to lottery-based stock demand after the MAX observation. But it might also arise due to an overreaction towards the news that generated the MAX return. In the first case, the buying pressure should increase the prices of high-MAX stocks directly after the MAX observation and lead to low returns afterwards. In the second case, the MAX return itself represents the overvaluation such that we would expect immediate price reversals. The following analyses based on portfolio sorts and Fama-MacBeth-regressions aim at differentiating these two competing hypotheses.

In order to examine when the overvaluation associated with MAX emerges, we provide conditional double sorts in Table 4. First, each stock is allocated to one decile portfolio based on the number of trading days between MAX realization and the end of month; that is, if MAX is observed directly before portfolio formation, the stock enters the low portfolio (first column in Table 4). Second, quintile portfolio sorts based on MAX are performed for each decile. Table 4 shows that the MAX effect is most pronounced if MAX is observed only shortly before portfolio formation. The corresponding monthly equally-weighted FFC-adjusted return premium of 2.13% is more than three times higher compared to the average MAX effect of 0.59% in our baseline analyses (see Table 2). Moreover, the MAX effect is smaller and no longer consistently significant in decile portfolios five to ten. These analyses show that we find no indication in favor of a lottery-based buying pressure after MAX has been observed by investors. On the contrary, high-MAX stocks underperform immediately after the MAX return has been realized. This finding is thus more in line with the alternative hypothesis that the MAX return itself is higher than fundamentally justified.

In the Online Appendix we show that the consideration of value-weighted returns, raw returns, and an extended sample period starting in 1927 yields the same conclusion.

Table 4. Timing of MAX in Portfolio Double Sorts
This table reports monthly equally-weighted FFC-adjusted subsequent returns from double portfolio sorts. First, each stock is allocated to one decile based on the number of days between the realization of MAX and the end of the month. Second, within each decile each stock is sorted to one quintile based on MAX. MAX denotes the maximum daily return of the previous month. The sample period is from January 1972 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. FFC-adjusted returns are stated in %.

	Days Between Realization of MAX and End of Month									
	low	2	3	4	5	6	7	8	9	high
low MAX	0.15	0.46	0.46	0.33	0.35	0.38	0.40	0.30	0.34	0.35
2	0.07	0.32	0.34	0.33	0.32	0.36	0.52	0.31	0.38	0.52
3	-0.15	0.15	0.22	0.27	0.38	0.35	0.49	0.31	0.26	0.35
4	-0.56	0.16	0.11	0.14	0.39	0.30	0.38	0.42	0.42	0.55
high MAX	-1.98	-0.42	-0.04	-0.34	0.12	-0.06	0.21	0.00	-0.14	0.29
5-1	-2.13	-0.89	-0.50	-0.67	-0.23	-0.44	-0.19	-0.30	-0.48	-0.06
t(5-1)	(-10.72)	(-3.98)	(-2.23)	(-3.08)	(-0.79)	(-1.88)	(-0.70)	(-1.13)	(-2.41)	(-0.27)

Fama-MacBeth-regressions further support the evidence in favor of an immediate underperformance of high-MAX stocks. Regressions in Table 5 include an interaction term between MAX and the number of days between MAX observation and month end. The corresponding regression coefficient is significantly positive in all specification showing that negative returns of high-MAX stocks are particularly strong directly after the occurrence of MAX.

In addition, we also examine the stock returns one trading day after the MAX observation. Untabulated results show that the quintile of high-MAX stocks underperforms the low-MAX stock quintile by 1.03% on the subsequent trading day. Again, we do not find that lottery-driven buying pressure has a price impact immediately after the MAX realization since the MAX return reverses instantaneously.

The empirical observation that high-MAX returns reverse very quickly might also be the consequence of potential micro-structure issues. For example, Conrad and Kaul (1989) show that short-term reversal effects are particularly strong for very short horizons. Since these reversal patterns are commonly related to bid-ask-bounces and illiquidity (Conrad et al., 1997 and Avramov et al., 2006), the interaction term significance might not be related to any kind of behavioral mechanism after all. However, our further analyses in Section 3.4

Table 5. Timing of MAX in Fama-MacBeth-Regressions
This table reports Fama-MacBeth-regression estimates for the sample period from January 1972 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. MAX is the maximum daily return of the previous month and d_{MAX} denotes the number of days between the realization of MAX and the end of the month. The other explanatory variables are described in the caption of Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	1.5434	1.5363	4.3463	4.3126	3.8510	2.5581
	(6.96)	(6.97)	(4.11)	(4.43)	(4.00)	(2.66)
MAX	-0.0595	-0.0967	-0.1199	-0.1145	-0.1239	-0.0893
	(-4.79)	(-7.32)	(-10.46)	(-10.33)	(-11.30)	(-10.91)
MAX x d_{MAX}		0.0028	0.0028	0.0029	0.0029	0.0032
		(8.33)	(9.17)	(9.06)	(9.27)	(10.05)
BETA			0.0533	-0.0008	0.0417	-0.0943
			(0.31)	(-0.00)	(0.26)	(-0.57)
ln(MV)			-0.1521	-0.1615	-0.1380	-0.0727
			(-2.98)	(-3.45)	(-3.00)	(-1.59)
BM			0.1535	0.2374	0.2241	0.1719
			(3.04)	(4.62)	(4.43)	(3.60)
MOM				0.0077	0.0076	0.0078
				(4.21)	(4.20)	(4.12)
ILLIQ					0.0189	0.0169
					(5.85)	(5.22)
REV						-0.0445
						(-7.68)

show that the timing of MAX also remains significantly relevant if we exclude small and penny stocks which are most affected by these micro-structure concerns.

In conclusion, we do not find any evidence supporting the preference-based conjecture that price pressure for lottery stocks leads to an overvaluation after a MAX return has been observed. Notwithstanding, there probably still are investors who like to buy those stocks that have experienced a jackpot return previously (Barber and Odean, 2008). However, the return reversal of their small and empirically undetectable buying pressure cannot be the driver of the MAX effect. If the subsequent return includes the delayed generation of the mispricing as well as its correction, a negative sign of this return would imply that the mispricing correction is stronger than the mispricing itself.

Of course, this still does not rule out explanations based on lottery preferences for sure. For example, investors might observe high intraday returns, consider them as a jackpot indicator, buy the stock at the same day, and thereby cause a MAX return which is higher than fundamentally justified. However, most of the lottery-driven buying activity is commonly related to private investors (Han and Kumar, 2013), who are presumably less engaged in trading on intraday return patterns compared to professional investors. We therefore consider it more likely that the MAX return itself seems to be the source of the overvaluation since the mispricing correction starts immediately after MAX realization. Therefore, the MAX return partly reflects an overreaction because new information has not been incorporated in the stock price correctly in an unbiased way. We investigate and provide empirical support for this information-driven mispricing approach in the following section.

3.3. Conditioning MAX on the Underlying Information

In this section, we take a closer look at the information that is responsible for the MAX return. Since the price movements are comparably strong on these days, they are most likely caused by the arrival of substantial new information. Thus, a mispricing on high-MAX days can arise if this information is not immediately reflected in the stock price in an unbiased way. Given that the severe price change indicates the arrival of high-impact information, these days are presumably most prone to the origin of mispricing.

These considerations lead to the natural question whether we should expect investors to over- or underreact on high-MAX days. While the concepts of both over- and underreaction are frequently applied to explain capital market phenomena, experimental research offers explicit insights which of the two opposed biases is more prevalent in specific situations. In a seminal paper, Griffin and Tversky (1992) show that individuals tend to overreact if the signal set has a high strength (extremeness of information) while underreaction dominates if the signal set is high in weight (reliability and validity of information). Antoniou et al. (2017) recently replicate the findings of a strength-weight bias in a well-incentivized experiment, too. The psychological findings have also been supported in empirical financial market research: Chan (2003), Tetlock (2010), and Savor (2012) show that returns tend to reverse following low-weight news, but tend to show continuation if the return is associated with high-weight information.

Since MAX represents an exceptionally extreme return observation, we argue that information strength is comparably high on these days.[10] If investors behave in line with

[10]This conjecture is also supported by Mohrschladt and Langer (2018). They theoretically transfer the experimental evidence to a financial market environment and show that returns are indeed largely determined by information strength rather than information weight.

the strength-weight bias, they overreact on high-MAX days. This implies that the MAX return is higher than fundamentally justified such that the stock yields comparably low subsequent returns. Thus, the empirical findings in the previous section are at first glance completely in line with behavioral predictions on biased information processing.

However, according to the experimental findings, investors should not always overreact on high-MAX days but only if information weight is rather low. In high-weight cases on the contrary, underreaction is supposed to be more prevalent. Consequently, relating the MAX effect to biased information processing implies that stocks with high MAX returns have high subsequent returns if MAX is due to reliable and valid high-weight information. This prediction constitutes the main hypothesis that we empirically test in this section. Thereby, we use firms' earnings announcements to identify those MAX returns that coincide with high information reliability. This procedure follows the common notion that earnings announcements contain comparably reliable information that is of high relevance for the correct pricing of securities (Bernard and Thomas, 1990 and Liang, 2003).[11]

We mark a MAX observation as high-weight if the firm announces its quarterly earnings in a symmetric three-day interval around the MAX date. The use of a three-day horizon follows La Porta et al. (1997) among others and accounts for potential pre-announcement leakage or small deviations between recorded COMPUSTAT date and actual announcement date (DellaVigna and Pollet, 2009). We then run our baseline portfolio sorts on MAX separately for those stocks with and without coinciding earnings announcement. The MAX return coincides with an earnings announcement date in 7.30% of all firm-month observations.[12] This corresponds to 253 observations per month for the restricted sample on average with a minimum monthly observation number of 23.

The portfolio sort findings are provided in Table 6. Most notably, MAX induces significantly lower subsequent returns if it does not coincide with an earnings announcement

[11]In our Online Appendix, we also use analyst recommendation data from the Institutional Brokers' Estimate System (IBES) and dividend announcement dates from CRSP to identify high-weight days since Savor (2012) and Aharony and Swary (1980) show that analyst reports and dividend announcements contain comparably reliable information, too. The corresponding findings support our conjecture that the MAX effect is information dependent.

[12]If MAX and earnings announcement date were uncorrelated, we would expect a sample proportion of roughly 4.76% based on a one third probability for a quarterly earnings announcement in the previous month and a probability of 3/21 that MAX falls in the earnings announcement event window. Thus, MAX observations occur disproportionally often around earnings announcements because returns are more likely to be extreme if substantial new information is released.

Table 6. Portfolio Sorts Based on MAX Dependent on Earnings Announcement Date
This table reports monthly quintile portfolio sorts based on the maximum daily return of the previous month MAX. The table provides equally-weighted subsequent FFC-adjusted returns α_{FFC} and the corresponding factor loadings. In addition, portfolio characteristics are provided. These variables are described in the caption of Table 1. The analyses refer to two subsamples: In Panel A, an observation is included if the MAX observation is not accompanied by an earnings announcement. Panel B considers all observations for which the MAX observation lies within a symmetric three-day interval around the firm's earnings announcement date. The sample period is from January 1972 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. ILLIQ is stated in million; α_{FFC}, MAX, TK, and REV are stated in %.

Panel A: MAX Observation Does Not Coincide with Earnings Announcement

	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	MAX	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
low	0.34	0.78	0.35	0.33	-0.06	2.14	0.63	19.92	0.86	15.27	1.26	-1.70	-2.10
2	0.32	0.96	0.53	0.32	-0.10	3.67	0.81	19.63	0.83	15.42	1.21	-1.91	-0.95
3	0.29	1.04	0.75	0.21	-0.16	5.22	0.90	19.09	0.87	16.60	2.06	-2.20	-0.11
4	0.18	1.10	1.05	0.09	-0.26	7.58	0.95	18.47	0.97	16.01	4.11	-2.55	1.14
high	-0.40	1.09	1.40	0.03	-0.39	16.36	0.89	17.52	1.48	5.13	15.13	-2.92	6.79
5-1	-0.74	0.31	1.05	-0.30	-0.33	14.21	0.26	-2.40	0.62	-10.14	13.86	-1.23	8.88
t(5-1)	(-3.89)	(6.28)	(6.81)	(-1.61)	(-2.43)	(20.07)	(8.40)	(-28.90)	(5.42)	(-3.01)	(7.68)	(-11.59)	(18.37)

Panel B: MAX Observation Coincides with Earnings Announcement

	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	MAX	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
low	0.32	0.84	0.40	0.30	-0.06	2.78	0.68	19.78	0.82	15.48	1.18	-1.76	-1.27
2	0.58	0.98	0.70	0.38	-0.12	4.74	0.84	19.46	0.80	16.86	1.50	-1.87	0.98
3	0.77	1.03	0.87	0.23	-0.09	6.73	0.91	19.05	0.83	18.94	2.30	-1.94	3.01
4	0.73	1.10	1.09	0.20	-0.24	9.63	0.95	18.60	0.91	16.74	4.20	-2.00	5.78
high	1.26	1.12	1.29	-0.00	-0.43	19.42	0.91	17.86	1.25	9.49	12.07	-1.75	14.57
5-1	0.94	0.28	0.89	-0.30	-0.37	16.65	0.23	-1.92	0.43	-5.99	10.90	0.00	15.84
t(5-1)	(3.35)	(3.95)	(7.07)	(-1.43)	(-2.78)	(23.77)	(9.30)	(-26.22)	(4.55)	(-2.32)	(8.05)	(0.04)	(20.28)

date (Panel A), but significantly higher subsequent returns otherwise (Panel B). The FFC-adjusted quintile return spread is -0.74% in Panel A and +0.94% in Panel B.[13] Thus, the return predictability associated with MAX crucially depends on the information that generates the MAX return. If an earnings announcement is the return source, investors seem to underreact towards the positive news such that MAX positively predicts subsequent returns. If the MAX-underlying information is merely high in strength but has comparably low weight, investors seem to overreact such that the relation between MAX and subsequent returns is negative. This pattern supports our conjecture that biased information processing as implied by a strength-weight bias drives the MAX effect. The overall negative

[13]The difference between the two subsamples is similar if unadjusted returns are applied instead (untabulated quintile spread of -0.75% (t-statistic of -2.67) in Panel A and 0.86% (t-statistic of 2.67) in Panel B). Our Online Appendix shows that the findings remain qualitatively the same with a value-weighting methodology is applied.

return predictability of MAX simply arises because MAX is far less often associated with an earnings announcement than without one. However, the MAX effect is not a general phenomenon, but information-dependent.

Referring to the other quintile portfolio characteristics in Table 6, Panels A and B are quite similar. At least the figures do not indicate, that other characteristic differences can explain the opposing findings between the two subsamples.[14] Merely the significant difference in TK-values vanishes if only those stocks are considered for which MAX and earnings announcement coincide. In these cases, MAX is less strongly linked to volatility such that the negative loss aversion impact of prospect theory is less severe. Following a preference-based MAX explanation, we should therefore expect a more negative MAX effect in Panel B since investors' proposed propensity to buy high-MAX stocks is less dampened by negative TK-values. However, the observed opposite subsequent return pattern further questions preference-based explanatory approaches.

The information-dependence of the MAX effect is also examined in Fama-MacBeth-regressions by considering a dummy variable EA_{MAX} that takes on the value one if MAX lies within a symmetric three-day interval around an earnings announcement and zero otherwise. The corresponding regression coefficients are provided in Table 7. While the impact of MAX is consistently negative, the interaction term of MAX and EA_{MAX} is significantly positive. Thus, the MAX effect crucially depends on the kind of underlying information.

3.4. Additional Analyses

In this section, we provide additional analyses on an information-driven mispricing explanation for the MAX effect. First, we examine whether the findings of the previous section can be explained by post-earnings announcement drift. Second, we provide support for our behavioral line of argument since the effect magnitude is higher among stocks with presumably higher limits to arbitrage. However, our findings still remain valid beyond the presumably most illiquid stocks.

[14] If anything, one might argue that the REV quintile spread is more pronounced in Panel B. But potential short-term reversal effects should reduce the subsequent return spreads such that short-term reversal effects would rather work against our findings in Panel B.

Table 7. The Interaction of Earnings Announcement Dates with MAX in Fama-MacBeth-Regressions

This table reports Fama-MacBeth-regression estimates for the sample period from January 1972 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. MAX denotes the maximum daily return of the previous month and EA_{MAX} is a dummy variable that equals 1 if the MAX observation lies within a symmetric three-day interval around the firm's earnings announcement date and 0 otherwise. The other explanatory variables are described in the caption of Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	1.5434	1.5541	4.4474	4.4055	3.9427	2.6651
	(6.96)	(7.03)	(4.21)	(4.52)	(4.10)	(2.77)
MAX	-0.0595	-0.0699	-0.0920	-0.0861	-0.0950	-0.0569
	(-4.79)	(-5.52)	(-9.41)	(-9.33)	(-10.40)	(-7.76)
MAX x EA_{MAX}		0.0916	0.0915	0.0899	0.0918	0.1006
		(10.01)	(10.40)	(10.42)	(10.73)	(11.77)
BETA			0.0647	0.0094	0.0528	-0.0782
			(0.37)	(0.06)	(0.33)	(-0.48)
ln(MV)			-0.1568	-0.1656	-0.1421	-0.0775
			(-3.07)	(-3.54)	(-3.09)	(-1.70)
BM			0.1540	0.2373	0.2239	0.1715
			(3.06)	(4.64)	(4.45)	(3.60)
MOM				0.0075	0.0075	0.0077
				(4.13)	(4.12)	(4.04)
ILLIQ					0.0189	0.0168
					(5.75)	(5.10)
REV						-0.0446
						(-7.88)

Influence of Post-Earnings Announcement Drift. A large strand of literature shows that earnings information is not fully reflected in stock prices at the announcement date (see for example Bernard and Thomas, 1989, Bernard and Thomas, 1990, Liang, 2003, and Kausar, 2017). This implies that positive earnings announcements induce positive subsequent returns and vice versa. This phenomenon is generally referred to as post-earnings announcement drift (PEAD). Since the MAX magnitude in Panel B of Table 6 reflects the market reaction towards the announced earnings, the positive relation between MAX and subsequent returns might simply be a consequence of PEAD. However, even if PEAD would suffice to explain the return patterns in Table 6, this would not weaken our main conjecture that the MAX effect is largely affected by biased information processing. This would merely imply that the well-known biased processing of earnings information can explain why the MAX effect is no universal phenomenon. Hence, we could still conclude that the subsequent return impact of MAX depends on the type of information that generates the extreme return observation.

Table 8. Consideration of Post Earnings Announcement Drift in Fama-MacBeth-Regressions
This table reports Fama-MacBeth-regression estimates for the sample period from January 1972 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. MAX denotes the maximum daily return of the previous month and EA_{MAX} is a dummy variable that equals 1 if the MAX observation lies within a symmetric three-day interval around the firm's earnings announcement date and 0 otherwise. SUE and EAret refer to the standardized unexpected earnings and the symmetric three-day return of the most recent earnings announcement. The other explanatory variables are described in the caption of Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)
intercept	2.6651	2.7030	2.6519	2.6934
	(2.77)	(2.77)	(2.75)	(2.76)
MAX	-0.0569	-0.0494	-0.0530	-0.0462
	(-7.76)	(-6.43)	(-7.31)	(-6.08)
MAX x EA_{MAX}	0.1006	0.0852	0.0594	0.0515
	(11.77)	(9.82)	(7.15)	(5.89)
BETA	-0.0782	-0.0501	-0.0691	-0.0435
	(-0.48)	(-0.31)	(-0.42)	(-0.27)
ln(MV)	-0.0775	-0.0832	-0.0778	-0.0834
	(-1.70)	(-1.80)	(-1.70)	(-1.81)
BM	0.1715	0.2092	0.1769	0.2115
	(3.60)	(3.81)	(3.71)	(3.87)
MOM	0.0077	0.0047	0.0068	0.0043
	(4.04)	(2.64)	(3.67)	(2.40)
ILLIQ	0.0168	0.0157	0.0156	0.0146
	(5.10)	(4.12)	(4.84)	(3.97)
REV	-0.0446	-0.0469	-0.0484	-0.0500
	(-7.88)	(-8.64)	(-8.44)	(-9.17)
SUE		0.3623		0.3338
		(15.50)		(14.99)
EAret			0.0458	0.0380
			(13.00)	(12.18)

Nonetheless, we control for PEAD in Fama-MacBeth-regressions. In order to measure PEAD, the literature mainly follows two approaches as outlined by Foster et al. (1984): The announcement is evaluated based on either the changes in quarterly earnings or earnings announcement returns. We therefore estimate standardized unexpected earnings per share (SUE) following Bali et al. (2014). Unexpected earnings per share are calculated as the difference between quarterly earnings per share and the earnings per share of the corresponding prior-year quarter. In order to obtain SUE, the unexpected earnings are divided by the quarterly earnings per share volatility of the previous eight quarters while we require a minimum of four observations. In addition, we take into account EAret which is the firm's stock return in a symmetric three-day interval around the last COMPUSTAT quarterly earnings announcement date.

Table 9. MAX Effect Dependence on Trade Size and Option Availability
This table reports monthly equally-weighted FFC-adjusted subsequent returns from portfolio triple sorts. First, each stock is allocated to a portfolio based on average trading volume per trade (Panel A) or option availability (Panel B). Panel A covers all NASDAQ stocks in the sample period from January 1987 to December 2016. Each month the sample is split at the median average trading volume per trade on the MAX realization day. Panel B uses all sample stocks from January 1996 to December 2016. The sample split depends on whether there are options outstanding for a stock on its MAX date. Second, each stock is assigned to one portfolio based on EA_{MAX}. EA_{MAX} is a dummy variable that equals 1 if the MAX observation lies within a symmetric three-day interval around the firm's earnings announcement date and 0 otherwise. Third, within these groups, each stock is allocated to a quintile portfolio based on the maximum daily return of the previous month MAX. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. FFC-adjusted returns are stated in %.

	Panel A				Panel B			
	High Trade Size		Low Trade Size		Options Available		No Options Available	
	EA_{MAX}=0	EA_{MAX}=1	EA_{MAX}=0	EA_{MAX}=1	EA_{MAX}=0	EA_{MAX}=1	EA_{MAX}=0	EA_{MAX}=1
low	0.62	0.67	0.84	0.52	0.37	0.18	0.66	0.60
2	0.38	0.59	0.67	0.78	0.28	0.39	0.56	0.77
3	0.23	0.75	0.68	0.56	0.08	0.11	0.46	0.92
4	-0.06	0.50	0.42	1.23	-0.23	0.03	0.38	1.26
high	-0.35	1.43	-0.36	2.89	-0.70	0.43	-0.28	1.97
5-1	-0.96	0.76	-1.20	2.37	-1.07	0.25	-0.94	1.37
t(5-1)	(-4.91)	(1.99)	(-4.31)	(2.84)	(-4.60)	(0.64)	(-2.90)	(2.55)
Δ	1.72		3.57		1.33		2.31	
t(Δ)	(4.52)		(4.37)		(4.12)		(4.56)	

Monthly Fama-MacBeth-regressions controlling for the impact of SUE and EAret are provided in Table 8. The interaction of MAX and EA_{MAX} remains significant in all specifications, that is, even after controlling for PEAD the impact of MAX remains substantially dependent on the underlying information source. If the MAX effect was due to lottery preferences only, one should expect no impact of the dummy EA_{MAX} after PEAD is controlled for. However, Table 8 also implies that the interaction term is related to PEAD: After including both SUE and EAret as control variable in column (4), the interaction term's coefficient magnitude is roughly halved in comparison to the baseline setting in column (1).

Role of Different Investor Groups. Literature suggests that stocks with high retail trading proportion are more prone to mispricing (see for example Kumar, 2009; Han and Kumar, 2013; Bali et al., 2017) while the availability of option contracts allows sophisticated investors to increase market efficiency (see for example Ross, 1976 and Kumar et al., 1998). We investigate these arguments with respect to the MAX effect in Table 9.

In order to measure retail trading activity on high-MAX days, we use the average dollar volume per trade. In the case of many retail trades, this trade size is expected to be comparably low. CRSP provides the corresponding data for NASDAQ stocks starting in November 1982. Since our analyses require a sufficient number of stocks for which MAX observation and earnings announcement day coincide, the restricted sample period begins in January 1987. Panel A of Table 9 shows that the MAX effect spread is indeed substantially higher if the MAX observation goes along with comparably small trades (3.57% vs. 1.72%). Thus, the stock market impact of judgment biases is substantially stronger if the retail trading proportion is high. This effect is mostly driven by the the underreaction towards earnings news while the overreaction on other MAX-days is rather similar between high and low trade size subsample.

In Panel B of Table 9, we investigate whether stocks without associated options are more prone to the MAX effect. We use Optionmetrics data beginning in January 1996 to classify stocks. The allocation depends on whether there is at least one outstanding option for a stock on the MAX realization day. The MAX effect spread is higher if there are no options available (2.31% vs. 1.33%) supporting the conjecture that stocks with corresponding option contracts are less prone to mispricing. More specifically, the return continuation after MAX returns with concomitant earnings announcement mostly vanishes if options are available. This supports the evidence in Jennings and Starks (1986) and Amin and Lee (1997) that informed trading in the option market increases market efficiency particularly around earnings announcements.

Role of Limits to Arbitrage. Theoretical models introduced by De Long et al. (1990) and Shleifer and Vishny (1997) argue that mispricing is more likely to persist if limits to arbitrage are strong. Based on that, we expect that MAX is associated with a higher return spread magnitude among stocks with presumably high limits to arbitrage. We apply market capitalization, Amihud (2002) illiquidity, and idiosyncratic volatility as corresponding proxies, since arbitrageurs' trading should be more difficult for smaller stocks, more expansive for illiquid stocks, and riskier for volatile stocks.

In Table 10, we first sort each stock in a top or bottom half portfolio based on one of the three proxies for each sample month. Second, each portfolio is split based on the realization day of MAX. In this second step, the sorting either depends on a concomitant earnings announcement or on the question whether MAX is observed in the first or the second half of the previous month. Third, we perform quintile portfolio sorts based on MAX.

These conditional triple sorts answer the question whether the MAX effect is more dependent on its realization date if limits to arbitrage are high. The answer is yes which supports the proposed mispricing line of argument for the MAX effect. For example, the MAX effect difference between EA_{MAX}=1 and EA_{MAX}=0 is 1.00% for highly capitalized firms while it is 2.14% for small firms. Hence, the conjectured impact of biased information processing is stronger if arbitrageurs face higher difficulties to trade against the mispricing. Moreover, Table 10 also shows that the magnitude of the MAX effect positively depends on each of the limits to arbitrage proxies.

Eliminating Potentially Illiquid Observations. Table 11 provides similar portfolio sorts as Table 10. It shows that the realization date of MAX remains relevant after the exclusion of small and penny stocks. A stock is considered small if it falls below the corresponding monthly NYSE/AMEX-20%-size-quantile. Penny stocks are identified as those stock that have a stock price below $5 (Cosemans and Frehen, 2017). According to Table 11, the MAX effect is again substantially information-dependent: It differs by significant 1.29% (1.32%) between MAX observations with and without accompanying earnings announcement. Moreover, the MAX effect is significantly stronger if MAX was realized at the end of the previous month indicating that subsequent lottery-based demand has no substantial price impact.

Table 10. Portfolio Triple Sorts Considering Limits to Arbitrage
This table reports monthly equally-weighted FFC-adjusted subsequent returns from portfolio triple sorts. First, each stock is allocated to a top or bottom half portfolio based on a limits to arbitrage proxy. These proxies include market capitalization (Panel A), Amihud (2002) illiquidity (Panel B), and idiosyncratic volatility (Panel C). Second, each stock is assigned to one portfolio based on EA_{MAX} or d_{MAX}. EA_{MAX} is a dummy variable that equals 1 if the MAX observation lies within a symmetric three-day interval around the firm's earnings announcement date and 0 otherwise. d_{MAX} denotes the number of days between the realization of MAX and the end of month. Third, within these groups, each stock is allocated to a quintile portfolio based on the maximum daily return of the previous month MAX. The sample period is from January 1972 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. FFC-adjusted returns are stated in %.

Panel A: Market Capitalization

	High Market Capitalization				Low Market Capitalization			
	EA_{MAX}=0	EA_{MAX}=1	$d_{MAX} \leq 15$	$d_{MAX} > 15$	EA_{MAX}=0	EA_{MAX}=1	$d_{MAX} \leq 15$	$d_{MAX} > 15$
low	0.27	0.37	0.28	0.29	0.63	0.72	0.60	0.63
2	0.21	0.28	0.19	0.31	0.59	1.05	0.53	0.69
3	0.09	0.37	0.02	0.20	0.45	0.83	0.36	0.70
4	0.04	0.25	-0.09	0.14	0.18	1.15	0.00	0.57
high	-0.39	0.71	-0.40	-0.04	-0.61	1.62	-0.69	-0.05
5-1	-0.66	0.34	-0.68	-0.33	-1.24	0.90	-1.29	-0.68
t(5-1)	(-4.75)	(1.56)	(-4.80)	(-2.04)	(-5.56)	(2.29)	(-6.28)	(-2.60)
Δ	1.00		0.35		2.14		0.61	
t(Δ)	(5.18)		(2.77)		(6.45)		(3.97)	

Panel B: Amihud Illiquidity

	High Amihud Illiquidity				Low Amihud Illiquidity			
	EA_{MAX}=0	EA_{MAX}=1	$d_{MAX} \leq 15$	$d_{MAX} > 15$	EA_{MAX}=0	EA_{MAX}=1	$d_{MAX} \leq 15$	$d_{MAX} > 15$
low	0.58	0.62	0.60	0.56	0.27	0.40	0.28	0.29
2	0.56	0.94	0.49	0.68	0.22	0.30	0.14	0.33
3	0.46	0.89	0.38	0.63	0.12	0.39	0.03	0.22
4	0.17	1.22	0.01	0.57	0.09	0.50	-0.03	0.19
high	-0.51	1.62	-0.63	0.09	-0.47	0.44	-0.46	-0.14
5-1	-1.09	1.00	-1.23	-0.47	-0.74	0.03	-0.74	-0.43
t(5-1)	(-4.82)	(2.42)	(-5.65)	(-1.77)	(-4.67)	(0.14)	(-4.59)	(-2.54)
Δ	2.09		0.76		0.77		0.30	
t(Δ)	(6.02)		(4.76)		(3.57)		(2.29)	

Panel C: Idiosyncratic Volatility

	High Idiosyncratic Volatility				Low Idiosyncratic Volatility			
	EA_{MAX}=0	EA_{MAX}=1	$d_{MAX} \leq 15$	$d_{MAX} > 15$	EA_{MAX}=0	EA_{MAX}=1	$d_{MAX} \leq 15$	$d_{MAX} > 15$
low	0.64	0.97	0.60	0.66	0.29	0.36	0.28	0.29
2	0.30	0.67	0.20	0.44	0.36	0.27	0.34	0.35
3	0.16	0.91	-0.01	0.51	0.26	0.49	0.23	0.39
4	-0.06	0.89	-0.10	0.27	0.21	0.67	0.13	0.35
high	-0.74	1.65	-0.82	-0.07	0.06	0.45	-0.04	0.23
5-1	-1.37	0.68	-1.42	-0.74	-0.23	0.10	-0.32	-0.07
t(5-1)	(-7.36)	(1.97)	(-7.52)	(-3.46)	(-2.48)	(0.59)	(-3.24)	(-0.62)
Δ	2.05		0.68		0.32		0.25	
t(Δ)	(6.46)		(3.61)		(1.78)		(2.94)	

4. Critical Discussion

The previous section presents evidence that is in line with the hypothesis that the MAX effect is driven by information-dependent patterns of over- and underreaction. Our line of argument thus triggers the following question: Do our findings rule out that the MAX effect is driven by lottery preferences for sure? – The answer is no, although we consider it unlikely that they are its major driving force. In order to reconcile our findings with lottery explanations, the following three conditions would have to be fulfilled simultaneously: First, investors choose which stocks to buy based on its realized return distribution. However, they do not follow commonly accepted prospect theory evaluation methods which imply a low attractiveness of high-MAX stocks, but focus on MAX alone. Second, investors with these kind of lottery preferences exert buying pressure for high-MAX stocks on the same day of the MAX return realization. Otherwise, we should not observe that high-MAX stocks underperform immediately after the high-MAX observation. Third, investors do not exert this buying pressure in the case of a fundamental news release potentially because they do not consider MAX to be a valid lottery-like payoff predictor in this case.[15] Otherwise we should also see low subsequent returns after high-MAX observations accompanied by fundamental news (at least after controlling for post-earnings announcement drift). In the following, we elaborate why we consider these three conditions rather unlikely.

According to Barberis et al. (2016), investors evaluate monthly returns of the previous five years using cumulative prospect theory preferences which leads to return predictability. We see no reason to expect that investors implicitly change to an evaluation method that favors low PT-stocks simply because the evaluation period has changed. Naturally, there are reasons to believe that prospect theory evaluation might play a minor role for a monthly horizon. For example, investors might consider the short period as unrepresentative or the short period might imply that prospect theory implications no longer hold as the setting is more experience-based than description-based.[16] But this would not explain why the

[15]This argument is proposed by Nguyen and Truong (2017) who show that the MAX effect is stronger if it is unrelated to earnings information. However, MAX is a valid predictor for future MAX returns in both subsamples in our analyses. Untabulated results show that the high-MAX quintiles have significantly higher MAX returns in the subsequent month, too – irrespective of a concomitant earnings announcement.

[16]Psychological research by Hertwig et al. (2004) points out that individuals no longer follow prospect theory preferences if their decisions are based on experience instead of description. For example individuals tend to underweight instead of overweight low probabilities in these scenarios. Since Barberis et al. (2016) argue that

Table 11. Portfolio Sorts Excluding Small and Penny Stocks
This table reports monthly equally-weighted FFC-adjusted subsequent returns from portfolio sorts. In Panel A, small caps that fall below the 20%-size-quantile based on NYSE and AMEX stocks are excluded from the sample each month. In Panel B, penny stocks that have a stock price below $5 are excluded from the sample. Then, within each month, each stock is assigned to one portfolio based on EA_{MAX} or d_{MAX}. EA_{MAX} is a dummy variable that equals 1 if the MAX observation lies within a symmetric three-day interval around the firm's earnings announcement date and 0 otherwise. d_{MAX} denotes the number of days between the realization of MAX and the end of the month. Within each portfolio, each stock is allocated to a quintile portfolio based on the maximum daily return of the previous month MAX. The sample period is from January 1972 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. The FFC-adjusted returns are stated in %.

	Panel A: Sample Excluding Small Caps				Panel B: Sample Excluding Penny Stocks			
	EA_{MAX}=0	EA_{MAX}=1	$d_{MAX} \leq 15$	$d_{MAX} > 15$	EA_{MAX}=0	EA_{MAX}=1	$d_{MAX} \leq 15$	$d_{MAX} > 15$
low	0.32	0.38	0.35	0.33	0.32	0.36	0.35	0.32
2	0.25	0.37	0.20	0.34	0.27	0.42	0.23	0.35
3	0.19	0.53	0.10	0.35	0.20	0.50	0.11	0.28
4	0.03	0.50	-0.13	0.22	-0.04	0.48	-0.15	0.15
high	-0.59	0.75	-0.65	-0.17	-0.69	0.68	-0.71	-0.28
5-1	-0.92	0.37	-1.00	-0.49	-1.01	0.31	-1.06	-0.60
t(5-1)	(-6.43)	(1.77)	(-6.58)	(-3.23)	(-9.04)	(1.80)	(-8.91)	(-4.84)
Δ	1.29		0.50		1.32		0.46	
t(Δ)	(7.26)		(4.11)		(8.44)		(4.55)	

investors instead switch to a very different evaluation technique and behave contrary to CPT-preferences while still using prior returns to form beliefs about future returns.

Further, the lottery demand is commonly assigned to private and unsophisticated investors who are strongly influenced by behavioral biases (Han and Kumar, 2013). We doubt that these non-professional investors both trade on intraday return patterns and reverse their behavior on earnings announcement days. Admittedly, investors might draw their attention to the earnings news and thereby ignore salient price patterns during announcement days. While this argument would imply a smaller MAX effect but no reverse effect after earnings announcements, it would also require that investors are prone to additional judgment biases such as attention constraints or availability biases. The potentially attention-grabbing nature of earnings announcements should even imply that these stocks enter the choice set of lottery traders with a higher probability. The higher number of lottery investors could result in an even higher degree of overpricing, hence implying that the relation between MAX and subsequent returns is more negative after earnings announcements, not

investors look at investment prospects (descriptive evidence), the daily returns of the previous month might rather be retrieved from the investors' recent experiences.

positive. The information dependence of the MAX effect would thus further require that the unsophisticated investors critically scrutinize their lottery demand around earnings announcements.

These considerations show that many questionable assumptions must be accepted in order to support a lottery-based explanation for the MAX effect. This is why we offer a potential alternative explanation for the anomalous return patterns. Our information-based explanation is similarly well-founded based on psychological evidence. While the lottery explanations are based on evaluation biases that influence the decision between different risky alternatives, we consider a judgment bias based on the biased processing of information strength and weight responsible. Though both approaches are theoretically appealing, the latter can more easily be reconciled with the empirical evidence: The strength-weight bias directly implies that the return predictability starts immediately after the MAX realization and that the effect sign depends on the underlying information source. As a consequence, we conclude that behavioral explanations beyond lottery preferences should be considered as a reasonable alternative for understanding the MAX effect.

5. Conclusion

Seminal work by Bali et al. (2011) shows that stocks with a high maximum daily return in the previous month strongly underperform in the subsequent month. While they relate the empirical findings to investors' lottery preferences following from cumulative prospect theory, they also point out that further research might foster the understanding of the phenomenon. More specifically, Bali et al. (2011) raise the question how the MAX effect potentially depends on the information which causes the MAX return. We examine this question and thereby provide evidence that the MAX effect might rather be driven by judgment biases of over- and underreaction than evaluation biases following cumulative prospect theory.

Our analyses show that high-MAX stocks are comparably unattractive if their daily returns are evaluated using cumulative prospect theory. Hence, CPT-investors cannot be responsible for the overvaluation of high-MAX stocks. Moreover, we cannot empirically identify any price pressure resulting from lottery investors after high MAX returns. Low subsequent returns can be observed immediately after the occurrence of MAX such that the mispricing seems to emerge on the MAX date itself. As a consequence, we conjecture that the MAX effect is caused by a strength-weight bias. According to Griffin and Tversky (1992), individuals tend to overreact towards extreme news (strength) while they tend to underreact if news is reliable and valid (weight). Given the extremeness of MAX returns, the underlying information is presumably striking, too. Thus, the low subsequent returns of high-MAX stocks are in line with a strength-weight bias. Moreover, this judgment bias also correctly predicts that the MAX effect reverses if the MAX return is associated with reliable earnings announcement data. Hence, the empirical observations are completely in line with psychological findings of biased information processing while evaluation biases following cumulative prospect theory provide no convincing explanation for the specific return patterns.

While research in the field of financial economics has frequently applied psychological insights in recent years, it often remains challenging to identify one of the many experimentally detected biases as the exact driving force of mispricing. However, in order to correctly model investor behavior and market outcomes it is vital to distinguish between the specific biases and their implications. Exemplified by the MAX effect, we show that a distinction between different biases is possible after closely examining the biases' specific empirical predictions. In fact, the MAX effect does not seem to be a general phenomenon but instead reverses in high-weight information environments. Thus, we conclude that besides evaluation biases, judgment biases seem to play a major role for the understanding of the MAX effect. While mispricing is indeed more likely to emerge if extreme returns are observed, the direction of the mispricing crucially depends on the underlying information. On the one hand, these findings might prove helpful for managers who provide financial information since they should be aware of their audience's specific biases. On the other hand, investors who process this information should critically evaluate whether they sufficiently acknowledge differences in the extremeness, validity, and reliability of news.

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Online Appendix for

"An Alternative Behavioral Explanation for the MAX Effect"

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1. Additional Summary Statistics

Table 1 presents summary statistics for the main variables of the analysis similar to Table 1 in the main Paper. However, Table 1 employs time-series averages of cross-sectional statistics instead of a pooled approach.

Table 1. Summary Statistics
This table reports time-series averages of monthly cross-sectional sample mean, standard deviation, 0.1-quantile, median, 0.9-quantile, and correlation coefficients for the main variables of interest. MAX denotes the maximum daily return of the previous month. IVOL is the annualized idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors. MV denotes the market value of equity. BM is the book-to-market ratio. MOM is the return of months $t-12$ to $t-2$. Amihud (2002) illiquidity measure, ILLIQ, and market beta, BETA, are estimated based on daily returns of the previous year. TK is the prospect theory value based on daily returns of the previous month following the methodology of Barberis et al. (2016). REV is the return of month $t-1$. ILLIQ is stated in million; MAX, TK, and REV are stated in %. The sample covers January 1972 to December 2016 on a monthly basis.

	MAX	IVOL	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
mean	7.0995	0.4120	0.8422	18.9483	0.9934	13.8490	4.6629	-2.2182	1.2343
SD	7.2846	0.3328	0.5616	1.9495	2.1014	54.7759	25.4675	1.8862	14.2612
$q_{0.1}$	2.2761	0.1503	0.1763	16.4963	0.2159	-36.3136	0.0081	-4.4856	-12.6876
$q_{0.5}$	5.2705	0.3251	0.7988	18.8338	0.7011	6.5265	0.2445	-1.8796	0.3481
$q_{0.9}$	13.3651	0.7596	1.5754	21.5509	1.7805	65.8154	8.0794	-0.4210	15.2368
Correlation Coefficients									
MAX	1.0000								
IVOL	0.8874	1.0000							
BETA	0.0676	0.0328	1.0000						
ln(MV)	-0.3542	-0.4863	0.3047	1.0000					
BM	0.1242	0.1884	-0.1147	-0.2559	1.0000				
MOM	-0.1205	-0.1537	0.0480	0.1544	-0.2151	1.0000			
ILLIQ	0.2679	0.3444	-0.1536	-0.3211	0.1511	-0.0539	1.0000		
TK	-0.0545	-0.3925	-0.0330	0.3640	-0.1854	0.0910	-0.1785	1.0000	
REV	0.3261	0.1227	-0.0180	0.0550	-0.0959	0.0140	0.0128	0.7462	1.0000

2. Analyses Based on Idiosyncratic Volatility

In the main part of the paper, we argue that the return predictability of MAX and IVOL is very difficult to disentangle empirically since they are strongly correlated (see correlation coefficient of 90% in Table 1 of the main paper). Since MAX carries the advantage that it can be pinned down to one trading day and since MAX is more frequently associated with lottery preferences, we examine the MAX effect instead of the IVOL puzzle in our main analyses. However, MAX effect and IVOL puzzle are often related to the same economic mechanisms (Hou and Loh, 2016). As a consequence, our analyses should produce similar results if IVOL is used instead of MAX. Thus, this section examines whether the IVOL puzzle is also information dependent. If IVOL is a proxy for perceived stock attractiveness following the traditional MAX line of argument, we expect that the IVOL puzzle exists irrespective of the information that is responsible for the different IVOL levels. On the contrary, if judgment biases and resulting patterns of over- and underreaction are the driving force, we expect the IVOL puzzle to be information dependent.

In order to decide whether IVOL is accompanied by high- or low-weight information we again utilize earnings announcement dates. We consider an IVOL observation as accompanied by high-weight information if the company announces its quarterly earnings in the IVOL estimation month. Table 2 presents the subsequent monthly returns of IVOL-sorted quintile portfolios for the two resulting subsamples. As Bali and Cakici (2008) show that the IVOL puzzle only exists among value-weighted portfolios, we also provide value-weighted portfolio returns in addition to the equally-weighted specification. According to Table 2, for both weighting schemes, there is a significantly more negative relation between IVOL and subsequent returns in the subsample without accompanying earnings announcement compared to the subsample with concomitant earnings announcement. Thus, the IVOL puzzle is substantially information dependent, too, although IVOL puzzle explanations based on preferences for historical return distributions do not imply such a dependence. Consequently, judgment biases in the processing of different information types should be considered relevant for understanding the IVOL puzzle.

These portfolio sorts findings are also supported in Fama-MacBeth-regressions if we consider a dummy variable EA_{IVOL} which equals one if an earnings announcement lies within the IVOL estimation horizon. Table 3 shows that an interaction term consisting of IVOL and EA_{IVOL} positively predicts one-month-ahead returns while the relationship between IVOL and one-month-ahead returns is negative.[17]

Table 2. Portfolio Sorts Based on Idiosyncratic Volatility
This table reports monthly equally- and value-weighted FFC-adjusted subsequent returns from portfolio sorts based on idiosyncratic volatility IVOL. IVOL is the annualized idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors. The portfolio sorts are provided for two subsamples. A stock is allocated to a subsample depending on whether the firm announced quarterly earnings in the previous month or not. The sample period is from January 1972 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. The FFC-adjusted returns are stated in %.

	Equally-Weighted Returns		Value-Weighted Returns	
	no EA in last month	EA in last month	no EA in last month	EA in last month
low	0.21	0.10	0.16	0.05
2	0.26	0.23	0.08	-0.03
3	0.24	0.28	0.07	0.03
4	0.20	0.16	-0.21	-0.06
high	-0.22	0.24	-1.04	-0.50
5-1	-0.43	0.14	-1.20	-0.55
t(5-1)	(-1.88)	(0.61)	(-6.25)	(-1.86)
Δ	0.58		0.65	
t(Δ)	(3.85)		(2.29)	

[17]The different implications of news- and non-news IVOL are also examined by DeLisle et al. (2016). They also find that the IVOL puzzle is particularly pronounced for non-news IVOL. However, the main objective of there analysis is to show that the return predictability of IVOL goes beyond its ability to proxy for limits to arbitrage. Therefore, DeLisle et al. (2016) do not compare the different implications of evaluation and judgment biases.

Table 3. The Interaction of Earnings Announcements with IVOL in Fama-MacBeth-Regressions This table reports Fama-MacBeth-regression estimates for the sample period from January 1972 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. IVOL is the annualized idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors and EA_{IVOL} equals one if there was an earnings announcement in this IVOL estimation month. The other explanatory variables are described in the caption of Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	1.4768	1.4513	4.7336	4.5934	4.3266	3.3021
	(7.21)	(7.05)	(4.82)	(5.06)	(4.79)	(3.67)
IVOL	-0.9358	-1.0844	-1.7345	-1.5788	-1.8488	-1.4221
	(-3.14)	(-3.57)	(-8.53)	(-8.14)	(-9.65)	(-7.52)
IVOL x EA_{IVOL}		0.4879	0.4683	0.4725	0.4836	0.5163
		(4.29)	(4.34)	(4.43)	(4.61)	(5.11)
BETA			0.0170	-0.0415	0.0132	-0.0809
			(0.10)	(-0.27)	(0.09)	(-0.51)
ln(MV)			-0.1693	-0.1736	-0.1589	-0.1050
			(-3.59)	(-4.01)	(-3.71)	(-2.47)
BM			0.1648	0.2474	0.2357	0.1774
			(3.30)	(4.84)	(4.66)	(3.75)
MOM				0.0078	0.0077	0.0075
				(4.28)	(4.26)	(4.03)
ILLIQ					0.0210	0.0201
					(6.03)	(5.71)
REV						-0.0475
						(-8.18)

3. Different Specifications of TK-Values

The analyses in Section 3.1 of the main paper show that CPT-preferences as estimated by Tversky and Kahneman (1992) cannot explain the return predictability associated with MAX. In this part of the Online Appendix, we use different parametrizations for the calculation of TK-values to show that these findings remain qualitatively the same across various specifications. First, we vary the degree of probability weighting since lottery-based MAX explanations focus on this particular evaluation bias. The base-line analyses apply the probability weighting parameters $\gamma = 0.61$ and $\delta = 0.69$ for the gain and the loss domain, respectively. Lower levels of γ and δ imply a stronger overweighting low probabilities while $\gamma = \delta = 1$ means that the objective probabilities are processed in an unbiased way. Following Barberis et al. (2016), we vary γ from 0.31 to 1.31 and set δ to $\delta = \gamma + 0.08$. In addition, we also estimate TK-values based on the CPT-components of value function curvature (convexity in the loss domain and concavity in the gain domain) and probability weighting only (TK_{CCPW}), that is, we disregard loss aversion ($\lambda = 1$).

Summary statistics and correlation coefficients for these altered TK-values are provided in Table 4. As expected, average TK-values are higher if loss aversion is ignored since this implies a lower impact of negative return observations. Moreover, TK_{CCPW} and MAX are positively related (correlation coefficient of 0.68). Hence, MAX is positively related to a CPT-based stock attractiveness measure if we disregard loss aversion. However, the correlation of MAX and TK-values remains negative in all other parametrizations irrespective of the chosen probability weighting parameter.

In addition, Fama-MacBeth-regressions in Table 5 show that MAX remains a highly significant predictor of subsequent returns no matter which TK-specification is considered. Most notably, despite its positive correlation with MAX, TK_{CCPW} does not capture the MAX effect. Hence, even different calculation approaches for TK cannot reconcile the MAX effect with CPT-preferences.

Table 4. Summary Statistics for Different TK-Values
This table reports pooled summary statistics including sample mean, standard deviation, 0.1-quantile, median, 0.9-quantile, and correlation coefficients. MAX denotes the maximum daily return of the previous month. TK_γ is the prospect theory value based on daily returns of the previous month following the methodology of Barberis et al. (2016). γ is the probability weighting parameter for the gain domain and varies across specifications. The probability weighting parameter for the loss domain is set to $\gamma + 0.08$ in each specifications. TK_{CCPW} employs the base specification $\gamma = 0.61$ but is estimated without the consideration of loss aversion, that is, TK_{PW} is based on value funtion curvature and probability weighting only. MAX and TK-values are stated %. The sample covers January 1972 to December 2016 on a monthly basis.

	MAX	$TK_{0.31}$	$TK_{0.41}$	$TK_{0.51}$	$TK_{0.61}$	$TK_{0.71}$	$TK_{0.81}$	$TK_{0.91}$	$TK_{1.01}$	$TK_{1.11}$	$TK_{1.21}$	$TK_{1.31}$	TK_{CCPW}
mean	7.53	-2.26	-2.39	-2.39	-2.33	-2.24	-2.13	-2.01	-1.89	-1.77	-1.65	-1.54	0.19
SD	9.11	2.05	2.24	2.24	2.18	2.09	2.01	1.94	1.87	1.80	1.73	1.66	1.25
$q_{0.1}$	2.11	-4.57	-4.92	-4.98	-4.90	-4.74	-4.55	-4.35	-4.14	-3.93	-3.73	-3.53	-0.86
$q_{0.5}$	5.26	-1.78	-1.90	-1.92	-1.88	-1.80	-1.71	-1.61	-1.51	-1.41	-1.31	-1.21	0.08
$q_{0.9}$	14.71	-0.58	-0.51	-0.44	-0.38	-0.31	-0.25	-0.18	-0.11	-0.05	0.00	0.05	1.30

Correlation Coefficients													
MAX	1.00												
$TK_{0.31}$	-0.10	1.00											
$TK_{0.41}$	-0.05	0.99	1.00										
$TK_{0.51}$	-0.05	0.97	0.99	1.00									
$TK_{0.61}$	-0.08	0.94	0.97	0.99	1.00								
$TK_{0.71}$	-0.13	0.90	0.94	0.97	0.99	1.00							
$TK_{0.81}$	-0.16	0.85	0.90	0.94	0.98	0.99	1.00						
$TK_{0.91}$	-0.20	0.81	0.86	0.91	0.95	0.98	1.00	1.00					
$TK_{1.01}$	-0.22	0.76	0.81	0.87	0.92	0.96	0.98	1.00	1.00				
$TK_{1.11}$	-0.24	0.72	0.77	0.84	0.90	0.94	0.97	0.99	1.00	1.00			
$TK_{1.21}$	-0.25	0.68	0.74	0.81	0.87	0.92	0.96	0.98	0.99	1.00	1.00		
$TK_{1.31}$	-0.26	0.65	0.71	0.78	0.84	0.90	0.94	0.97	0.98	0.99	1.00	1.00	
TK_{CCPW}	0.68	0.53	0.60	0.63	0.62	0.60	0.57	0.53	0.50	0.48	0.46	0.44	1.00

Table 5. Fama-MacBeth-Regressions with Various TK-Specifications
This table reports Fama-MacBeth-regression estimates for the sample period from January 1972 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. The explanatory variables are described in the caption of Table 1. The exact specification of TK varies between columns. TK_{γ} is the prospect theory value based on daily returns of the previous month following the methodology of Barberis et al. (2016). γ is the probability weighting parameter for the gain domain and varies across specifications. The probability weighting parameter for the loss domain is set to $\gamma + 0.08$ in each specifications. TK_{CCPW} employs the base specification $\gamma = 0.61$ but is estimated without the consideration of loss aversion, that is, TK_{PW} is based on value funtion curvature and probability weighting only. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	$TK_{0.31}$	$TK_{0.41}$	$TK_{0.51}$	$TK_{0.61}$	$TK_{0.71}$	$TK_{0.81}$	$TK_{0.91}$	$TK_{1.01}$	$TK_{1.11}$	$TK_{1.21}$	$TK_{1.31}$	TK_{CCPW}
intercept	3.5665	3.6124	3.6527	3.6657	3.6215	3.4907	3.2756	3.0327	2.8273	2.6839	2.5949	2.9616
	(4.03)	(4.13)	(4.23)	(4.30)	(4.29)	(4.15)	(3.87)	(3.54)	(3.25)	(3.03)	(2.89)	(3.19)
MAX	-0.0368	-0.0373	-0.0346	-0.0300	-0.0252	-0.0222	-0.0231	-0.0275	-0.0331	-0.0381	-0.0420	-0.0731
	(-5.29)	(-5.37)	(-5.08)	(-4.53)	(-3.85)	(-3.32)	(-3.29)	(-3.75)	(-4.38)	(-4.94)	(-5.38)	(-6.40)
BETA	-0.0291	-0.0259	-0.0237	-0.0231	-0.0258	-0.0329	-0.0434	-0.0543	-0.0631	-0.0692	-0.0731	-0.0540
	(-0.18)	(-0.16)	(-0.15)	(-0.15)	(-0.17)	(-0.21)	(-0.28)	(-0.35)	(-0.40)	(-0.44)	(-0.46)	(-0.33)
ln(MV)	-0.1123	-0.1141	-0.1157	-0.1163	-0.1146	-0.1096	-0.1013	-0.0919	-0.0839	-0.0782	-0.0747	-0.0876
	(-2.66)	(-2.73)	(-2.81)	(-2.87)	(-2.86)	(-2.75)	(-2.53)	(-2.26)	(-2.03)	(-1.86)	(-1.75)	(-1.99)
BM	0.1743	0.1740	0.1734	0.1724	0.1711	0.1698	0.1690	0.1688	0.1692	0.1697	0.1702	0.1708
	(3.66)	(3.65)	(3.64)	(3.61)	(3.57)	(3.53)	(3.50)	(3.49)	(3.49)	(3.50)	(3.51)	(3.57)
MOM	0.0077	0.0077	0.0077	0.0077	0.0078	0.0078	0.0079	0.0079	0.0079	0.0079	0.0078	0.0077
	(4.10)	(4.12)	(4.15)	(4.20)	(4.25)	(4.29)	(4.30)	(4.29)	(4.27)	(4.24)	(4.21)	(4.16)
ILLIQ	0.0186	0.0187	0.0187	0.0187	0.0186	0.0183	0.0179	0.0175	0.0172	0.0171	0.0170	0.0174
	(5.54)	(5.55)	(5.53)	(5.51)	(5.46)	(5.38)	(5.30)	(5.23)	(5.18)	(5.16)	(5.15)	(5.28)
TK	0.1818	0.1798	0.1971	0.2229	0.2464	0.2522	0.2282	0.1804	0.1273	0.0818	0.0474	0.4209
	(6.76)	(6.41)	(6.01)	(5.54)	(5.02)	(4.43)	(3.75)	(2.99)	(2.22)	(1.51)	(0.92)	(3.72)
REV	-0.0583	-0.0615	-0.0653	-0.0693	-0.0724	-0.0727	-0.0691	-0.0628	-0.0562	-0.0509	-0.0471	-0.0665
	(-10.65)	(-11.14)	(-11.52)	(-11.60)	(-11.30)	(-10.75)	(-10.14)	(-9.50)	(-8.83)	(-8.20)	(-7.68)	(-8.90)

4. Analyses Based on an Extended Sample Since 1927

The analyses in this part of the Online Appendix cover a sample period from 1927 to 2016 as we do not require at least two quarterly earnings announcement dates in the previous year for an observation to be included in the sample. Since COMPUSTAT does not provide book equity data for the early years of this prolonged sample period, we use book equity data from Kenneth R. French's homepage to supplement our original dataset. All other sample specifications and requirements remain unchanged compared to the main part of the paper. This new sample definition leads to 2,392,844 firm-month-observations. Summary statistics and correlation coefficients are provided in Table 6.

Tables 7 and 8 support a robust MAX effect and show that cumulative prospect theory cannot explain the anomaly via the use of TK-values. Tables 9 and 10 provide evidence that the MAX effect is stronger if MAX is realized at the end of the previous month.

Table 6. Summary Statistics – Sample since 1927
This table reports pooled summary statistics for the variables of interest. This includes sample mean, standard deviation, 0.1-quantile, median, 0.9-quantile, and correlation coefficients. MAX denotes the maximum daily return of the previous month. IVOL is the annualized idiosyncratic return volatility of the previous month with respect to the three Fama-French-factors. MV denotes the market value of equity. BM is the book-to-market ratio. MOM is the return of months $t-12$ to $t-2$. Amihud (2002) illiquidity measure, ILLIQ, and market beta, BETA, are estimated based on daily returns of the previous year. TK is the prospect theory value based on daily returns of the previous month following the methodology of Barberis et al. (2016). REV is the return of month $t-1$. ILLIQ is stated in million; MAX, TK, and REV are stated in %. The sample covers June 1927 to December 2016 on a monthly basis.

	MAX	IVOL	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
mean	7.2884	0.4207	0.8394	18.6861	1.0299	14.0276	5.6655	-2.2411	1.1897
SD	9.0161	0.4082	0.6271	2.1457	4.7076	68.8808	49.4762	2.1184	16.8678
$q_{0.1}$	1.9900	0.1346	0.1255	16.0238	0.1736	-44.0784	0.0014	-4.7326	-14.2857
$q_{0.5}$	5.0000	0.3077	0.7823	18.5339	0.6390	5.9321	0.2005	-1.7830	0.0000
$q_{0.9}$	14.2857	0.8155	1.6506	21.5486	1.8224	69.6719	7.9607	-0.3829	16.2469
Correlation Coefficients									
MAX	1.0000								
IVOL	0.9048	1.0000							
BETA	-0.0050	-0.0585	1.0000						
ln(MV)	-0.2716	-0.3809	0.2322	1.0000					
BM	0.0926	0.1164	0.0019	-0.1174	1.0000				
MOM	-0.1001	-0.1245	0.0605	0.1180	-0.0700	1.0000			
ILLIQ	0.1901	0.2372	-0.0639	-0.1746	0.1201	-0.0219	1.0000		
TK	-0.0994	-0.4142	0.0234	0.3099	-0.0972	0.0766	-0.1087	1.0000	
REV	0.3074	0.1375	-0.0076	0.0464	-0.0388	-0.0004	0.0216	0.6705	1.0000

Table 7. Portfolio Sorts based on MAX – Sample since 1927
This table reports monthly equally-weighted quintile portfolio sorts based on the maximum daily return of the previous month MAX. The table provides subsequent FFC-adjusted returns α_{FFC} and the corresponding factor loadings. In addition, portfolio characteristics are provided. These variables are described in Table 1. The sample period is from June 1927 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. ILLIQ is stated in million; α_{FFC}, MAX, TK, and REV are stated in %.

	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	MAX	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
low	0.36	0.78	0.23	0.13	-0.02	2.13	0.68	19.03	0.91	14.33	1.60	-1.58	-1.84
2	0.33	0.99	0.38	0.19	-0.07	3.56	0.90	18.70	1.00	15.59	1.77	-1.73	-0.66
3	0.20	1.12	0.59	0.21	-0.12	4.98	1.03	18.24	1.15	16.88	2.98	-1.94	0.30
4	0.07	1.19	0.86	0.21	-0.19	7.10	1.13	17.70	1.41	17.01	5.62	-2.17	1.66
high	-0.40	1.20	1.31	0.33	-0.30	14.54	1.14	16.85	2.50	11.00	25.99	-2.43	6.78
5-1	-0.76	0.41	1.08	0.20	-0.28	12.42	0.46	-2.18	1.59	-3.33	24.39	-0.85	8.61
t(5-1)	(-6.31)	(8.55)	(9.06)	(1.54)	(-3.15)	(21.16)	(14.20)	(-34.84)	(5.94)	(-1.34)	(5.78)	(-10.95)	(22.31)

Table 8. MAX in Fama-MacBeth-Regressions – Sample since 1927
This table reports Fama-MacBeth-regression estimates for the sample period from June 1927 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. The explanatory variables are described in Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	1.4509	4.9462	4.8329	4.4451	2.0605	3.6847
	(8.03)	(6.03)	(6.40)	(6.03)	(3.16)	(5.77)
MAX	-0.0533	-0.0903	-0.0873	-0.0977	-0.0843	-0.0355
	(-4.17)	(-10.70)	(-10.73)	(-12.77)	(-12.29)	(-5.27)
BETA		0.0992	0.0072	0.0483	-0.0677	-0.0404
		(0.83)	(0.07)	(0.43)	(-0.60)	(-0.35)
ln(MV)		-0.1948	-0.1995	-0.1790	-0.0746	-0.1349
		(-4.70)	(-5.20)	(-4.80)	(-2.32)	(-4.16)
BM		0.0928	0.1488	0.1413	0.1202	0.1102
		(3.16)	(5.20)	(5.02)	(4.28)	(4.00)
MOM			0.0075	0.0075	0.0084	0.0079
			(4.33)	(4.31)	(4.77)	(4.44)
ILLIQ				0.0188	0.0139	0.0190
				(3.49)	(2.64)	(3.52)
TK					-0.3136	0.1399
					(-8.61)	(3.92)
REV						-0.0729
						(-15.44)

Table 9. Timing of MAX in Portfolio Double Sorts – Sample since 1927
This table reports monthly equally-weighted FFC-adjusted subsequent returns from double portfolio sorts. First, each stock is allocated to one decile based on the number of days between the realization of MAX and the end of month. Second, each stock is sorted to one quintile based on MAX. MAX denotes the maximum daily return of the previous month. The sample period is from June 1927 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. FFC-adjusted returns are stated in %.

	Days Between Realization of MAX and End of Month									
	low	2	3	4	5	6	7	8	9	high
low MAX	0.24	0.41	0.43	0.36	0.36	0.38	0.41	0.30	0.37	0.39
2	-0.06	0.28	0.41	0.35	0.32	0.29	0.38	0.24	0.48	0.32
3	-0.14	0.14	0.24	0.22	0.30	0.25	0.37	0.30	0.34	0.26
4	-0.66	-0.06	-0.02	-0.08	0.05	0.13	0.30	0.27	0.17	0.24
high MAX	-1.83	-0.66	-0.26	-0.40	-0.06	-0.23	0.02	-0.11	-0.32	0.15
5-1	-2.07	-1.07	-0.70	-0.76	-0.43	-0.61	-0.40	-0.41	-0.69	-0.25
t(5-1)	(-11.93)	(-6.12)	(-4.09)	(-4.31)	(-2.22)	(-3.42)	(-2.35)	(-2.29)	(-4.28)	(-1.36)

Table 10. Timing of MAX in Fama-MacBeth-Regressions – Sample since 1927
This table reports Fama-MacBeth-regression estimates for the sample period from June 1927 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. MAX is the maximum daily return of the previous month and d_{MAX} denotes the number of days between the end of the month and the realization of MAX. The other explanatory variables are described in Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	1.4509	1.4491	5.0137	4.9027	4.5143	3.1555
	(8.03)	(8.07)	(6.09)	(6.47)	(6.12)	(4.25)
MAX	-0.0533	-0.1036	-0.1423	-0.1406	-0.1536	-0.1042
	(-4.17)	(-7.38)	(-13.64)	(-13.63)	(-15.47)	(-11.45)
MAX x d_{MAX}		0.0036	0.0037	0.0037	0.0038	0.0040
		(10.77)	(11.88)	(11.95)	(12.23)	(13.07)
BETA			0.0930	0.0019	0.0479	-0.0799
			(0.78)	(0.02)	(0.43)	(-0.68)
ln(MV)			-0.1982	-0.2030	-0.1825	-0.1150
			(-4.76)	(-5.28)	(-4.89)	(-3.10)
BM			0.0930	0.1492	0.1410	0.1093
			(3.18)	(5.22)	(5.02)	(4.00)
MOM				0.0076	0.0075	0.0079
				(4.36)	(4.32)	(4.34)
ILLIQ					0.0199	0.0173
					(3.64)	(3.12)
REV						-0.0561
						(-12.41)

5. Analyses Based on Different Return Calculation Methodologies

Table 4 in the main paper presents evidence that the MAX effect is particularly pronounced if the MAX return is observed at the very end of the month. These portfolio sorts apply equally-weighted FFC-adjusted returns. Tables 11 and 12 show that the findings remain qualitatively the same if raw or value-weighted returns are used instead. Similarly, we also present value-weighted portfolio characteristics of MAX quintiles in Tables 13 and 14.

Table 11. Timing of MAX in Portfolio Double Sorts – Raw Returns
This table reports time-series averages of monthly equally-weighted subsequent raw returns from double portfolio sorts. First, each stock is allocated to one decile based on the number of days between the realization of MAX and the end of month. Second, within each decile each stock is sorted to one quintile based on MAX. MAX denotes the maximum daily return of the previous month. The sample period is from January 1972 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. Subsequent raw returns are stated in %.

	Days Between Realization of MAX and End of Month									
	low	2	3	4	5	6	7	8	9	high
low MAX	1.08	1.40	1.42	1.27	1.32	1.36	1.34	1.24	1.30	1.34
2	1.05	1.36	1.39	1.35	1.37	1.41	1.55	1.35	1.42	1.58
3	0.85	1.21	1.26	1.32	1.45	1.40	1.52	1.33	1.34	1.41
4	0.42	1.14	1.17	1.21	1.38	1.27	1.38	1.41	1.36	1.59
high MAX	-1.04	0.53	0.90	0.63	0.99	0.86	1.15	0.96	0.86	1.30
5-1	-2.12	-0.87	-0.52	-0.64	-0.33	-0.50	-0.19	-0.29	-0.44	-0.04
t(5-1)	(-7.36)	(-2.81)	(-1.72)	(-2.03)	(-1.07)	(-1.74)	(-0.59)	(-0.92)	(-1.47)	(-0.13)

Table 12. Timing of MAX in Portfolio Double Sorts – Value-Weighted Returns
This table reports monthly value-weighted FFC-adjusted subsequent returns from double portfolio sorts. First, each stock is allocated to one decile based on the number of days between the realization of MAX and the end of month. Second, within each decile each stock is sorted to one quintile based on MAX. MAX denotes the maximum daily return of the previous month. The sample period is from January 1972 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. FFC-adjusted returns are stated in %.

	Days Between Realization of MAX and End of Month									
	low	2	3	4	5	6	7	8	9	high
low MAX	0.25	0.01	0.17	0.01	0.11	0.12	0.22	0.27	0.07	0.07
2	-0.31	-0.04	-0.07	0.36	0.09	0.06	0.25	-0.00	-0.16	0.32
3	-0.21	-0.09	-0.21	-0.19	-0.03	0.05	0.25	0.13	-0.07	0.09
4	-0.57	-0.04	0.05	-0.08	-0.19	-0.01	0.05	-0.09	-0.03	-0.17
high MAX	-1.53	-0.82	-0.41	-0.50	0.03	-0.33	-0.16	-0.42	-0.41	0.05
5-1	-1.78	-0.83	-0.58	-0.51	-0.09	-0.45	-0.37	-0.68	-0.47	-0.02
t(5-1)	(-7.23)	(-3.48)	(-1.75)	(-1.56)	(-0.34)	(-1.37)	(-1.49)	(-2.50)	(-1.84)	(-0.06)

Table 13. Portfolio Sorts based on MAX – Value-Weighted Returns
This table reports monthly quintile portfolio sorts based on the maximum daily return of the previous month MAX. The table provides value-weighted subsequent FFC-adjusted returns α_{FFC} and the corresponding factor loadings. In addition, portfolio characteristics are provided. These variables are described in the caption of Table 1. The sample period is from January 1972 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. ILLIQ is stated in million; α_{FFC}, MAX, TK, and REV are stated in %.

	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	MAX	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
low	0.09	0.83	-0.20	0.16	0.03	2.23	0.84	23.24	0.59	15.92	0.02	-1.27	-0.34
2	0.03	1.02	-0.10	0.08	-0.01	3.66	1.05	22.85	0.55	18.07	0.03	-1.30	1.47
3	0.11	1.15	0.05	0.00	-0.09	5.20	1.19	22.33	0.55	20.66	0.08	-1.38	3.07
4	-0.06	1.22	0.40	-0.18	-0.11	7.50	1.29	21.59	0.58	26.01	0.22	-1.53	4.98
high	-0.42	1.28	0.80	-0.20	-0.22	13.96	1.31	20.68	0.69	26.34	1.20	-1.28	11.71
5-1	-0.52	0.46	1.01	-0.37	-0.25	11.73	0.47	-2.55	0.10	10.42	1.18	-0.01	12.05
t(5-1)	(-2.75)	(5.77)	(7.77)	(-2.47)	(-2.25)	(23.98)	(10.26)	(-28.45)	(2.48)	(1.97)	(5.68)	(-0.16)	(18.64)

Table 14. Portfolio Sorts Based on MAX Dependent on Earnings Announcement Date – Value-Weighted Returns

This table reports monthly quintile portfolio sorts based on the maximum daily return of the previous month MAX. The table provides value-weighted subsequent FFC-adjusted returns α_{FFC} and the corresponding factor loadings. In addition, portfolio characteristics are provided. These variables are described in the caption of Table 1. The analyses refer to two subsamples: In Panel A, an observation is included if the MAX observation is not accompanied by an earnings announcement. Panel B considers all observations for which the MAX observation lies within a symmetric three-day interval around the firm's earnings announcement date. The sample period is from January 1972 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. ILLIQ is stated in million; α_{FFC}, MAX, TK, and REV are stated in %.

Panel A: MAX Observation Does Not Coincide with Earnings Announcement

	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	MAX	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
low	0.09	0.83	-0.21	0.16	0.04	2.21	0.84	23.23	0.59	16.01	0.02	-1.27	-0.40
2	0.02	1.03	-0.10	0.08	-0.02	3.61	1.05	22.86	0.55	17.98	0.03	-1.31	1.35
3	0.08	1.15	0.05	0.02	-0.09	5.13	1.19	22.30	0.56	20.66	0.08	-1.42	2.82
4	-0.14	1.25	0.42	-0.15	-0.13	7.36	1.31	21.51	0.59	26.48	0.23	-1.64	4.42
high	-0.68	1.30	0.82	-0.21	-0.24	13.73	1.32	20.55	0.72	27.31	1.29	-1.50	10.80
5-1	-0.77	0.48	1.02	-0.37	-0.28	11.52	0.48	-2.68	0.13	11.29	1.27	-0.22	11.19
t(5-1)	(-3.66)	(5.92)	(7.81)	(-2.44)	(-2.33)	(23.38)	(10.15)	(-28.93)	(2.92)	(2.00)	(5.90)	(-3.06)	(17.32)

Panel B: MAX Observation Coincides with Earnings Announcement

	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	MAX	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
low	0.20	0.84	-0.09	0.12	0.02	2.78	0.86	22.53	0.56	17.09	0.05	-1.33	0.39
2	0.36	1.05	0.33	0.26	-0.07	4.69	1.04	22.11	0.53	18.42	0.11	-1.17	3.79
3	0.40	1.14	0.29	0.08	-0.03	6.63	1.15	21.62	0.53	23.63	0.19	-1.14	6.10
4	0.61	1.08	0.67	-0.18	-0.16	9.46	1.22	21.06	0.57	24.55	0.44	-1.08	9.06
high	0.95	1.17	1.09	-0.02	-0.21	16.68	1.25	20.22	0.68	21.24	1.84	-0.68	16.49
5-1	0.75	0.33	1.19	-0.13	-0.23	13.90	0.39	-2.31	0.12	4.15	1.79	0.65	16.10
t(5-1)	(2.19)	(3.94)	(6.76)	(-0.71)	(-2.41)	(26.70)	(10.26)	(-27.48)	(3.18)	(1.30)	(5.65)	(6.43)	(19.86)

6. Winsorizing in Fama-MacBeth-Regressions

Tables 15 to 17 present the Fama-MacBeth-regressions from the main part of the paper, but all independent variables are winsorized at 1% and 99%. The findings remain qualitatively the same such that we can rule out that our conclusions are merely due to extreme outliers.

Table 15. MAX in Fama-MacBeth-Regressions – Winsorized Explanatory Variables
This table reports Fama-MacBeth-regression estimates for the sample period from January 1972 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. The other explanatory variables are described in the caption of Table 1. All explanatory variables are winsorized at 1% and 99%. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	1.6031	4.3051	4.0960	3.2734	1.6329	3.1241
	(7.67)	(4.38)	(4.51)	(3.62)	(1.96)	(3.84)
MAX	-0.0737	-0.1039	-0.0952	-0.1103	-0.1049	-0.0485
	(-4.62)	(-9.33)	(-9.06)	(-10.86)	(-11.25)	(-6.52)
BETA		0.1228	0.0681	0.1314	-0.0077	0.0347
		(0.71)	(0.43)	(0.83)	(-0.05)	(0.23)
ln(MV)		-0.1504	-0.1573	-0.1142	-0.0443	-0.0924
		(-3.15)	(-3.59)	(-2.62)	(-1.12)	(-2.37)
BM		0.2681	0.4499	0.3982	0.3578	0.3166
		(3.37)	(5.89)	(5.42)	(5.02)	(4.61)
MOM			0.0097	0.0094	0.0101	0.0095
			(4.64)	(4.53)	(4.70)	(4.40)
ILLIQ				0.0451	0.0380	0.0465
				(6.50)	(5.49)	(6.24)
TK					-0.2006	0.2424
					(-4.58)	(5.85)
REV						-0.0730
						(-10.77)

Table 16. Timing of MAX in Fama-MacBeth-Regressions – Winsorized Explanatory Variables
This table reports Fama-MacBeth-regression estimates for the sample period from January 1972 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. MAX is the maximum daily return of the previous month and d_{MAX} denotes the number of days between the realization of MAX and the end of the month. The other explanatory variables are described in the caption of Table 1. All explanatory variables are winsorized at 1% and 99%. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	1.6031	1.5845	4.3262	4.1238	3.2833	2.0951
	(7.67)	(7.60)	(4.42)	(4.56)	(3.65)	(2.33)
MAX	-0.0737	-0.1173	-0.1487	-0.1402	-0.1566	-0.1215
	(-4.62)	(-7.32)	(-11.91)	(-11.67)	(-13.40)	(-13.18)
MAX x d_{MAX}		0.0034	0.0034	0.0035	0.0035	0.0038
		(9.67)	(10.48)	(10.30)	(10.49)	(11.03)
BETA			0.1094	0.0558	0.1196	-0.0294
			(0.64)	(0.36)	(0.76)	(-0.18)
ln(MV)			-0.1519	-0.1592	-0.1152	-0.0542
			(-3.19)	(-3.64)	(-2.66)	(-1.27)
BM			0.2710	0.4527	0.4006	0.3248
			(3.41)	(5.93)	(5.46)	(4.67)
MOM				0.0098	0.0095	0.0096
				(4.68)	(4.57)	(4.39)
ILLIQ					0.0459	0.0420
					(6.56)	(5.96)
REV						-0.0441
						(-6.85)

Table 17. The Interaction of Earnings Announcement Dates with MAX in Fama-MacBeth-Regressions – Winsorized Explanatory Variables

This table reports Fama-MacBeth-regression estimates for the sample period from January 1972 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. MAX denotes the maximum daily return of the previous month and EA_{MAX} is a dummy variable that equals 1 if the MAX observation lies within a symmetric three-day interval around the firm's earnings announcement date and 0 otherwise. The other explanatory variables are described in the caption of Table 1. All explanatory variables are winsorized at 1% and 99%. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	1.6031	1.6054	4.4730	4.2608	3.4192	2.2454
	(7.67)	(7.70)	(4.59)	(4.73)	(3.81)	(2.50)
MAX	-0.0737	-0.0845	-0.1163	-0.1076	-0.1234	-0.0841
	(-4.62)	(-5.19)	(-10.61)	(-10.37)	(-12.45)	(-9.35)
MAX x EA_{MAX}		0.1313	0.1329	0.1297	0.1343	0.1470
		(9.53)	(10.39)	(10.30)	(10.75)	(11.78)
BETA			0.1258	0.0702	0.1363	-0.0074
			(0.73)	(0.45)	(0.86)	(-0.05)
ln(MV)			-0.1588	-0.1654	-0.1214	-0.0612
			(-3.35)	(-3.80)	(-2.81)	(-1.43)
BM			0.2752	0.4552	0.4024	0.3261
			(3.49)	(6.02)	(5.54)	(4.72)
MOM				0.0096	0.0093	0.0094
				(4.58)	(4.46)	(4.28)
ILLIQ					0.0461	0.0422
					(6.65)	(6.02)
REV						-0.0441
						(-7.01)

7. Use of Analyst Recommendations and Dividend Announcements to Identify High-Weight Information

Empirical analyses by Savor (2012) suggest that analyst recommendations contain reliable high-weight information, too. In addition to earnings announcement dates, we therefore also use analyst recommendation dates to distinguish high- and low-weight MAX events. Analyst report dates are sourced from the Institutional Brokers' Estimate System (IBES). We require at least two analyst recommendations in the previous year for a stock to be included in the sample. This procedure yields 594,775 observations from December 1993 to December 2016. Within this truncated sample period, 11.98% of the MAX observations fall within a symmetric three-day interval around an analyst report date and are labeled as high-weight.

Similar to Table 6 in the main paper, Table 18 reports quintile portfolio sorts based on MAX for the two subsamples. Panel A contains those observations for which MAX does not coincide with the publication of an analyst report while Panel B is restricted to those observations for which MAX is realized around an analyst report date. According to Table 18, the MAX effect is only present if there is no accompanying analyst report published. In these high-strength situations investors seemingly overreact towards the extreme positive information as information weight is presumably low. If information weight is high however, the significant return spread associated with MAX vanishes (Panel B). The difference in differences of 0.47% between Panels A and B is significant with a t-statistic of 2.39 Hence, Table 18 further supports our conjecture that the MAX effect is information-dependent since it vanishes if MAX is accompanied by high-weight news.

This line of argument is further supported in Fama-MacBeth-regressions using a dummy variable AR_{MAX} that equals one if MAX lies within a symmetric three-day interval around an analyst report date and zero otherwise. Table 19 shows that an interaction term of MAX and AR_{MAX} significantly predicts one-month-ahead stock returns such that the MAX effect depends on the accompanying information.

In addition, we also carry out very similar analyses using dividend announcement dates since Aharony and Swary (1980) show that these announcements also carry comparably relevant information. The dividend announcement dates are obtained from CRSP; again, we require at least two corresponding announcements in the previous year for a stock to be included in the sample. The sample period covers January 1972 to December 2016 and includes 838,494 observations while 5.04% of the MAX observations fall within a symmetric three-day interval around a dividend announcement date. The quintile portfolio sorts for the two subsamples are provided in Table 20: The MAX effect shows significant existence only if there is no concomitant dividend announcement. Since the difference in differences of 0.47% between Panels A and B is significant with a t-statistic of 2.65, the MAX effect is again shown to be strongly information dependent. Fama-MacBeth-regressions provide further support using a dummy variable DIV_{MAX} that equals one if MAX lies within a symmetric three-day interval around a dividend announcement date and zero otherwise. Table 21 shows that an interaction term of MAX and DIV_{MAX} significantly predicts one-month-ahead stock returns such that the MAX effect depends on the accompanying information.

Table 18. Portfolio Sorts Based on MAX Dependent on Analyst Report Date
This table reports monthly quintile portfolio sorts based on the maximum daily return of the previous month MAX. The table provides equally-weighted subsequent FFC-adjusted returns α_{FFC} and the corresponding factor loadings. In addition, portfolio characteristics are provided. These variables are described in the caption of Table 1. The analyses refer to two subsamples: In Panel A, an observation is included if the MAX observation is not accompanied by an analyst report. Panel B considers all observations for which the MAX observation lies within a symmetric three-day interval around the an analyst report date. The sample period is from December 1993 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. ILLIQ is stated in million; α_{FFC}, MAX, TK, and REV are stated in %.

Panel A: MAX Observation Does Not Coincide with Analyst Report

	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	MAX	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
low	0.41	0.74	0.20	0.42	-0.02	2.21	0.75	21.35	0.58	14.85	0.09	-1.62	-1.91
2	0.34	0.90	0.38	0.43	-0.09	3.56	0.91	20.97	0.57	14.36	0.11	-1.82	-0.96
3	0.19	1.03	0.60	0.36	-0.18	4.87	1.04	20.53	0.59	15.41	0.16	-2.07	-0.23
4	0.14	1.16	0.86	0.08	-0.31	6.79	1.16	20.10	0.65	16.76	0.28	-2.34	1.00
high	-0.11	1.26	1.24	-0.27	-0.62	13.43	1.23	19.44	1.06	11.10	0.92	-2.49	6.08
5-1	-0.52	0.53	1.05	-0.70	-0.61	11.22	0.49	-1.92	0.48	-3.74	0.83	-0.86	7.99
t(5-1)	(-2.65)	(7.73)	(8.63)	(-4.56)	(-5.54)	(14.75)	(13.77)	(-34.00)	(3.23)	(-0.66)	(3.25)	(-8.53)	(12.15)

Panel B: MAX Observation Coincides with Analyst Report

	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	MAX	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
low	0.51	0.82	0.11	0.32	-0.03	2.62	0.82	22.16	0.51	14.05	0.03	-1.69	-1.57
2	0.29	0.99	0.17	0.31	-0.07	4.17	1.01	21.70	0.49	15.65	0.03	-1.82	0.13
3	0.23	1.11	0.50	0.22	-0.18	5.78	1.12	21.25	0.50	17.94	0.05	-1.99	1.55
4	0.20	1.21	0.68	-0.08	-0.25	8.27	1.25	20.82	0.52	19.98	0.08	-2.05	3.91
high	0.46	1.15	0.96	-0.23	-0.47	18.11	1.30	20.32	0.67	16.13	0.23	-1.13	14.96
5-1	-0.05	0.33	0.86	-0.55	-0.43	15.49	0.47	-1.85	0.16	2.08	0.20	0.56	16.53
t(5-1)	(-0.21)	(3.86)	(7.22)	(-3.79)	(-4.89)	(23.67)	(11.43)	(-43.65)	(2.41)	(0.43)	(4.21)	(3.95)	(17.03)

Table 19. The Interaction of Analyst Report Dates with MAX in Fama-MacBeth-Regressions
This table reports Fama-MacBeth-regression estimates for the sample period from December 1993 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. MAX denotes the maximum daily return of the previous month and AR_{MAX} is a dummy variable that equals 1 if the MAX observation lies within a symmetric three-day interval around an analyst report date and 0 otherwise. The other explanatory variables are described in the caption of Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	1.4374	1.4724	4.6881	4.5488	4.3750	3.9318
	(4.99)	(5.20)	(3.28)	(3.38)	(3.25)	(3.00)
MAX	-0.0542	-0.0683	-0.0771	-0.0755	-0.0758	-0.0699
	(-2.75)	(-3.22)	(-5.39)	(-5.42)	(-5.50)	(-5.10)
MAX x EA_{MAX}		0.0464	0.0545	0.0546	0.0549	0.0555
		(4.90)	(6.73)	(7.10)	(7.11)	(7.02)
BETA			0.2078	0.0506	0.0621	0.0171
			(0.71)	(0.19)	(0.23)	(0.06)
ln(MV)			-0.1571	-0.1562	-0.1486	-0.1277
			(-2.31)	(-2.47)	(-2.35)	(-2.08)
BM			-0.2423	-0.1430	-0.1531	-0.1674
			(-2.21)	(-1.33)	(-1.46)	(-1.71)
MOM				0.0022	0.0022	0.0021
				(0.70)	(0.69)	(0.66)
ILLIQ					0.0701	0.0700
					(2.08)	(2.10)
REV						-0.0086
						(-1.66)

Table 20. Portfolio Sorts Based on MAX Dependent on Dividend Announcement Date
This table reports monthly quintile portfolio sorts based on the maximum daily return of the previous month MAX. The table provides equally-weighted subsequent FFC-adjusted returns α_{FFC} and the corresponding factor loadings. In addition, portfolio characteristics are provided. These variables are described in the caption of Table 1. The analyses refer to two subsamples: In Panel A, an observation is included if the MAX observation is not accompanied by a dividend announcement. Panel B considers all observations for which the MAX observation lies within a symmetric three-day interval around the a dividend announcement date. The sample period is from January 1972 to December 2016. The t-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using twelve lags. ILLIQ is stated in million; α_{FFC}, MAX, TK, and REV are stated in %.

Panel A: MAX Observation Does Not Coincide with Dividend Announcement

	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	MAX	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
low	0.37	0.72	0.23	0.38	-0.01	1.81	0.57	20.24	0.85	15.24	0.60	-1.51	-1.68
2	0.33	0.89	0.27	0.42	-0.04	2.89	0.73	20.26	0.80	14.38	0.61	-1.56	-0.37
3	0.19	0.96	0.36	0.45	-0.05	3.85	0.81	20.02	0.80	14.68	0.78	-1.63	0.62
4	0.13	1.03	0.47	0.49	-0.08	5.18	0.87	19.66	0.84	14.74	1.15	-1.73	1.88
high	-0.24	1.03	0.66	0.48	-0.17	9.43	0.88	19.01	1.05	12.53	2.98	-1.80	5.47
5-1	-0.62	0.31	0.43	0.11	-0.15	7.63	0.31	-1.23	0.20	-2.71	2.39	-0.29	7.16
t(5-1)	(-6.29)	(10.50)	(10.33)	(2.20)	(-2.35)	(25.60)	(11.63)	(-14.30)	(2.62)	(-1.51)	(5.18)	(-5.50)	(25.42)

Panel B: MAX Observation Coincides with Dividend Announcement

	α_{FFC}	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	MAX	BETA	ln(MV)	BM	MOM	ILLIQ	TK	REV
low	0.38	0.74	0.22	0.31	-0.06	1.96	0.58	20.28	0.83	15.08	0.69	-1.50	-1.33
2	0.47	0.90	0.34	0.50	-0.03	3.10	0.74	20.25	0.79	15.04	0.61	-1.52	0.24
3	0.31	0.93	0.35	0.49	-0.04	4.14	0.81	19.99	0.80	15.60	0.73	-1.54	1.68
4	0.35	0.98	0.52	0.49	-0.08	5.63	0.86	19.65	0.81	15.79	1.11	-1.57	3.33
high	0.23	1.04	0.67	0.47	-0.07	10.38	0.87	19.15	0.88	15.43	2.58	-1.29	8.49
5-1	-0.15	0.31	0.45	0.15	-0.01	8.43	0.29	-1.13	0.04	0.35	1.89	0.21	9.82
t(5-1)	(-0.81)	(6.01)	(5.20)	(1.84)	(-0.17)	(32.48)	(12.32)	(-14.50)	(1.17)	(0.20)	(4.67)	(3.76)	(31.89)

Table 21. The Interaction of Dividend Announcement Dates with MAX in Fama-MacBeth-Regressions
This table reports Fama-MacBeth-regression estimates for the sample period from January 1972 to December 2016 based on monthly data. The dependent variable is the stock return of the subsequent month. MAX denotes the maximum daily return of the previous month and DIV_{MAX} is a dummy variable that equals 1 if the MAX observation lies within a symmetric three-day interval around a dividend announcement date and 0 otherwise. The other explanatory variables are described in the caption of Table 1. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using twelve lags.

	(1)	(2)	(3)	(4)	(5)	(6)
intercept	1.5339	1.5387	4.0006	3.7123	3.6053	2.9210
	(8.13)	(8.18)	(4.85)	(4.83)	(4.51)	(3.67)
MAX	-0.0688	-0.0731	-0.0962	-0.0927	-0.0961	-0.0468
	(-5.82)	(-6.03)	(-10.66)	(-10.89)	(-11.67)	(-5.15)
MAX x DIV_{MAX}		0.0557	0.0515	0.0487	0.0491	0.0575
		(5.25)	(5.00)	(4.90)	(4.99)	(5.98)
BETA			0.2760	0.2079	0.2078	0.0647
			(1.97)	(1.70)	(1.71)	(0.53)
ln(MV)			-0.1350	-0.1322	-0.1266	-0.0935
			(-3.57)	(-3.77)	(-3.46)	(-2.59)
BM			0.0702	0.1792	0.1751	0.1256
			(1.20)	(3.15)	(3.10)	(2.25)
MOM				0.0082	0.0082	0.0082
				(3.87)	(3.88)	(3.78)
ILLIQ					0.0143	0.0063
					(1.42)	(0.59)
REV						-0.0456
						(-8.60)