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Moving average distance as a predictor of equity returns

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Abstract

The distance between short- and long-run moving averages of prices (MAD) predicts future equity returns in the cross section. Annualized value-weighted alphas from the accompanying hedge portfolios are around 9%, and the predictability goes beyond momentum, 52-week highs, profitability, and other prominent anomalies. MAD-based investment payoffs survive reasonable trading costs faced by institutions, and are stronger on the long side relative to the short counterpart.

KEYWORDS

anchoring bias, crossing rules, market efficiency, moving averages, technical analysis

1 | INTRODUCTION

We show that large (small) ratios of 21- to 200-day moving averages of prices predict high (low) average returns in the cross section. This trading strategy (termed moving average distance, MAD) yields robust investment payoffs that do not decay even after several months. The predictability is stronger on the long side relative to the short counterpart, unlike many other cross-sectional predictors (Stambaugh, Yu, and Yuan, 2012), and remains significant in recent years. Specifically, the long side yields strongly significant value-weighted alphas of about 9% for up to twelve months, whereas the corresponding short-side alphas do not fall below −1.5%.

The predictive power of MAD goes beyond momentum (Jegadeesh and Titman, 1993), 52-week highs (George and Hwang, 2004), and a long list of other anomalies. Further, while the MAD effect remains statistically and economically significant after accounting for momentum, the profitability of the momentum factor (UMD) is insignificant in the presence of an MAD factor. The MAD-based strategy remains viable in the more recently developed five-factor model of Fama and French (2015), and after accounting for the global financial crisis. Finally, we show that unlike standard momentum, MAD continues to produce economically meaningful payoffs in the most recent years.

We provide an explanation for our result based on the psychological bias of anchoring, wherein individuals rely too heavily on readily obtainable (but often irrelevant) signals in forming assessments (Tversky and Kahneman, 1974).[1] We posit that the MAD effect occurs because investors get anchored to long-run moving averages. As an example, suppose the anchor (the long-run moving average) is 40. Now suppose that recent public news suggests that the price should be 60. The number 60 is so far away from 40 that the investor underreacts. This implies that the short-run moving average adjusts only to, say, 50 (reflecting a large distance of 10), and the price, which still has a distance of 10 to cover, subsequently drifts upward to 60. Now suppose the anchor is 40, and information flows indicate that the price should be 41. This is not far from the anchor, so the misreaction is minimal, and the price quickly adjusts to 41. This argument demonstrates how the distances between short- and long-run moving averages reflect the degree of underreaction in prices.[2] The anchoring hypothesis predicts that MAD should be stronger

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for sudden (versus gradual) changes in the current values of prices relative to their long-term averages, which is when the degree of underreaction should be greater. We find support for this conjecture.

Moving average-based rules, of course, have been extensively considered in earlier literature. Indeed, our paper complements Alexander (1961), Van Horne and Parker (1968), Brock, LeBaron, and Lakonishok (1992), and, more recently, Han, Yang, and Zhou (2013). A primary focus of this work is on binary rules that apply when short- and long-term moving averages intersect.[3] We contribute to this literature by showing that an indicator based on the distance between short- and long-run averages predicts returns. Also, some work on technical indicators, such as Brock et al. (1992), and Donaldson and Kim (1993), focuses on trading rules applied to market indices. We instead adopt a cross-sectional approach (Jegadeesh and Titman, 1993; Han, Yang, and Zhou, 2013). Thus, we use regression analysis, followed by a consideration of the relative performance of individual stock portfolios sorted on our return predictor.

In a recent and important paper, Han, Zhou, and Zhu (2016) (HZZ) cross-sectionally forecast future equity returns based on moving averages over various horizons, although they do not focus on the distance between short- and long-run averages. We show that while the comprehensive moving average-based variable of HZZ remains significant in our analysis, MAD survives the consideration of this variable.

More generally, the research on equity predictors and trading strategies is by now quite mature and the question naturally arises as to the contribution of our paper to this body of research. In this context, there are three noteworthy aspects to our work. First, the predictability we document is stronger on the long side relative to the short side, and robustly prevails in states of high and low sentiment, liquidity, and volatility, which contrasts with other predictors (e.g., Stambaugh, Yu, and Yuan, 2012). Second, the predictability survives in recent decades when most anomalies have attenuated (Chordia, Subrahmanyam, and Tong, 2014). Third, MAD captures the momentum (UMD) factor, indicating that MAD performs favorably incremental to standard momentum.

Our research suggests that active managers should pay attention to the distance between short- and long-run moving averages of prices in developing models for forecasting equity returns. We show that trading rules based on this distance present significant profits in historical data after accounting for reasonable trading cost estimates.

2 | METHODOLOGY AND DATA

We consider all U.S. firms listed on the NYSE, AMEX, and NASDAQ with share codes 10 and 11 (i.e., common stock) and positive equity book values in Compustat for the previous year. We exclude stocks with an end-of-month price below \$5, stocks that are not traded during the month, and stocks that do not have return or earnings observations for the previous 12 months.

To mitigate backfilling biases, we require that a firm be listed on Compustat for at least two years before it is included in the sample (Fama and French, 1993). At the end of June of every year, we update the previous fiscal year's accounting data to make sure that information for predicting future stock returns is available in real time. The final sample starts in July 1977, when all accounting reports for 1976 are publicly available, and ends in December 2018. Altogether, we capture 1,353,679 monthly returns for 13,828 firms. Following Shumway (1997), we incorporate delisting returns based on the CRSP daily delisting file into our return data.

Our proposed predictive variable of the cross section is formed in two steps. We initially compute the moving average distance ratio (MRAT) for every stock as

$$\mathrm{MRAT} \equiv \frac{\mathrm{MA}(21)}{\mathrm{MA}(200)} \tag{1}$$

where MA(21) is the short-run (past 21-day) stock price moving average, and MA(200) is the corresponding long-term (200-day) moving average. In calculating moving averages, stock prices are adjusted for splits and dividend distributions.

The numerator of Eq. (1) reflects short-term trends. Since the price over a single day is a noisy proxy for the short term, we average over the most recent prices, and pick a horizon of about a month in trading day terms. Our results are robust to considering other short-term moving averages ranging from five to 35 trading days.[4] We pick MA(200) to capture the long-term trend; the results are robust to considering MA(250), the approximate annual moving average in trading days. [Brock, LeBaron, and Lakonishok (1992) argue that MA(200) is a popular long-term moving average among market participants.]

In common technical rules, a buy (sell) signal occurs when shorter-term moving averages cross longer-term counterparts from below (above), according to an MRAT greater (smaller) than unity.[5] These rules (often termed the "golden cross" and the "death cross," respectively) are based on the premise that the ratio of the short- to the long-run moving average captures investor misreaction. Our specific anchoring rationale, explored in Section 4, suggests that investors underreact when the discrepancy between short- and long-run moving averages is high. Thus, an MRAT close to unity might cause only a minor investor misreaction that may not be detectable in asset returns.[6] This observation indicates that more predictive power could potentially be gained by conditioning on a large MRAT, as opposed to investigating a linear relation between MRAT and future returns.

Accordingly, in the second step of our procedure, we first divide stocks into deciles based on their MRAT values, and then pick subsets of stocks with extreme values of MRAT from the top and bottom deciles. Specifically, the long portfolio is a subset of top decile stocks with MRAT values greater than one plus a constant sigma, while the short portfolio consists of bottom decile stocks with MRAT values smaller than one minus sigma. We calculate sigma as the monthly cross-sectional standard deviation of MRAT. We then form a new variable termed MAD that equals one for long-leg stocks, minus one for short-leg stocks, and zero otherwise. Experimenting on two standard deviations typically makes the empirical findings stronger at the cost of having several months with relatively small number of investable stocks in the portfolio.

Our goal is to see whether MAD allows practitioners to earn statistically and economically significant returns in the cross section of equities. To this end, we first perform cross-sectional regressions, followed by analysis of MAD-sorted portfolios. To ensure that our predictor variable does not merely capture well-established phenomena or other technical trading rules, our regression analysis controls for 19 predictive characteristics that are described below. We also control for a binary signal denoted MAS, which equals 1 if the current price exceeds the 200-day moving average and zero otherwise, the MACD convergence/divergence measure,[7] four past return variables reflecting price reversals, and intermediate-term momentum (Jegadeesh, 1990; DeBondt and Thaler, 1985; Jegadeesh and Titman, 1993).

Below, we describe the 19 control characteristics used in our analysis (Appendix A provides details on variable construction). The market value of equity (ME) accounts for the negative size-return relation (Banz, 1981; Reinganum, 1981; Fama and French, 1992). The book-to-market ratio (BE/ME) captures the value effect (Fama and French, 1992). The trend (TREND) of Han, Zhou, and Zhu (2016) employs moving averages for the past 3, 5, 10, 50, 100, 200, 400, 600, 800, and 1,000 days to forecast the next month's price trend. Idiosyncratic volatility is based on the volatility of residuals from Fama–French time-series regressions per Ang et al. (2006).

Turnover (TURN) is constructed as the ratio of trading volume to shares outstanding (Datar, Naik, and Radcliffe, 1998). The Amihud (2002) illiquidity measure (ILLIQ) is the annual average of daily absolute return per dollar of daily trading volume. The 52-week high (52H) captures the instrument proposed by George and Hwang (2004).

Standardized unexpected earnings (SUE) is the difference between current quarterly earnings per share (EPS) and the corresponding previous year's EPS divided by the standard deviation of quarterly EPS using the most recent eight quarters (Ball and Brown, 1968). Standardized unexpected revenue growth (SURGE) controls for postrevenue announcement drift; it is calculated in the same way as SUE but with revenues instead of EPS. Net stock issues (NS) controls for high returns following stock repurchases (Ikenberry, Lakonishok, and Vermaelen, 1995) and low returns following stock issues (Pontiff and Woodgate, 2008).

As in Fama and French (2008), we construct asset growth (dA/A) as the previous year's annual change in assets per split-adjusted share. Following Cohen, Gompers, and Vuolteenaho (2002), and Fama and French (2006), we control for firm profitability (Y/B), which is computed as equity income divided by book equity. The investment-to-asset ratio (I/A) is formed as in Titman, Wei, and Xie (2004), and Xing (2008). Return on equity (ROE) (Haugen and Baker, 1996) and return on assets (ROA) are calculated as income before extraordinary items divided by the most recent quarter's book equity or total assets, respectively.

Finally, we control for gross profitability, accruals, return on assets, and new operating assets (see, respectively, Novy-Marx, 2013; Sloan, 1996; Chen, Novy-Marx, and Zhang, 2011; Hirshleifer et al. 2004). To account for the credit risk effect, we consider the Ohlson (1980) distress O-score (OS), as in Campbell, Hilscher, and Szilagyi (2008).

Table 1 displays descriptive statistics for stock returns and control variables. In brief, there is large variability in profitability (Y/B), investment-to-asset ratio (I/A), return on assets (ROA), return on equity (ROE), illiquidity (ILLIQ), and MACD relative to their means; however, these variables are not the focus of our analysis. The last column reports the average time-series correlation between the various variables and MRAT. While most correlations are near zero, there is more substantial correlation with momentum and 52-week high (0.58 and 0.64, respectively). Still, the correlations are imperfect. This is the first indication that momentum and 52-week high, while related, are still distinct phenomena that do not capture the information content of the moving average distance. In the analysis to follow, we show that the predictive power of MAD is economically significant and incremental to momentum, 52-week high, other prominent anomalies, and various technical rules.

TABLE 1 Descriptive statistics

Variable	Observations (000)	Mean	Standard Deviation	Min.	Max.	Percentile 5th	25th	Median	75th	95th	Correlation with *M*RAT
Monthly return (*R*)	1,354	0.019	0.138	–0.944	13.50	–0.165	–0.047	0.010	0.072	0.226	0.293
Log size (ME)	1,354	12.749	1.948	6.948	20.82	9.832	11.304	12.607	14.021	16.200	0.017
Book-to-market ratio (BE/ME)	1,354	0.655	0.591	0.000	61.87	0.092	0.295	0.529	0.856	1.598	–0.213
Trend (TREND)	1,354	0.254	0.120	–0.882	2.336	0.037	0.169	0.271	0.342	0.423	0.024
Return over months –12 to –2 (MOM)	1,354	0.221	0.684	–0.982	98.57	–0.414	–0.091	0.118	0.373	1.118	0.584
Idiosyncratic volatility (IVOL)	1,354	0.116	0.064	0.000	2.433	0.046	0.072	0.102	0.145	0.232	0.102
Turnover (TURN)	1,337	1.232	2.187	0.000	381.1	0.073	0.278	0.670	1.502	4.084	0.096
Illiquidity (ILLIQ)	1,336	1.048	14.068	0.000	8812	0.000	0.002	0.024	0.257	3.627	–0.017
52-week high price (52H)	1,354	0.815	0.167	0.016	1.000	0.473	0.727	0.861	0.946	1.000	0.636
Standardized unexpected earnings (SUE)	1,354	0.095	1.369	–3.728	3.742	–2.401	–0.730	0.140	0.976	2.386	0.184
Standardized unexpected revenue growth (SURGE)	1,346	0.708	1.284	–3.669	3.689	–1.843	–0.030	0.907	1.691	2.451	0.085
Net stock issues (NS)	1,340	0.075	0.420	–12.87	14.01	–0.061	0.000	0.006	0.032	0.349	–0.016
Asset growth (dA/A)	1,339	0.077	0.434	–13.71	12.92	–0.227	–0.002	0.073	0.167	0.479	–0.044
Profitability (Y/B)	1,353	–0.003	15.937	–9033	790.0	–0.308	0.044	0.107	0.163	0.300	–0.007
Investment-to-asset ratio (I/A)	1,140	0.244	25.783	–10.51	5840	–0.067	0.010	0.055	0.130	0.405	–0.002
Gross profitability premium (GP)	1,351	0.320	0.284	–8.932	4.305	0.025	0.105	0.284	0.473	0.817	0.027
Accruals (Ac/A)	1,064	–0.026	0.094	–1.335	3.600	–0.149	–0.069	–0.032	0.008	0.123	–0.039
Return on assets (ROA)	1,347	0.009	4.103	–1310	280.1	–0.143	0.010	0.043	0.091	0.202	0.001
Return on equity (ROE)	1,350	–0.001	9.271	–5958	607.7	–0.076	0.010	0.027	0.044	0.092	0.003
Net operating assets (NOA)	1,231	0.893	42.273	–54.58	13457	0.024	0.355	0.631	0.797	1.155	–0.004
Distress O-score (*OS*)	1,080	0.331	1.691	–393.4	120.4	–2.059	–0.656	0.332	1.306	2.810	0.075
Moving average convergence/divergence (MACD)	1,354	0.001	1.78	–808.9	515.1	–0.010	–0.002	0.000	0.003	0.012	0.010
Moving average distance ratio (MRAT)	1,354	1.047	0.204	0.067	5.395	0.750	0.938	1.034	1.137	1.374	1.000

Note: The table displays descriptive statistics for stock returns and firm characteristics defined in Appendix A. The first four columns report sample means, standard deviations, minimums, and maximums. The next five columns report sample percentiles at the 5, 25, 50 (median), 75, and 95 levels. The last column reports sample correlations between each variable and the moving average distance ratio (MRAT). Specifically, MRAT is the ratio of 21-day to 200-day moving averages of prices. The sample is from July 1977 through December 2018.

3 | MAD AND STOCK RETURNS

In this section, we explore the ability of MAD to predict the cross section of future stock returns. We show that, unlike the vast majority of market anomalies, the MAD effect persists during recent years, as well as across various states of the economy including high versus low investor sentiment, market volatility, and aggregate liquidity. Further, MAD profits are stronger on the long side than the short side.

3.1 | Cross-sectional regressions

We first employ the Fama and MacBeth (1973) cross-sectional regression setup. For each month, we regress monthly stock returns on MRAT or MAD, the above-described predictive characteristics, technical indicators, and past return instruments. Table 2 reports slope coefficients for our predictor, as well as for past returns over months 2 to 12 (MOM), the 52-week high price (52H), and the trend variable (TREND) proposed by Han, Zhou, and Zhu (2016). As these three variables employ past returns, prices, and trends, we pay special attention to their interaction with our predictor. Estimated slope coefficients for all other control variables are reported in Appendix B.

In Panel A of Table 2, analogously to the other control variables we use the continuous moving average ratio (MRAT) and continuous versions of control variables. In Panel B, the control variables along with MAD are MOM1, 52H1, and TREND1, which, like MAD, are equal one for long-leg stocks, minus one for short-leg stocks, and zero otherwise. For each variable, we first divide stocks into deciles based on their MOM, 52H, or TREND values, and then pick subsets of stocks with extreme values greater than a constant sigma, or smaller than minus sigma, respectively. We calculate sigma as the corresponding monthly cross-sectional standard deviation of MOM, 52H, or TREND.[8]

The dependent variable in the first test is the one-month-ahead return. The MRAT coefficient is highly significant ($t = 4.92$). The TREND coefficient is also positive and strongly significant. The MOM and 52H coefficients are positively associated with the future one-month return on a stand-alone basis, but turn insignificant and negative in a comprehensive regression. For an investment horizon of 2–6 months, the coefficient on our predictor remains large (5.67) and significant ($t = 3.60$), even after accounting for MOM, 52H, and TREND, either individually or all together. The coefficients for MAS and MACD are indistinguishable from zero (see Appendix B) in the presence of our predictor. The evidence thus suggests that our proposed predictor contains unique information vis-à-vis well-known predictive variables that employ past returns, prices, and trends. The coefficient is also positive at the 7- to 12-month investment horizon but turns insignificant (2.51, $t = 1.51$). Interestingly, for an investment horizon greater than one month, momentum yields a negative slope coefficient, even significantly so for 7-12 month investment horizon, consistent with long-run reversals. In contrast, while our strategy attenuates over increasing investment horizons, it does not reverse.

We next examine the more recent 2001–2018 period. This period is especially challenging because Chordia, Subrahmanyam, and Tong (2014) show that anomalies have tended to decline in significance during recent years. Consistent with these studies, we demonstrate in Appendix B that over the 2001–2018 period, SUE, ROE, NOA, and other effects all attenuate. In contrast, our investment rule produces a positive and significant coefficient.

We further analyze different economic states. We follow the vast literature on momentum. For example, Antoniou, Doukas, and Subrahmanyam (2013) and Stambaugh, Yu, and Yuan (2012) show that momentum profitability obtains more strongly during high sentiment periods. Moreover, Avramov, Cheng, and Hameed (2016) show that momentum is stronger when markets are highly liquid, and Wang and Xu (2015) consider the impact of volatility on momentum. Accordingly, we perform cross-sectional regressions for high versus low sentiment, volatility, liquidity (stratified by medians) and positive/zero, or negative market return states defined based on the past two-year market performance as in Cooper, Gutierrez, and Hameed (2004). The sentiment index follows Baker and Wurgler (2006), market illiquidity is per Amihud (2002), and market volatility is the monthly standard deviation of daily returns. At the bottom of Panel A of Table 2, we confirm that, unlike momentum, our effect is large and significant in all sentiment, volatility, and liquidity states. The positive but insignificant coefficient in the case of down-markets is probably affected by the fact that the number of down-market months is small; specifically, only 10% of the sample months are followed by negative two-year market returns.[9]

Panel B of Table 2 completes the analysis with our variable of focus, MAD, and the analogous control variables: MOM1, 52H1, and TREND1. The results with MAD and the corresponding control variables in Panel B are in line with the results in Panel A. Indeed, the t-statistic on the coefficient for MAD for the one-month-ahead return is a healthy 6.65. Results for different states of the economy also are similar to those in Panel A.[10]

TABLE 2 Cross-sectional regressions

Dependent variable		Observations	MRAT	MOM	52H	TREND
Panel A. MRAT and continuous control variables						
R_{t+1}		820,609	1.47**	–0.00	–0.76	45.19**
			(4.92)	(–0.03)	(–1.67)	(8.42)
$R_{t+2:t+6}$		813,170	5.67**	–0.71	4.44**	–5.97
			(3.60)	(–1.83)	(2.59)	(–0.51)
$R_{t+7:t+12}$		784,720	2.51	–1.25**	–0.13	–10.00
			(1.51)	(–3.84)	(–0.06)	(–0.84)
R_{t+1}	2001–2018	362,772	1.43**	–0.06	–0.60	18.30**
			(3.06)	(–0.50)	(–0.89)	(2.64)
	High sentiment	517,523	1.36**	0.05	–0.08	43.15**
			(3.52)	(0.51)	(–0.15)	(6.32)
	Low sentiment	303,086	1.64**	–0.08	–1.79*	48.31**
			(3.88)	(–0.55)	(–2.54)	(7.09)
	High volatility	391,566	1.43**	0.10	–1.75*	43.77**
			(3.01)	(0.47)	(–2.28)	(5.80)
	Low volatility	429,043	1.50**	–0.10	0.14	46.47**
			(3.82)	(–1.01)	(0.30)	(7.97)
	High illiquidity	376,845	1.14**	0.05	–0.57	61.79**
			(2.70)	(0.70)	(–0.87)	(14.53)
	Low illiquidity	443,764	1.80**	–0.05	–0.95	28.66**
			(4.12)	(–0.38)	(–1.50)	(3.58)
	Positive market	733,998	1.48**	0.00	–0.48	48.24**
			(4.49)	(0.00)	(–1.06)	(8.45)
	Negative market	86,611	1.35	–0.02	–3.02	20.67*
			(1.82)	(–0.08)	(–1.74)	(2.49)
Dependent variable		**Observations**	**MAD**	**MOM1**	**52H1**	**TREND1**
Panel B. MAD and analogously defined control variables						
R_{t+1}		820,609	0.51**	0.03	–0.13	0.95**
			(6.65)	(0.28)	(–1.76)	(7.49)
$R_{t+2:t+6}$		813,170	1.96**	–0.28	–0.07	–0.29
			(6.12)	(–0.65)	(–0.35)	(–1.50)
$R_{t+7:t+12}$		784,720	0.25	–1.28**	–0.04	–0.10
			(0.66)	(–3.28)	(–0.06)	(–0.43)
R_{t+1}	2001–2018	362,772	0.23**	–0.06	–0.02	0.37**
			(2.61)	(–0.46)	(–1.83)	(3.77)
	High sentiment	517,523	0.57**	0.09	–0.06	1.01**
			(4.61)	(0.80)	(–0.72)	(7.44)
	Low sentiment	303,086	0.42**	–0.07	–0.23*	0.84**
			(3.70)	(–0.41)	(–2.07)	(6.11)
	High volatility	391,566	0.44**	0.09	–0.32**	1.11**
			(3.56)	(0.57)	(–2.77)	(6.00)
	Low Volatility	429,043	0.57**	–0.03	0.04	0.80**
			(6.69)	(–0.33)	(0.64)	(8.06)

(Continues)

TABLE 2 (Continued)

Dependent variable		Observations	MAD	MOM1	52H1	TREND1
	High illiquidity	376,845	0.59**	0.07	–0.03	1.10**
			(5.33)	(0.58)	(–0.31)	(9.68)
	Low illiquidity	443,764	0.42**	–0.02	–0.23*	0.79**
			(4.14)	(–0.16)	(–2.29)	(4.34)
	Positive market	733,998	0.55**	0.05	–0.04	1.01**
			(7.26)	(0.60)	(–0.57)	(7.42)
	Negative market	86,611	0.12	–0.20	–0.88**	0.43
			(0.40)	(–0.53)	(–3.62)	(1.81)

Note: The table reports average slopes (multiplied by 10^4) and their *t*-values (in parentheses) obtained from Fama and MacBeth (1973) regressions. The dependent variable is the stock return over (i) the next month, (ii) months 2–6, and (iii) months 7–12. MRAT in Panel A is the ratio of 21-day to 200-day moving averages of prices. The control variables are defined in Appendix A, and their slope coefficients are reported in Appendix B. In Panel B, MAD, MOM1, 52H1, and TREND1 equal one, negative one, or zero. MAD is one (negative one) if the ratio of 21-day to 200-day moving averages of prices (MRAT) belongs to the top (bottom) decile, provided that it is also greater (smaller) than one plus (minus) a parameter σ. Otherwise, it is equal to zero. The parameter σ is the monthly cross-sectional standard deviation of MRAT. MOM1, 52H1, and TREND1 are defined analogously to MRAT for the underlying variables. The analysis is implemented for the entire sample period (July 1977 to December 2018), for the most recent period (2001–2018), and for various market states: (a) positive versus negative sentiment per Baker and Wurgler (2006), (b) below versus above median previous months' market volatility, (c) below versus above median previous months' market illiquidity per Amihud (2002), and (d) positive and negative market states per Cooper, Gutierrez, and Hameed (2004). Standard errors are based on Bartlett's kernel, which, in turn, implements the Newey–West covariance estimator. One and two asterisks indicate significance at the 5% and 1% levels, respectively.

Recently, Harvey, Liu, and Zhu (2016) argue that in light of the numerous attempts to detect factors that explain the cross section of expected returns, higher hurdle criteria should be applied for assessing the significance of new explanatory variables. In most cases within Table 2, the *t*-ratios obtained for MAD are higher than the suggested threshold value of 3.0. We re-examine the economic and statistical significance of MAD-based strategies in the next section, based on a portfolio approach.

3.2 | Portfolio analysis

We next employ portfolio sorts in our attempt to identify incremental cross-sectional patterns in average stock returns. Throughout the analysis, we only use value-weighted portfolios (i.e., portfolios wherein stocks are weighted by market capitalization on the last trading day of the formation month). The first two columns of Table 3 report next months' average returns and returns for months 2 through 6. Portfolios are sorted sequentially, first on MAD-based top and bottom deciles and then on the top 30%, mid 40%, and the bottom 30% of MOM, 52H, and TREND. In all cases, top MAD portfolios yield average returns that are significantly higher than their bottom counterparts. For example, for the bottom MOM stocks, top and bottom MAD portfolios yield average next-month returns of 1.60% and –0.27%, and average returns for months 2-6 of 7.86% and –0.08%, respectively.

In the last two columns of Table 3, we sort in the reverse order to the first two columns: That is, portfolios are sorted first on one of the characteristics and then on MAD. Again, for all instances, stocks with the highest values of MAD yield average returns that are considerably larger than returns for those with the lowest values.

Appendix C reports double-sort results on MAD and in turn: (i) size (ME), (ii) book-to-market (BE/ME), (iii) turnover (TURN), (iv) illiquidity (ILLIQ), (v) standardized unexpected earnings (SUE), (vi) previous month's return (R_{t-1}), (vii) returns for months 13-24 ($R_{t-13:t-24}$), and (viii) volatility (IVOL). The appendix shows that return differentials between top and bottom MAD portfolios are uniformly positive and mostly significant across all time horizons and among all characteristics. In unreported tests, we also conduct independent sorts. We find that top MAD stocks yield higher returns in all cases relative to bottom MAD stocks, but with moderately reduced significance levels due to sparsely populated portfolios during the early years.

We next assess the cumulative profitability of trading strategies that employ MAD deciles. Figure 1 displays the value of a \$1 position invested at the end of July 1977 in either the top or bottom deciles based on MAD. The figure also displays the performance of a market proxy (the value-weighted CRSP index). Investments are rebalanced on a monthly basis. The buy portfolio outperforms the market with terminal values of about \$960, while the sell portfolio achieves a corresponding end value of \$0.35. The market achieves a performance of \$92, in comparison. Thus, while Stambaugh, Yu, and Yuan (2012) and Avramov et al. (2013) show that most anomalies derive their profitability principally from the short leg, Figure 1 shows that top MAD stocks (comprising the long leg of MAD) materially outperform.

TABLE 3 The interaction between MAD and (i) momentum, (ii) 52-week high price, and (iii) trend

			MAD First		MAD Last	
MAD Decile	R_{t+1}	$R_{t+2:t+6}$	R_{t+1}	$R_{t+2:t+6}$	R_{t+1}	$R_{t+2:t+6}$
Panel A. MAD						
Top	1.81	8.02				
Bottom	0.23	0.74				
Diff.	1.58**	7.27**				
Panel B. MAD and MOM						
Top	MOM bottom 30%		1.60	7.86	0.69	6.25
Bottom			–0.27	–0.08	0.13	0.20
Diff.			1.87**	7.94**	0.56	6.05**
Top	MOM core 40%		1.69	8.57	1.67	7.88
Bottom			0.24	0.60	0.55	0.81
Diff.			1.45**	7.97**	1.12**	7.07**
Top	MOM top 30%		2.18	7.54	2.07	8.57
Bottom			0.69	1.50	1.15	0.24
Diff.			1.49**	6.04**	0.92*	8.33**
Panel C. MAD and 52H						
Top	52H bottom 30%		2.03	7.41	1.60	3.10
Bottom			0.29	0.01	0.33	0.45
Diff.			1.74**	7.4**	1.27*	2.65**
Top	52H core 40%		2.04	8.45	2.05	7.98
Bottom			0.35	0.52	–0.49	6.18
Diff.			1.69**	7.93**	2.54**	1.80
Top	52H top 30%		1.35	8.15	1.84	9.10
Bottom			–0.02	1.88	–3.07	8.88
Diff.			1.37**	6.27**	4.91**	0.22
Panel D. MAD and TREND						
Top	TREND bottom 30%		1.25	8.20	0.87	8.29
Bottom			–0.80	–0.46	–0.22	0.18
Diff.			2.05**	8.66**	1.09*	8.11**
Top	TREND core 40%		1.79	8.19	1.48	8.03
Bottom			0.42	1.98	0.70	0.20
Diff.			1.37**	6.21**	0.78*	7.83**
Top	TREND top 30%		2.42	7.62	2.26	7.72
Bottom			0.88	0.20	1.38	0.75
Diff.			1.54**	7.42**	0.88*	6.97**

Note: The table reports average portfolio returns for the next month and months 2 through 6 via 3 × 3 sorts on MAD and momentum (MOM), MAD and 52-week high price (52H), and MAD and price trend (TREND), as defined in Appendix A. Top (bottom) MAD portfolios consist of the highest (lowest) MRAT decile stocks (where MRAT is the ratio of 21-day to 200-day moving averages of prices) provided that MRAT is greater than one plus σ for the top decile and MRAT is smaller than one minus σ for the bottom decile, where σ is the monthly cross-sectional standard deviation of MRAT. The sample is from July 1977 to December 2018. One and two asterisks indicate significance at the 5% and 1% levels, respectively.

We next consider investment horizons that range from one to 12 months using decile-based hedge portfolios that are long (short) the MAD-based top (bottom) decile. When the investment horizon is longer than one month, portfolios with different time horizons are equally weighted per the rebalancing procedure advocated by Jegadeesh and Titman (1993). Table 4 summarizes the MAD payoffs over various holding periods and factor controls.

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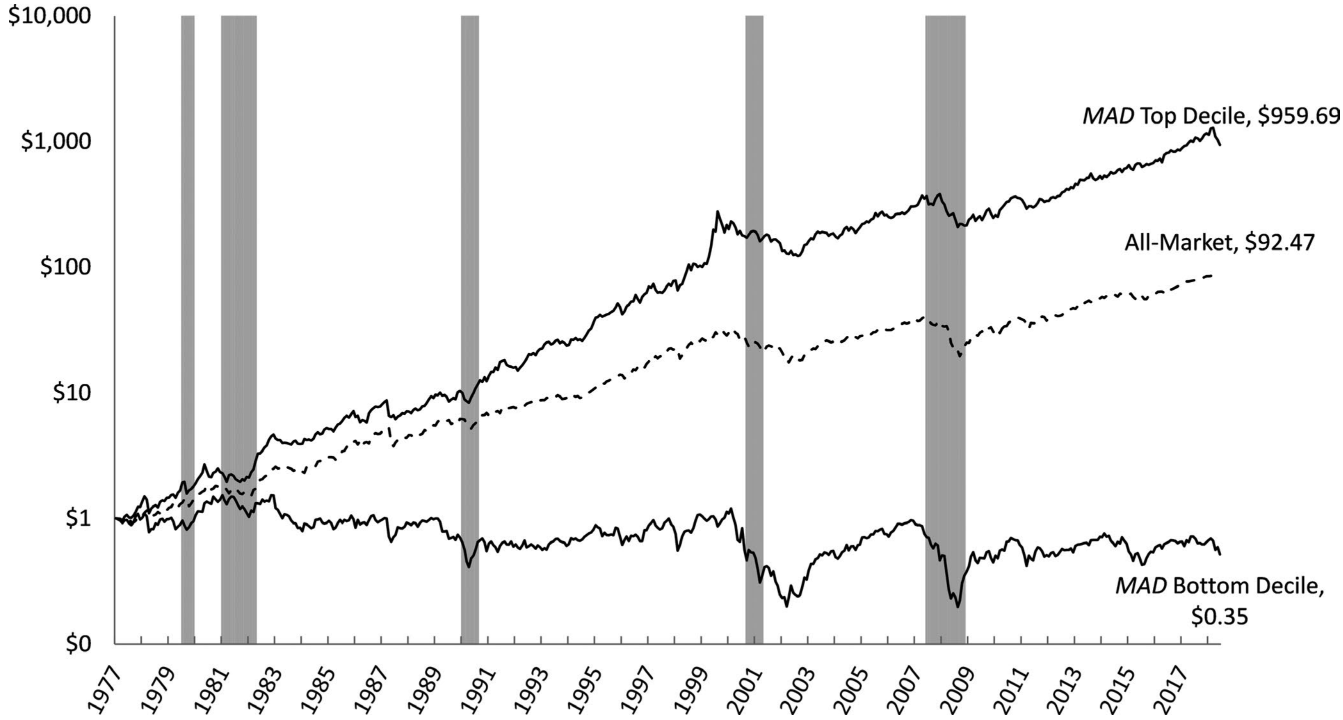

FIGURE 1 MAD-based investing. The figure depicts the value of $1 invested each month for the next month in buy and sell value-weighted portfolios corresponding to MAD strategies. The two MAD portfolios are the top (bottom) deciles based on MRAT (the ratio of 21-day to 200-day moving averages of prices) provided that that MRAT is greater than one plus σ for top decile and MRAT is smaller than one minus σ for bottom decile, where σ is the monthly cross-sectional standard deviation of MRAT. The "all-market" return is that on the CRSP value-weighted composite index. Gray bars represent NBER-defined recessions

The first test provides annual alpha estimates from regressing top-minus-bottom portfolio payoffs on the three Fama–French (1993) factors and UMD (the cross-sectional momentum factor proposed by Daniel et al., 1997). The MAD strategy yields alphas ranging from 5.43% (t = 3.13) for the 12-month horizon and 8.35% (t = 2.92) for the one-month horizon. Note that while the MAD effect declines as the horizon increases, it is present even after 12 months, and does not reverse.

Because MAD strategies are formed using subsets of stocks within the extreme deciles, in the next test we construct a variant of UMD so that we can fairly compare MAD and momentum. In particular, let U and D be the top and bottom deciles of the UMD portfolio, respectively. Then, UMD1 is the return spread between subsets of stocks in U and D, constructed as follows. The long portfolio of UMD1 consists of stocks in U with positive return values greater than a constant sigma, while the short portfolio consists of stocks in D with negative return values smaller than minus sigma. We define sigma as the cross-sectional standard deviation of returns over the past two to twelve months.[11] The evidence shows that controlling for UMD1, alphas are uniformly positive with sizeable magnitudes in the range of 5.41%–8.30%.

Recently, Fama and French (2015, 2016) propose a five-factor model based on the market, market capitalization, and the book-to-market ratio (items in the three-factor model), as well as investment and profitability. Fama and French (2015) use comparative statics from a present value relation to justify their five-factor model, and show that this framework eliminates several persistent anomalies including market beta, net share issues, and volatility. To examine whether our MAD phenomena survive this model, we regress returns of the MAD long-short portfolios on the five factors and momentum and a dummy variable for the financial crisis conditions in 2008 and 2009.[12] The third and fourth tests in Table 4, without and with a dummy variable for the financial crisis, respectively, also indicate large and significant alphas for all time horizons.

In a recent paper, Hou, Xue, and Zhang (2020) argue that abnormal profits from investing in anomalies attenuate when the impact of microcap stocks is mitigated by value-weighting returns. To mitigate the impact of small stocks, we already exclude stocks with end-of-month price below or equal to $5. Also excluded are stocks in their first year post-initial public offering and stocks that do not have daily trading activity. While these filters lessen the impact of microcaps, in the next test in Table 4 we also consider portfolios that exclude microcaps. Excluding microcap stocks, below the NYSE bottom quintile benchmark, alphas remain significantly positive with magnitude ranging from 6.87% to 9.33%.

TABLE 4 Annual alphas from MAD portfolios

Portfolio strategy	Holding period (months) 1	3	6	12
Panel A. MAD portfolios				
MAD top minus bottom				
Three FF factors and UMD	8.35**	8.29**	7.32**	5.43**
	(2.92)	(3.54)	(3.64)	(3.13)
Three FF factors and UMD1	8.30*	8.05**	6.96**	5.41**
(based on σ)	(2.45)	(2.75)	(2.72)	(2.67)
Five FF factors and UMD	9.69**	10.01**	9.68**	7.21**
	(3.32)	(4.22)	(4.85)	(4.13)
Five FF factors, UMD, and	9.05**	9.95**	9.42**	6.67**
A dummy for 2008–2009	(3.02)	(4.08)	(4.59)	(3.72)
No microcap stocks				
Five FF factors and UMD	8.92**	9.33**	9.15**	6.87**
	(2.86)	(3.69)	(4.30)	(3.66)
MAD top				
Five FF factors, UMD, and	9.00**	8.54**	8.67**	8.26**
A dummy for 2008–2009	(5.08)	(5.90)	(6.79)	(7.10)
MAD bottom				
Five FF factors, UMD, and a dummy for 2008–2009	–0.05	–1.41	–0.75	1.59
	(–0.02)	(–0.69)	(–0.41)	(0.99)
Panel B. MOM portfolios				
MOM top minus bottom				
Three FF factors	17.58**	15.51**	13.68**	8.86**
	(4.67)	(4.48)	(4.36)	(3.34)
Three FF factors and MAD	2.25	2.53	3.63	2.71
	(0.96)	(1.04)	(1.44)	(1.12)

Note: The table reports annual alphas (in %) and their t-values (in parentheses) obtained from regressing monthly decile-based hedge portfolio returns on the three/five Fama–French factors along with two alternative versions of momentum (UMD). Stock returns are value-weighted. Annual alphas are obtained by multiplying monthly alphas by 12 (no compounding). The MAD decile takes long (short) position in the top (bottom) MRAT decile (where MRAT is the ratio of 21-day to 200-day moving averages of prices), as long as the MRAT distance from one is at least σ, the monthly cross-sectional standard deviation of all stocks' MRAT. UMD is the momentum factor from Ken French website. The UMD1 factor mimics monthly returns on a portfolio that buys a subset of top momentum decile stocks whose returns over the past two to twelve months exceed a constant σ, and sells those bottom momentum decile stocks whose returns over the past two to twelve months fall below minus σ. We estimate σ as the monthly cross-sectional standard deviation of returns over the past two to twelve months. The market capitalization cutoff for microcap stocks is the NYSE bottom quintile threshold. The sample is from July 1977 to December 2018. One and two asterisks indicate significance at the 5%, and 1% levels, respectively.

The following two tests in Table 4 report alphas that correspond to the top and bottom portfolios separately. For the one-month horizon, the long side yields an alpha as high as 9.00% ($t = 5.08$), while the short-side counterpart is only − 0.05% ($t = -0.02$). Similar qualitative features obtain for the other time horizons. This indicates that unlike for momentum, where losers contribute materially to the strategy's profits (Hong, Lim, and Stein, 2000), MAD is mostly profitable on the long side.

To directly compare the performance of MAD with momentum, Panel B reports alphas for long-short regular momentum portfolios. Consistent with prior work, momentum alphas are all highly significantly positive when the three standard Fama–French factors are included as controls. Upon adding the MAD factor in the last test, momentum alphas drop to as low as one eighth of their original values, and forego significance. Thus, while the MAD portfolios in Panel A survive UMD and its MAD-analogous version, UMD1, MAD subsumes the standard momentum factor.

TABLE 5 Break-even transaction costs

Variable	Mean	Standard deviation	Min.	Max.
Panel A. Turnover				
MAD top	34.9	15.2	1.1	86
MAD bottom	38.5	20.6	1.5	99

	Holding period (months)			
Portfolio strategy	**1**	**3**	**6**	**12**
Panel B. Break-even transaction costs				
MAD top minus bottom				
Three FF factors and UMD	94	279	356	742
Three FF factors and UMD1 (based on σ)	93	271	336	690
Five FF factors, UMD, and A dummy for 2008–2009	101	332	579	1,102
MAD top				
Five FF factors, UMD, and A dummy for 2008–2009	142	387	707	1,453

Note: Panel A reports the descriptive statistics for monthly turnover (in %) over a one-month horizon for MAD-based top and bottom deciles. Panel B reports transaction costs that would zero out average abnormal returns (alphas) on the decile-based hedge value-weighted portfolios whose alphas are reported in Table 4. The sample is from July 1977 to December 2018.

4 | TRANSACTION COST ANALYSES

Do investment approaches that employ MAD similarly survive reasonable transaction costs after accounting for turnover in these strategies?[13] Panel A of Table 5 reports descriptive statistics for the monthly turnover of MAD top and bottom decile portfolios. Turnover is calculated as dollars traded per dollar of market capitalization (as, e.g., in Barber and Odean, 2001). The numbers simply imply the fraction of market capitalization turned over as a result of trading the firms that move into and out of portfolios. We find that the mean turnover for the top decile is 34.9% with a minimum of 1.1% and a maximum of 86%. The turnover figures for the bottom decile are slightly higher, at 38.5%, 1.5%, and 99%, respectively. [These figures exclude the first month of the sample, in which the turnover, by definition, is 100%.] Overall, the average holding time of a stock for the one-month horizon is about three months.

Panel B of Table 5 reports break-even transaction costs (TC) that would eliminate average abnormal profits of our proposed strategies in Table 4. These costs are calculated as follows. Let R_{lt} and R_{st} denote the returns on the long and short MAD deciles in month t, respectively. Similarly, let $\mathrm{TO}_{\mathrm{lt}}$ and $\mathrm{TO}_{\mathrm{st}}$ respectively denote the long- and short-side turnover in month t. Then, we calculate the TC that yields an alpha of zero when the quantity

$$\left[R_{\mathrm{lt}} - \mathrm{TO}_{\mathrm{lt}} \times \mathrm{TC}\right] - \left[R_{\mathrm{st}} + \mathrm{TO}_{\mathrm{st}} \times \mathrm{TC}\right]$$

is regressed on the relevant factors. Turnover (TO) is calculated every month directly from the exact changes in the relevant long or short portfolio composition. To illustrate, suppose for a one-month horizon, the long-side portfolio A is composed of 30% IBM, 30% Microsoft, 15% Alphabet, and 25% Apple (by market capitalization). If Alphabet and Apple stocks are to be sold for the next month's portfolio, then the long-side portfolio turnover ($\mathrm{TO}_{\mathrm{lt}}$) for that month is the proportion of those stocks in the portfolio (i.e., 40%). Similarly, for the three-month horizon if portfolio A is one of the three (equal-weighted) long-side portfolios and this portfolio is the one to be updated this month, then turnover is the product of the proportion of the stocks to be sold in portfolio A of 40% and the share of portfolio A in the total portfolio (33.3%), which yields 13.3%. Similarly, for the six-month horizon if portfolio A is the one to be updated out of six equally weighted portfolios, then turnover is 40% multiplied by 16.67% or 6.67%.

The figures in the table reflect the long-side alphas scaled each month by the long portfolio turnover plus the short-side alphas scaled by the short portfolio turnover. The results show that break-even costs increase with the holding period because longer holding periods imply lower turnover and thus lower transaction costs. Focusing on the one-month holding period, cutoff costs are 94, 93, and 101 bps depending on the underlying factor model. The corresponding figures for the 12-month holding period are as high as 742, 690, and 1,102 bps. In the last row of Panel B, we provide the break-even costs for the long-only leg of the MAD strategy; this calculation is pertinent as the profits from the strategy obtain predominantly from the long side (viz. Table 4). These break-even costs range from 142 to 1,453 bps over various horizons.

Korajczyk and Sadka (2004) estimate an all-stock effective spread for the 1967-1999 period. Their estimates range from 0.16 to 141 bps with a mean of 5.59 bps. Focusing on momentum trading, they estimate top and bottom momentum decile mean transaction costs at 5.01 bps (top) versus 14.97 bps (bottom) and 5.49 bps (top) versus 14.50 bps (bottom) depending on the exact implemented methodology. Moreover, based on Novy-Marx and Velikov (2016), the estimated average monthly costs of trading momentum and post-earnings-announcement drift for 1963-2013 range from 10 to 40 bps. The monthly break-even costs in Panel A are well above these estimates.[14]

5 | ANCHORING AND MAD

Why does the MAD effect obtain? One possibility is that investors continue to overreact to public signals that differ from the historical average. This accords with the feedback trading modeled in De Long et al. (1990). However, if investors do overreact, we should observe a long-run reversal of the MAD effect. In the results reported in Table 4, we find no evidence of reversals for returns up to 12 months after portfolio formation based on MAD. Similar unreported tests confirm that the same holds true up to 36 months after portfolio formation. Thus, the evidence accords with investor underreaction, rather than overreaction. We propose that investors underreact to MAD due to an anchoring bias (Tversky and Kahneman, 1974). In this bias, agents get fixated on a salient, but often irrelevant, anchor, so that their estimates move insufficiently relative to the anchor.

What are reasonable anchors? George and Hwang (2004) suggest that it is the 52-week high price. We propose a complementary anchor: a smoothed history of the stock's recent price performance. This anchor is suggested by earlier work. Thus, Kaustia, Alho, and Puttonen (2008) indicate that estimates of future market performance in the European Union are influenced by whether subjects are given a historical estimate from a rising stock market (Sweden) or a falling one (Japan). Further, Welch (2000) suggests that economists' estimates of the equity premium are influenced by past market performance and Kaplanski et al. (2016) find a similar influence on investors' forecasts of future market performance.

Based on the preceding arguments, we conjecture that investors' anchors about future stock prices are set around the historical moving averages of prices and fundamentals. Investors underreact to the arrival of new information that triggers a large deviation of prices from the anchor. Thus, the anchoring bias accords with why high (low) MAD stocks predict higher (lower) returns.

Our anchoring-based explanation implies that investors process small amounts of information, which generate small deviations, better than large amounts of information that cause sudden large deviations from the anchor and, in turn, a significant price underreaction. To verify this assertion, we next explore the interaction between MAD and the level of "suddenness." We repeat the Fama–MacBeth regression analyses reported in Table 2 with two additional explanatory variables, which represent the interaction of MAD with the level of suddenness: *SuddenUp* and *SuddenDown*. These variables are defined as follows. First,

TABLE 6 Cross-sectional regressions—sudden versus gradual deviations from anchor

Dependent variable	Observations	MAD	*SuddenUp*	*SuddenDown*	MOM1	52-HIGH1	TREND1
R_{t-1}	820,609	0.26**	0.81**	–0.39*	–0.01	–0.13	0.94**
		(3.42)	(5.65)	(–2.11)	(–0.10)	(–1.74)	(7.40)

Note: The table repeats the Fama–MacBeth regression analysis reported in Panel B of Table 2 with two additional explanatory variables: *SuddenUp* and *SuddenDown*, which stand for the interaction of MAD with the level of deviation suddenness. For each stock in top decile, we first calculate the suddenness level of positive deviations as the maximum positive monthly change in individual stocks' MRAT values in the last quarter. *SuddenUp* is equal to one if this level is above the top decile monthly median level and zero otherwise. *SuddenDown* is calculated the same way but with minimum negative changes and bottom decile. One and two asterisks indicate significance at the 5%, and 1% levels, respectively.

for each stock in the top decile, the suddenness of positive deviations is calculated as the maximum positive monthly change in the stock's MRAT during the previous quarter. The variable *SuddenUp* is equal to one if this maximum is above the top decile's monthly median level and zero otherwise. *SuddenDown* is calculated analogously for negative changes.

The results reported in Table 6 are in line with the anchoring explanation. The *SuddenUp* coefficient is positive and highly significant, suggesting that MAD-based predictability is stronger when positive deviations are sudden. The *SuddenDown* coefficient is negative and also significant, indicating that the same conclusion applies when negative deviations are sudden as well.

Finally, dividing the top-minus-bottom MAD decile portfolio into stocks with above- and below-median values of suddenness, we find that the portfolio of stocks with sudden deviations yields an annual average return of 22.89% (alpha of 12.15%, t = 3.32), whereas the portfolio with more gradual deviations yields 14.10% (alpha of 5.34%, t = 1.79). Overall, we find that MAD strategy produces higher returns when changes in MAD are sudden, supporting the anchoring rationale.

6 | CONCLUSION

We show that a high (low) distance between short- and long-run moving averages of prices (MAD) strongly predicts high (low) equity returns and the predictability survives a host of controls, including standard momentum and the 52-week high effect. Further, MAD subsumes UMD, the standard momentum factor, and is stronger on the long side relative to the short side. Moreover, MAD not only survives the 2008-2009 crisis, but also remains profitable in the recent 2001-2018 period. Our results complement existing research based on technical predictors in the cross section of equity returns. Specifically, they suggest a greater focus by practitioners on the distance between long- and short-run averages of prices, as opposed to the use of simple crossing rules that are activated when short-run averages cross long-run ones. In future research, it would be worth examining whether MAD also works at the aggregate market and sector levels, and in international settings.

ENDNOTES

[1] As an example of this bias, in Ariely, Loewenstein, and Prelec (2003), participants are asked to write the last two digits of their social security number and then asked to assess how much they would pay for items of unknown value. Participants having higher numbers bid up to more than double relative to those with lower numbers, indicating that they anchor on these digits.

[2] George and Hwang (2004) and Cen, Hilary, and Wei (2013) apply the anchoring bias to the 52-week high effect and the security analysis industry, respectively (see also George, Hwang, and Li, 2015). Li and Yu (2012) apply the George and Hwang (2004) reasoning to aggregate market index levels and market returns. Bouchaud et al. (2019) use the concept of sticky expectations to explain the profitability anomaly, and Da, Gurun, and Warachka (2014) argue that momentum arises due to slow diffusion of news, but they do not consider moving averages. Our work is complementary to these studies.

[3] See also Lo, Mamaysky, and Wang (2000), Chincarini and Kim (2006), and Lo and Hasanhodzic (2009).

[4] A month is a reasonable calendar heuristic for the retail investor. Park (2010) employs 50 days as the short-run horizon together with the 52-week high effect to explain intermediate-term momentum profits. We find that the 50-day horizon is not a good proxy for the short run because it fails to produce significant profits for value-weighted portfolios, in the more recent years, and after accounting for several control variables including the corresponding crossing rule.

[5] See, for example, https://www.investopedia.com/terms/b/buy-signal.asp. Han, Yang, and Zhou (2013) and Huang and Huang (2020) provide an empirical analysis of crossing rules (also termed "filter rules"). For earlier work on such rules, see Alexander (1961), Fama and Blume (1966), Levy (1967), Jensen and Benington (1970), Brock, Lakonishok, and LeBaron (1992), Allen and Karjalainen (1999), Bessembinder and Chan (1998), and Chan and Osler (1998).

[6] Indeed, using the 200-day moving average as a long-term proxy, and 50-day and 21-day counterparts as the short-term ones, we find that considering an indicator variable, which represents whether the golden cross and death cross are triggered in a particular month, leaves our central result largely unchanged. For next months' returns, the version of this variable that uses a 50-day proxy for the short run is marginally significant (t = 2.25), whereas the 21-day version is not significant (t = 1.17). Inclusion of the variable leaves the coefficient on *MAD* virtually unchanged from its value in Table 2, Panel B, and its t-statistic remains above 6. Full details are available from the authors.

[7] Appel (2005) proposes this measure, which involves first computing the signed distance between short- and long-run moving averages and then using a binary signal based on the signed difference between the distance and its moving average (see, e.g., goo.gl/eCkrk8).

[8] Using *MAD* along with continuous versions of *MOM*, *52H*, and *TREND*, makes virtually no difference to the results.

[9] In unreported tests, we confirm that *MAD* coefficient remains large and highly significant when controlling also for changes in analysts' recommendations, which accounts for the potential return effects of recommendation revisions (Stickel, 1992; Womack, 1996), and dispersion in analyst forecasts, as in Diether, Malloy, and Scherbina (2002). As both variables are confined to stocks covered by analysts in the Institutional Brokers' Estimate System (I/B/E/S) database, we do not include them in the main regressions.

[10] Including continuous versions of *MOM*1, *52H*1, and *TREND*1 makes no material difference to the *MAD* coefficients.

[11] In unreported tests, we find that using two times sigma as the threshold leads to very similar conclusions.

[12] The crisis dummy is statistically insignificant in all regressions.

[13] Chan, Jegadeesh, and Lakonishok (1999) argue that momentum strategies survive transaction cost estimates after accounting for their turnover. We apply an analogous approach to *MAD*-based strategies.

[14] Recall that the portfolios are rebalanced monthly. To interpret the annual numbers, consider the 12-month long-only break-even cost of 1421 bps. If the actual cost is, say, an effective spread of 1%, and you replace, say, 0.8, of one out of the 12 overlapping portfolios, the actual cost is only 1%*0.8/12 = 0.07% of your total portfolio every month, or 0.84% per year. This number is far lower than the break-even annual cost. Similar conclusions apply for other horizons and portfolios.

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APPENDIX A

Variable Definitions

Moving average distance ratio (MRAT) = 21-day moving average/200-day moving average of stock prices.

MA signal (MAS) = a dummy variable that is equal to one if current stock price> 200-day moving average, and zero otherwise.

Moving average convergence/divergence (MACD) = the difference between 26-day and 12-day exponential moving averages of stock price.

Return (R) = monthly total return. Delisting returns are added to the most recent month.

Momentum (MOM) = stock return over the past 2–12 months.

Past returns (R_{t-i}) = returns over one month (R_{t-1}), months 13–24 ($R_{t-13:t-24}$), and months 25–36 ($R_{t-25:t-36}$).

52-week high price (52H) = current price/highest price during the last 52 weeks.

Log size (ME) = log of end-of-month price times shares outstanding (in thousands).

Book-to-market ratio (BE/ME) = book equity/market value of equity. As in Davis, Fama, and French (2000), BE is the stockholders' book equity, plus balance sheet deferred taxes and investment tax credit, minus book value of preferred stock.

Trend (TREND) = expected return from Han, Zhou, and Zhu (2016, pp. 354–355), computed as the product of the average 12-month slope coefficients in cross-sectional regressions of returns on past moving averages for 3, 5, 10, 50, 100, 200, 400, 600, 800, and 1000 days (scaled by price levels) and the most recent realized values of these moving averages.

Idiosyncratic volatility (IVOL) = standard deviation of monthly residuals from the Fama–French three-factor model over a 60-month rolling window.

Turnover (TURN) = monthly shares traded/shares outstanding. The volume prior to 1992 for NASDAQ firms is corrected by a factor of 2 here and in illiquidity below.

Illiquidity (ILLIQ) = annual average of Amihud's daily illiquidity measure [$(|\text{return}|/\text{volume})\times 10^6$].

Standardized unexpected earnings (SUE) = the difference between current quarterly EPS and the corresponding previous year EPS divided by the standard deviation of quarterly EPS changes over the preceding eight quarters.

Standardized unexpected revenue growth (SURGE) = the difference between current quarterly revenue and the corresponding previous year's revenue divided by the standard deviation of quarterly revenue changes over the preceding eight quarters.

Accruals (Ac/A) = the difference between accrual and cash flow components of earnings, scaled by lagged total assets, as in Sloan (1996).

Asset Growth (dA/A) = the previous year's annual proportional change in assets per split-adjusted share, as in Fama and French (2008).

Net stock issues (NS) = annual change in the logarithm of split-adjusted shares outstanding, as in Pontiff and Woodgate (2008).

Profitability (Y/B) = equity income (income before extraordinary items, minus dividends on preferred, if available, plus income statement deferred taxes, if available)/book equity, as in Fama and French (2006).

Net operating assets (NOA) = the difference between operating assets and operating liabilities, divided by lagged total assets, as in Hirshleifer, Hou, Teoh, and Zhang (2004).

Gross profitability (GP) = gross profits/total assets, as in Novy-Marx (2016).

Distress O-score (OS) = Ohlson' (1980) distress O-score.

Return on assets (ROA) = income before extraordinary items/lagged total assets.

Investment-to-asset ratio (I/A) = change in gross property, plant and equipment, plus change in inventories divided by lagged total assets, as in Chen, Novy-Marx, and Zhang (2011).

Return on equity (ROE) = quarterly income before extraordinary items divided by quarterly lagged book equity, as in Hou, Xue, and Zhang (2015).

APPENDIX B

Slope estimates for control variables included in the regressions of

Dependent variable	ME	BE/ ME	R_{t-1}	$R_{t-13:t-24}$	$R_{t-25:t-36}$	SURGE	IVOL	TURN	ILLIQ	SUE	NS	dA/A	Y/B	I/A	GP	Ac/A	ROA	ROE	NOA	OS	MAS	MACD
Panel A. MRAT and continuous control variables																						
R_{t+1}	–0.10	0.23	–1.74	–0.08	–0.01	0.15	–3.51	–0.02	–0.03	0.08	–0.42	0.09	0.02	–0.16	0.43	–0.56	0.29	1.00	–0.37	0.00	–0.07	0.03
	(–3.24)	(2.93)	(–7.02)	(–1.49)	(–0.09)	(8.69)	(–3.36)	(–0.57)	(–2.53)	(4.18)	(–1.91)	(0.57)	(0.34)	(–0.92)	(2.95)	(–1.93)	(0.90)	(2.52)	(–3.96)	(0.09)	(–1.21)	(0.06)
$R_{t+2:t+6}$	–0.25	1.08	0.71	–0.35	0.35	0.39	–0.44	–0.74	–0.04	0.10	–2.52	1.13	0.05	–0.31	2.23	–2.88	0.59	2.59	–1.96	0.07	–0.02	0.14
	(–1.89)	(2.91)	(0.85)	(–1.25)	(1.18)	(5.85)	(–0.10)	(–4.29)	(–0.92)	(1.32)	(–2.61)	(1.77)	(0.18)	(–0.40)	(2.97)	(–2.20)	(0.46)	(3.67)	(–4.10)	(0.49)	(–0.11)	(0.12)
$R_{t+7:t+12}$	–0.19	1.17	1.79	–0.38	–0.03	0.04	–6.95	–0.53	0.03	–0.07	–3.90	0.64	0.68	0.44	2.34	–3.91	0.89	–1.30	–2.08	0.10	0.78	0.49
	(–1.26)	(2.35)	(1.96)	(–0.94)	(–0.08)	(0.32)	(–1.23)	(–2.58)	(0.44)	(–0.87)	(–3.50)	(0.96)	(1.40)	(0.42)	(2.42)	(–2.50)	(0.60)	(–0.83)	(–3.42)	(0.58)	(3.32)	(0.27)
2001–2018	–0.11	0.09	–1.33	–0.06	–0.06	0.15	–3.63	–0.05	–0.02	0.02	–0.32	0.13	–0.02	–0.47	0.38	0.21	0.57	–0.09	–0.19	0.04	–0.08	–0.23
	(–3.25)	(1.00)	(–3.89)	(–0.80)	(–0.77)	(5.46)	(–2.44)	(–2.03)	(–1.02)	(0.88)	(–1.01)	(0.58)	(–0.63)	(–1.54)	(1.81)	(0.48)	(2.20)	(–0.57)	(–1.74)	(1.95)	(–1.01)	(–0.32)
High sentiment	–0.09	0.30	–1.93	–0.04	–0.02	0.14	–4.46	0.02	–0.02	0.09	–0.52	–0.11	0.10	–0.04	0.56	–0.62	0.31	0.97	–0.40	0.02	–0.11	–0.24
	(–2.64)	(3.29)	(–5.88)	(–0.53)	(–0.37)	(6.86)	(–3.50)	(0.36)	(–2.39)	(3.98)	(–2.00)	(–0.62)	(1.15)	(–0.17)	(3.04)	(–1.94)	(0.88)	(3.22)	(–3.48)	(0.74)	(–1.47)	(–0.70)
Low sentiment	–0.11	0.12	–1.44	–0.15	0.02	0.17	–2.06	–0.08	–0.04	0.08	–0.28	0.38	–0.10	–0.34	0.24	–0.46	0.25	1.03	–0.31	–0.02	–0.02	0.44
	(–2.37)	(1.05)	(–4.15)	(–1.66)	(0.25)	(4.99)	(–1.18)	(–1.53)	(–1.57)	(2.79)	(–0.70)	(1.41)	(–0.99)	(–1.25)	(1.11)	(–1.00)	(0.43)	(1.39)	(–2.19)	(–0.60)	(–0.23)	(0.37)
High volatility	–0.09	0.11	–2.14	–0.09	–0.09	0.15	–3.19	0.02	–0.06	0.08	–0.36	0.20	0.08	–0.26	0.57	–0.67	0.10	1.25	–0.27	–0.02	–0.01	0.94
	(–1.89)	(1.05)	(–5.24)	(–1.11)	(–1.16)	(5.36)	(–2.03)	(0.26)	(–3.02)	(2.52)	(–1.15)	(0.92)	(0.86)	(–1.05)	(2.68)	(–1.78)	(0.23)	(2.14)	(–1.84)	(–0.59)	(–0.09)	(2.15)
Low volatility	–0.11	0.33	–1.37	–0.07	0.07	0.16	–3.80	–0.05	0.00	0.09	–0.48	–0.02	–0.03	–0.07	0.31	–0.45	0.45	0.76	–0.45	0.02	–0.13	–0.79
	(–3.36)	(4.15)	(–3.95)	(–1.13)	(1.12)	(6.50)	(–2.92)	(–1.00)	(–0.10)	(5.11)	(–1.71)	(–0.11)	(–0.30)	(–0.28)	(1.92)	(–1.20)	(1.22)	(2.22)	(–3.49)	(0.92)	(–1.93)	(–1.04)
High illiquidity	–0.11	0.38	–2.07	–0.06	0.07	0.17	–4.15	0.00	–0.03	0.11	–0.54	0.21	0.09	–0.10	0.66	–1.15	0.08	1.84	–0.42	–0.02	–0.11	0.41
	(–2.73)	(4.40)	(–5.30)	(–0.78)	(0.83)	(7.09)	(–2.64)	(0.00)	(–2.74)	(4.25)	(–1.58)	(0.92)	(0.72)	(–0.47)	(3.80)	(–3.20)	(0.14)	(2.79)	(–3.07)	(–0.62)	(–1.39)	(0.54)
Low illiquidity	–0.08	0.07	–1.40	–0.10	–0.08	0.14	–2.87	–0.04	–0.03	0.06	–0.31	–0.04	–0.04	–0.22	0.21	0.03	0.49	0.15	–0.31	0.02	–0.03	–0.34
	(–2.12)	(0.67)	(–4.17)	(–1.29)	(–1.13)	(5.35)	(–2.00)	(–1.61)	(–1.45)	(2.73)	(–1.00)	(–0.24)	(–1.28)	(–0.76)	(0.99)	(0.08)	(1.80)	(1.09)	(–2.39)	(0.51)	(–0.36)	(–0.58)
Positive market	–0.09	0.22	–1.69	–0.06	0.01	0.15	–3.39	–0.03	–0.03	0.09	–0.38	0.08	0.00	–0.20	0.33	–0.57	0.47	1.15	–0.41	0.01	–0.07	–0.10
	(–2.74)	(2.70)	(–6.36)	(–1.05)	(0.18)	(8.30)	(–3.11)	(–0.73)	(–2.50)	(4.81)	(–1.57)	(0.54)	(0.07)	(–1.06)	(2.21)	(–1.80)	(1.47)	(2.71)	(–4.16)	(0.23)	(–1.12)	(–0.19)
Negative market	–0.21	0.24	–2.10	–0.26	–0.14	0.15	–4.50	0.05	–0.08	0.04	–0.80	0.09	0.18	0.15	1.30	–0.44	–1.18	–0.27	0.00	–0.03	–0.07	1.00
	(–2.43)	(1.28)	(–2.93)	(–1.30)	(–1.13)	(2.42)	(–1.32)	(0.90)	(–1.33)	(0.60)	(–1.31)	(0.22)	(1.01)	(0.30)	(3.45)	(–0.59)	(–1.39)	(–0.72)	(–0.00)	(–0.58)	(–0.43)	(1.44)
Panel B. MAD and analogously defined control variables																						
R_{t+1}	–0.09	0.22	–2.84	–0.10	–0.01	0.15	–3.43	–0.01	–0.04	0.09	–0.51	0.07	0.03	–0.14	0.45	–0.55	0.23	1.10	–0.38	0.00	0.10	0.33
	(–2.94)	(2.86)	(–8.38)	(–1.81)	(–0.25)	(8.10)	(–2.92)	(–0.24)	(–2.69)	(4.46)	(–2.27)	(0.47)	(0.46)	(–0.80)	(2.99)	(–1.93)	(0.71)	(2.72)	(–4.06)	(0.08)	(1.46)	(0.61)
$R_{t+2:t+6}$	–0.24	0.94	1.74	–0.41	0.33	0.40	–4.42	–0.73	–0.03	0.14	–2.77	1.04	0.01	–0.33	2.21	–2.90	0.36	2.91	–1.91	0.07	1.32	0.17
	(–1.78)	(2.52)	(2.38)	(–1.48)	(1.10)	(5.73)	(–0.82)	(–3.94)	(–0.82)	(1.86)	(–2.78)	(1.53)	(0.04)	(–0.42)	(2.92)	(–2.23)	(0.28)	(3.80)	(–3.94)	(0.52)	(5.84)	(0.15)

(Continues)

APPENDIX B (Continued)

Dependent variable	ME	BE/ME	R_{t-1}	$R_{t-13:t-24}$	$R_{t-25:t-36}$	SURGE	IVOL	TURN	ILLIQ	SUE	NS	dA/A	Y/B	I/A	GP	Ac/A	ROA	ROE	NOA	OS	MAS	MACD
$R_{t+7:t+12}$	–0.18	1.18	2.23	–0.37	0.03	0.03	–6.62	–0.50	0.02	–0.08	–3.93	0.64	0.66	0.47	2.33	–3.91	0.91	–1.22	–2.06	0.10	0.96	0.56
	(–1.20)	(2.33)	(2.63)	(–0.92)	(0.07)	(0.26)	(–0.96)	(–2.40)	(0.29)	(–1.03)	(–3.52)	(0.96)	(1.37)	(0.44)	(2.40)	(–2.49)	(0.60)	(–0.79)	(–3.42)	(0.61)	(3.47)	(0.31)
2001-2018	–0.09	0.11	–1.57	–0.07	–0.05	0.14	–2.95	–0.04	–0.02	0.02	–0.41	0.11	–0.02	–0.42	0.39	0.24	0.58	–0.09	–0.18	0.05	0.01	–0.09
	(–2.66)	(1.10)	(–3.89)	(–0.98)	(–0.66)	(4.75)	(–1.81)	(–1.67)	(–0.99)	(0.83)	(–1.24)	(0.48)	(–0.62)	(–1.36)	(1.81)	(0.56)	(2.30)	(–0.58)	(–1.71)	(2.00)	(0.12)	(–2.66)
High sentiment	–0.08	0.29	–2.85	–0.08	–0.05	0.14	–5.31	0.02	–0.03	0.10	–0.60	–0.15	0.10	–0.05	0.58	–0.63	0.27	1.06	–0.40	0.02	0.14	–0.16
	(–2.43)	(3.51)	(–7.09)	(–1.17)	(–0.75)	(6.70)	(–3.80)	(0.36)	(–2.30)	(4.88)	(–2.34)	(–0.89)	(1.13)	(–0.24)	(3.31)	(–1.97)	(0.71)	(3.51)	(–3.36)	(0.81)	(1.80)	(–0.49)
Low sentiment	–0.11	0.12	–1.44	–0.15	0.02	0.17	–2.06	–0.08	–0.04	0.08	–0.28	0.38	–0.10	–0.34	0.24	–0.46	0.25	1.03	–0.31	–0.02	–0.02	0.44
	(–2.37)	(1.05)	(–4.15)	(–1.66)	(0.25)	(4.99)	(–1.18)	(–1.53)	(–1.57)	(2.79)	(–0.70)	(1.41)	(–0.99)	(–1.25)	(1.11)	(–1.00)	(0.43)	(1.39)	(–2.19)	(–0.60)	(–0.23)	(0.37)
High volatility	–0.08	0.12	–3.32	–0.11	–0.10	0.14	–2.44	0.03	–0.07	0.08	–0.44	0.22	0.10	–0.24	0.61	–0.65	0.03	1.35	–0.29	–0.02	0.03	1.00
	(–1.82)	(1.10)	(–6.44)	(–1.32)	(–1.22)	(4.83)	(–1.34)	(0.50)	(–3.21)	(2.67)	(–1.40)	(0.98)	(1.07)	(–0.93)	(2.91)	(–1.72)	(0.06)	(2.31)	(–2.00)	(–0.61)	(0.27)	(2.11)
Low volatility	–0.10	0.31	–2.41	–0.09	0.06	0.16	–4.32	–0.04	0.00	0.11	–0.56	–0.06	–0.03	–0.05	0.30	–0.47	0.41	0.87	–0.46	0.02	0.16	–0.50
	(–3.06)	(3.91)	(–6.37)	(–1.41)	(0.94)	(6.70)	(–3.15)	(–0.80)	(–0.31)	(5.88)	(–1.99)	(–0.33)	(–0.32)	(–0.20)	(1.83)	(–1.24)	(1.05)	(2.53)	(–3.57)	(0.89)	(2.25)	(–0.67)
High illiquidity	–0.11	0.35	–3.91	–0.07	0.05	0.17	–4.67	0.02	–0.03	0.13	–0.62	0.21	0.11	–0.10	0.68	–1.21	–0.01	2.05	–0.45	–0.02	0.07	0.84
	(–2.42)	(4.04)	(–8.26)	(–0.95)	(0.59)	(7.38)	(–2.70)	(0.30)	(–3.08)	(4.29)	(–1.85)	(0.86)	(0.83)	(–0.50)	(3.64)	(–3.52)	(–0.02)	(2.89)	(–3.45)	(–0.84)	(0.73)	(0.92)
Low illiquidity	–0.07	0.09	–1.79	–0.13	–0.08	0.13	–2.19	–0.03	–0.04	0.06	–0.39	–0.06	–0.04	–0.18	0.22	0.10	0.47	0.15	–0.30	0.03	0.13	–0.18
	(–2.08)	(0.83)	(–4.33)	(–1.66)	(–1.20)	(5.03)	(–1.40)	(–1.26)	(–1.68)	(2.92)	(–1.31)	(–0.34)	(–1.31)	(–0.63)	(1.10)	(0.25)	(1.65)	(1.09)	(–2.35)	(0.74)	(1.39)	(–0.26)
Positive market	–0.08	0.21	–2.88	–0.08	0.00	0.16	–3.65	–0.02	–0.03	0.10	–0.45	0.07	0.01	–0.19	0.34	–0.58	0.40	1.28	–0.42	0.00	0.15	0.19
	(–2.49)	(2.52)	(–7.84)	(–1.38)	(–0.04)	(8.30)	(–2.96)	(–0.48)	(–2.62)	(5.15)	(–1.89)	(0.44)	(0.16)	(–1.03)	(2.22)	(–1.84)	(1.27)	(2.88)	(–4.29)	(0.18)	(2.09)	(0.33)
Negative market	–0.18	0.30	–2.54	–0.25	–0.11	0.11	–1.65	0.07	–0.09	0.03	–0.96	0.09	0.20	0.28	1.35	–0.36	–1.19	–0.34	–0.01	–0.02	–0.29	1.00
	(–1.99)	(1.62)	(–4.08)	(–1.56)	(–0.88)	(1.61)	(–0.40)	(1.35)	(–1.42)	(0.41)	(–1.54)	(0.20)	(1.01)	(0.59)	(3.86)	(–0.46)	(–1.45)	(–0.84)	(–0.03)	(–0.45)	(–1.43)	(1.88)

APPENDIX C

MAD versus firm characteristics

Note

MAD Decile		MAD First R_{t+1}	MAD First $R_{t+2:t+6}$	MAD Last R_{t+1}	MAD Last $R_{t+2:t+6}$		MAD First R_{t+1}	MAD First $R_{t+2:t+6}$	MAD Last R_{t+1}	MAD Last $R_{t+2:t+6}$
Top	ME Bottom 30%	2.05	9.04	1.99	8.87	BE/ME Bottom 30%	1.79	7.26	1.91	8.20
Bottom		0.29	0.03	0.22	0.61		–0.26	–1.67	–0.41	–2.56
Diff.		1.76**	9.01**	1.77**	8.26**		2.05**	8.93**	2.32**	10.78**
Top	ME Core 40%	1.89	7.66	1.88	7.73	BE/ME Core 40%	1.81	8.34	1.82	8.21
Bottom		0.20	1.04	0.15	0.84		0.38	1.69	0.36	1.72
Diff.		1.69**	6.62**	1.73**	6.89**		1.43**	6.65**	1.46**	6.51**
Top	ME Top 30%	1.52	7.57	1.54	7.94	BE/ME Top 30%	1.85	8.38	1.51	8.38
Bottom		0.18	1.02	0.72	1.29		0.49	1.47	0.56	2.11
Diff.		1.34**	6.55**	0.82**	6.65**		1.36**	6.91**	0.95*	6.27**
Top	TURN Bottom 30%	1.78	9.01	1.68	9.06	ILLIQ Bottom 30%	1.61	7.14	1.54	7.63
Bottom		0.22	0.83	0.11	1.40		0.15	0.77	0.34	0.68
Diff.		1.56**	8.18**	1.57**	7.66**		1.46**	6.37**	1.20*	6.95**
Top	TURN Core 40%	1.97	8.44	1.91	8.58	ILLIQ Core 40%	1.84	7.48	1.72	7.63
Bottom		0.42	1.31	0.42	0.78		0.37	0.70	0.16	0.37
Diff.		1.55**	7.13**	1.49**	7.80**		1.47**	6.78**	1.56**	7.26**
Top	TURN Top 30%	1.66	6.10	2.02	7.70	ILLIQ Top 30%	1.98	9.22	1.91	9.34
Bottom		–0.13	–0.15	0.08	0.30		0.01	0.47	0.18	0.02
Diff.		1.79**	6.25	1.94**	7.40**		1.97**	8.75**	1.73**	9.32**
Top	SUE Bottom 30%	1.29	6.49	1.20	6.01	R_{t-1} Bottom 30%	2.20	7.42	2.28	7.31
Bottom		0.07	0.80	0.19	0.36		1.28	–0.41	0.93	0.44
Diff.		1.22**	5.69**	1.01*	5.65**		0.92*	7.83**	1.35**	6.87**
Top	SUE Core 40%	1.81	8.50	1.73	8.07	R_{t-1} Core 40%	1.66	8.33	1.86	7.85
Bottom		0.43	0.55	0.58	1.69		0.42	1.09	0.48	1.09
Diff.		1.38**	7.95**	1.15**	6.38**		1.24**	7.24**	1.38**	6.76**
Top	SUE Top 30%	2.34	8.96	2.27	9.08	R_{t-1} Top 30%	1.64	8.29	1.79	8.73
Bottom		0.11	0.71	–0.13	1.03		–1.11	1.12	–1.69	1.16
Diff.		2.23**	8.25**	2.40*	8.05**		2.75**	7.17**	3.48**	7.57**
Top	IVOL Bottom 30%	1.81	8.95	1.58	7.63	$R_{t-13:t-24}$ Bottom 30%	1.74	8.33	1.67	8.2
Bottom		1.01	2.67	0.69	2.11		0.24	2.10	0.39	1.27
Diff.		0.80*	6.28**	0.89*	5.52**		1.50**	6.23**	1.28**	6.93**
Top	IVOL Core 40%	2.16	9.05	1.96	9.35	$R_{t-13:t-24}$ Core 40%	1.85	8.24	1.73	8.24
Bottom		0.95	1.37	0.91	2.44		0.38	1.17	0.34	1.20
Diff.		1.21**	7.68*	1.05**	6.91**		1.47**	7.07**	1.39**	7.04**
Top	IVOL Top 30%	1.89	7.90	2.11	8.62	$R_{t-13:t-24}$ Top 30%	1.66	6.10	1.76	7.62
Bottom		0.04	1.73	0.56	2.05		–0.13	–0.15	0.15	–0.02
Diff.		1.85**	6.17**	1.55**	6.57**		1.79**	6.25**	1.61**	7.64**

Note: The table reports average portfolio returns for the next month and months 2 through 6 for 3 × 3 sorts on MAD and one additional characteristic, as defined in Appendix A. Top (bottom) MAD portfolios consist of the top (bottom) MRAT decile stocks (where MRAT is the ratio of 21-day to 200-day moving average of prices) provided that MRAT is greater than one plus σ for top portfolios and MRAT smaller than one minus for bottom portfolios, and σ is the monthly cross-sectional standard deviation of MRAT. The sample is from July 1977 to December 2018. One and two asterisks indicate significance at the 5% and 1% levels, respectively.