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.

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 or *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

[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 higher numbers, indicating that they anchor on these digits.

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 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 which 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, LeBaron, and Lakonishok (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.

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[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).

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 account for reasonable trading cost estimates.

1. 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 value 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

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

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 amongst market participants.]

[4] Moving averages over the past month and over the past 50 days are popular short-term proxies (see, for example, https://tinyurl.com/wa9y5jz and https://tinyurl.com/surexwr). A month is a reasonable calendar heuristic for the retail investor. Further, we find that the 50-day short-run horizon is not a good proxy for the short-run, suggesting a greater focus instead on the 21-day moving averages.

In common technical rules, a buy (sell) signal occurs when shorter-term moving averages cross longer-term counterparts from below (above), according with 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. However, 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 our second step, 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 see whether *MAD* allows practitioners to earn statistically and economically

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5 See, e.g., 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, leave our central result largely unchanged. For next months' returns, the version of this variable which 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* remains virtually unchanged from its value in Table 2, Panel B, and its t-statistic remains above 6. Full details are available from the authors.

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 18 predictive characteristics that are described below. We also control for a binary signal denoted *MAS*, which equals one 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 18 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

[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).

deviation of quarterly EPS using the most recent eight quarters (Ball and Brown, 1968). Standardized unexpected revenue growth (*SURGE*) controls for post-revenue 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, 2006).

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-assets ratio (*I/A*) is formed as in Titman, Wei, and Xie (2004), and Xing (2008). Return on equity (*ROE*) (Haugen and Baker, 1996) is calculated as income before extraordinary items divided by the most recent quarter's book equity.

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-Assets (*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.

2. *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.

2.1 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 *MOM*1, *52H*1, and *TREND*1, 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 7-12 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 does attenuate over increasing investment horizons, it does not reverse.

We next examine the 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,

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

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 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: *MOM*1, *52H*1, and *TREND*1. 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

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[9] In unreported tests we confirm that *MAD* coefficient remains large and highly significant when controlling also for change in outstanding recommendations, which accounts for the potential effect 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.

different states of the economy also are similar to those in Panel A.[10]

Recently, Harvey, Liu, and Zhu (2016) argue that in light of the numerous attempts to detect factors that explain 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 we obtain *t*-ratios for *MAD* that 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.

2.2 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 months 2-6 returns of 7.86% and –0.08%, respectively. In the last two columns, 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 those for those with the lowest values.

Appendix C reports double-sort results on *MAD* and, in turn: (i) size (*ME*), (ii) book-to-

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

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.

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.

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 three-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 *UMD*1 is the return spread between subsets of stocks in *U* and *D*, constructed as follows. The long portfolio of *UMD*1 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 *UMD*1, 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 as well as momentum and a dummy variable for the financial crisis conditions in 2008 and 2009.[12] This third test in Table 4 also indicates large and significant alphas for all time horizons.

[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.

The next 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 of 9.37% (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 eighths of their original values, and forego significance. Thus, while the *MAD* portfolios in Panel A survive *UMD* and its *MAD*-analogous version, *UMD*1, *MAD* subsumes the standard momentum factor.

3. 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. The mean turnover for the top decile is 34.9% with a minimum at 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

[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.

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 TO_{lt} and TO_{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

$$[R_{lt} - TO_{lt} \times TC] - [R_{st} + TO_{st} \times TC]$$

is regressed on the relevant factors. The figures in the table thus 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 breakeven 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 breakeven 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 break-even costs in Panel A are well above these estimates.

We also calculate the value-weighted grand mean for the percentage quoted spread for all stocks (obtained from CRSP on a daily basis). This spread does not account for the lower transaction costs institutions can negotiate, but it is a reasonable estimate for a retail investor. We find that for stocks in the top decile, the average percentage quoted spread equals 321 bps on a value-weighted basis, while for the bottom decile it equals 510 bps. Comparing these estimates to the breakeven cost estimates in Table 5, Panel B, we conclude that for retail investors, the long-horizon 12-month strategy is more viable than the shorter-horizon ones.

4. 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) suggest that economists' estimates of the equity premium and are influenced by past market performance and Kaplanski et al. (2016) find 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, 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 three quarters. The variable *SuddenUp* is equal 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 highly 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 23.97% (alpha of 12.57%, t = 3.51), whereas the portfolio with more gradual deviations yields 14.30% (alpha of 5.62%, t = 2.60). Overall, we find that *MAD* strategy produces higher returns when changes in *MAD* are sudden, supporting the anchoring rationale.

5. 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 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 if *MAD* also works at the aggregate market and sector levels, and in international settings.

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Table 1. Descriptive statistics

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.

Variable	Observations (000)	Mean	Standard Deviation	Min.	Max.	Percentile 5th	25th	median	75th	95th	Correlation with *MRAT*
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 (*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
Assets 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-Assets (*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

Table 2. Cross-sectional regressions

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*, *MOM*1, *52H*1, and *TREND*1 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*. *MOM*1, *52H*1, and *TREND*1 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.

Panel A. *MRAT* and Continuous Control Variables

Dependent Variable		**Observations**	***MRAT***	***MOM***	***52H***	***TREND***
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)

Panel B. *MAD* and Analogously Defined Control Variables

Dependent Variable		Observations	*MAD*	*MOM*1	*52H*1	*TREND*1
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)
	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)

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

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.

MAD			***MAD First***		***MAD Last***	
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			1.60	7.86	0.69	6.25
Bottom	*MOM* Bottom 30%		–0.27	–0.08	0.13	0.20
Diff.			1.87**	7.94**	0.56	6.05**
Top			1.69	8.57	1.67	7.88
Bottom	*MOM* Core 40%		0.24	0.60	0.55	0.81
Diff.			1.45**	7.97**	1.12**	7.07**
Top			2.18	7.54	2.07	8.57
Bottom	*MOM* Top 30%		0.69	1.50	1.15	0.24
Diff.			1.49**	6.04**	0.92*	8.33**
			Panel C. *MAD* and *52H*			
Top			2.03	7.41	1.60	3.10
Bottom	*52H* Bottom 30%		0.29	0.01	0.33	0.45
Diff.			1.74**	7.4**	1.27*	2.65**
Top			2.04	8.45	2.05	7.98
Bottom	*52H* Core 40%		0.35	0.52	–0.49	6.18
Diff.			1.69**	7.93**	2.54**	1.80
Top			1.35	8.15	1.84	9.10
Bottom	*52H* Top 30%		–0.02	1.88	–3.07	8.88
Diff.			1.37**	6.27**	4.91**	0.22
			Panel D. *MAD* and *TREND*			
Top			1.25	8.20	0.87	8.29
Bottom	*TREND* Bottom 30%		–0.80	–0.46	–0.22	0.18
Diff.			2.05**	8.66**	1.09*	8.11**
Top			1.79	8.19	1.48	8.03
Bottom	*TREND* Core 40%		0.42	1.98	0.70	0.2
Diff.			1.37**	6.21**	0.78*	7.83**
Top			2.42	7.62	2.26	7.72
Bottom	*TREND* Top 30%		0.88	0.20	1.38	0.75
Diff.			1.54**	7.42**	0.88*	6.97**

Table 4. Annual alphas from *MAD* portfolios

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 *UMD*1 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 sample is from July1977 to December 2018. One and two asterisks indicate significance at the 5%, and 1% levels, respectively.

		Holding Period (months)			
Portfolio Strategy		**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 *UMD*1	8.30*	8.05**	6.96**	5.41**
	(based on σ)	(2.45)	(2.75)	(2.72)	(2.67)
	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)
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	–0.05	–1.41	–0.75	1.59
	a dummy for 2008-2009	(–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)
MOM Top minus Bottom	Three FF factors and *MAD*	2.25	2.53	3.63	2.71
		(0.96)	(1.04)	(1.44)	(1.12)

Table 5. Break-even transaction costs

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.

Panel A. Turnover

Variable	**Mean**	**Standard Deviation**	**Min.**	**Max.**
MAD Top	34.9	15.2	1.1	86
MAD Bottom	38.5	20.6	1.5	99

Panel B. Break-even Transaction Costs

Portfolio Strategy		**Holding Period (months)**			
		1	**3**	**6**	**12**
MAD Top minus Bottom	Three FF factors and *UMD*	94	279	356	742
	Three FF factors and *UMD*1 (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

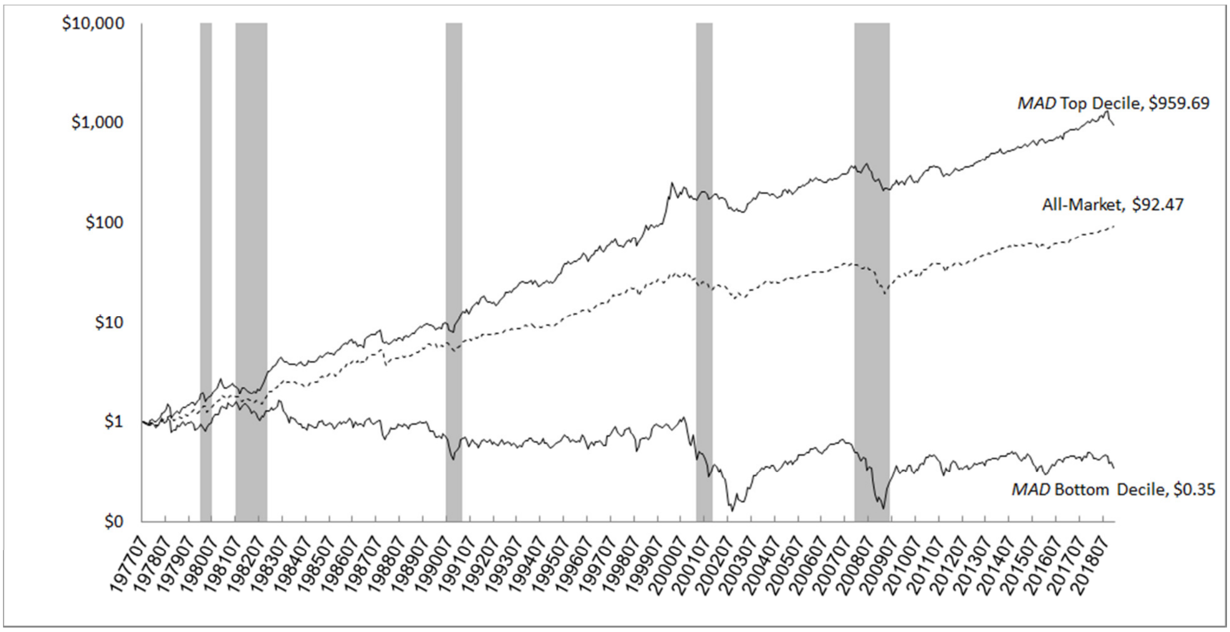
Table 6. Cross-sectional regressions – Sudden versus gradual deviations from anchor

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 three quarters. *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.

Dependent Variable	Observations	*MAD*	*SuddenUp*	*SuddenDown*	*MOM*1	*52-HIGH*1	*TREND*1
R_{t-1}	820,609	0.18**	1.04**	–0.54**	–0.02	–0.14	0.93***
		(2.60)	(6.66)	(–3.01)	(–0.27)	(–1.80)	(7.41)

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.



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 (*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 $[(|return|/volume)\times 10^6]$.

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-Assets (*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 Table 2

Panel A. *MRAT* and Continuous Control Variables

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+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

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+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)
$R_{t+7:t+12}$	–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

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 σ 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.

MAD		*MAD First*		*MAD Last*			*MAD First*		*MAD Last*	
Decile		R_{t+1}	$R_{t+2:t+6}$	R_{t+1}	$R_{t+2:t+6}$		R_{t+1}	$R_{t+2:t+6}$	R_{t+1}	$R_{t+2:t+6}$
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	*M*E 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	*M*E 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**