Stock Return Predictability:
New Evidence from Moving Averages of Prices and Firm Fundamentals

Doron Avramov[a]

Guy Kaplanski[b]

Avanidhar Subrahmanyam[c]

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

JEL classification codes: G12, G14

[a] IDC Herzliya, Herzliya, Israel; email: davramov@idc.ac.il

[b]Bar-Ilan University, Ramat-Gan, Israel; email: guykap@biu.ac.il.

[c]The Anderson School at UCLA, Los Angeles, CA 90095-1481; email: subra@anderson.ucla.edu. Corresponding author; phone: (310) 825-5355; fax: (310) 206-5455.

We thank Yakov Amihud, Chen Yao, Si Cheng, Guofu Zhou, Xue Wang, and seminar participants at Chinese University of Hong Kong (Shenzhen), Korean University, Korea Advanced Institute of Science and Technology, National University of Singapore, National University of Taiwan, Nanyang Technological University, Tsinghua University (SEM), Xiamen University, and the CICF2018 conference, for valuable comments and suggestions.

Stock Return Predictability:
New Evidence from Moving Averages of Prices and Firm Fundamentals

Abstract

The distances between short- and long-run moving averages of prices and deviations of accounting fundamentals from their preceding means both predict cross-sectional stock returns. This predictive power goes well beyond momentum, the 52-week high, profitability, and other prominent predictors, and applies at the market and industry levels. The price-based distance also predicts returns in international settings. We use data on corporate news releases to support the notion that the predictability arises because investors underreact to deviations from prevailing anchors. The evidence indicates that fundamentals-based anchoring predicts returns incremental to the price-based analog and both forms of predictability are economically significant.

1. Introduction

In a capital market that is efficient, prices are random walks because they aggregate all publicly available information (Lo and MacKinlay, 1988). This form of efficiency is readily enforceable via simple forms of arbitrage and as such, might be expected to hold. In reality, however, practitioners use several technical trading rules (see, for example, Brock, LeBaron, and Lakonishok, 1992; Lo, Mamaysky, and Wang, 2000; and Han, Yang, and Zhou, 2013). Such rules are also used in portfolio management (Chincarini and Kim, 2006; Lo and Hasanhodzic, 2009). We show that a little-explored variable in the academic literature, the signed distance between short- and long-run moving averages of past prices, has strong predictive power for returns, in both U.S. and cross-country settings. This predictive ability survives a comprehensive set of other technical rules, including momentum (Jegadeesh and Titman, 1993) and 52-week highs (George and Hwang, 2004). Indeed, the predictor is profitable in all standard momentum deciles and yields significant profits on both long- and short-legs, unlike many other cross-sectional predictors (Stambaugh, Yu, and Yuan, 2012). We propose and provide evidence that such predictability obtains because investors are anchored to long-term averages, so that they underreact to deviations from such averages.[1] We uncover another new result by showing that anchoring extends to firm fundamentals as well. Specifically, deviations of key accounting characteristics from their preceding means strongly predict cross-sectional returns.[2]

We first show that the greater the positive (negative) distance between a short-run (21-

[1] George and Hwang (2004) show that the nearness of the price to its past 52-week high strongly predicts stock returns and also provide an anchoring rationale for their finding (see also George, Hwang, and Li, 2015). Our proposed anchor is complementary to theirs.

[2] Earlier literature analyzes binary crossing rules involving moving averages. Usually, such rules signal a buy when a short-run moving average crosses a long-run one from below and vice versa. For instance, Appel (2005) proposes the convergence/divergence (*MACD*) 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). Here, we demonstrate that a stock's future performance is a *continuous* function of the distance between moving averages of stock prices as well as accounting variables.

day) and a long-run (200-day) average, the higher (lower) is the average return. This strategy (that we term moving average distance, or *MAD*) yields profits that do not decay even after several months. Returns from the strategy are in excess of 12% per year, and *MAD* survives a long list of other anomalies, including, as already mentioned, standard momentum and the 52-week high, as well as a moving average binary crossing rule, the recently proposed trend factor of Han, Zhou, and Zhu (2016), short- and long-run reversals, post announcement earnings drift, analysts' revisions, and forecast dispersion. *MAD* profitability remains significant in the recent 2001-2016 period, when a number of other anomalies have been shown to decay considerably (McLean and Pontiff, 2016; Chordia, Roll, and Subrahmanyam, 2014). Finally, Fama-MacBeth-type regressions and portfolio analyses across countries provide reliable evidence that the *MAD* rule yields material profits in this setting as well.

Why should such a rule yield positive abnormal profits? Since the returns to the strategy survive standard factor models, and top *MAD* stocks do not display materially higher risk measures relative to other stocks, a risk-based explanation is challenging. This leaves us with the possibility that the results are attributable to investor misreaction. Because *MAD* profits do not show signs of reversal even after two years, our evidence accords with investor underreaction being the source of profits, as opposed to continuing overreaction. Moreover, the gradual information diffusion-based underreaction advocated by Hong and Stein (1999) and Hong, Lim, and Stein (2000), or the frictions-based underreaction proposed by Hou and Moskowitz (2005) do not accord with the *MAD* effect we observe. In particular, top *MAD* stocks are not markedly different from other stocks in terms of size, institutional holdings, or forecast dispersion. Further, top *MAD* stocks tend to be liquid and have higher turnover than other stocks.

We propose an explanation for our result based on the psychological bias of anchoring, which is the notion that agents rely too heavily on readily obtainable (but often irrelevant) signals in forming assessments (Tversky and Kahneman, 1974).[3] We posit that the *MAD* effect occurs because investors get anchored to the 200-day moving average, which is a smoothed estimate of the stock's recent price history. Such an anchor is suggested by Welch (2000), Kaustia, Alho, and Puttonen (2008), and Kaplanski et al. (2016), who indicate that agents' forecasts of future market performance are anchored to past performance. The bias implies that agents deviate insufficiently from the anchor in forming estimates of future prices. Thus, suppose some material news causes a large price move and results in a large departure of the short-term moving average from investors' prevailing anchor, the long-term moving average. Agents underreact to the news, which implies that the price drifts upward (downward) if the distance is large positive (negative).[4]

We go beyond positing the anchoring rationale by testing specific hypotheses suggested by this bias. We propose an implication of anchoring: Investors should continue to underreact to positive news that follows a positive *MAD*, but the corresponding underreaction to negative news should be muted. This is because when *MAD* is positive, favorable news that boosts prices further above the anchor should cause underreaction, but adverse news that moves prices down towards the anchor should cause a more muted reaction. [A reverse argument holds for large negative *MAD*.] Supporting this conjecture, we show that when *MAD* is large positive, the drift following positive earnings surprises, new buy recommendations (over the next six months), and dividend initiations is considerably higher than the drift for firms with a large negative *MAD*. Conversely, when *MAD* is large negative, the drift following negative earnings surprises, new

[3] 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 lower numbers bid up to more than double relative to those with higher numbers, indicating that they anchor on these digits.
[4] 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.

sell recommendations, and seasoned equity issues is considerably lower (more negative) than for firms with a large positive *MAD*. This shows that investors underreact to news that leans in the same direction as *MAD*, supporting the anchoring rationale.

If anchoring is indeed the cause of *MAD*-based predictability, then our rationale should apply more broadly. That is, investors may get anchored not just to price-based moving averages, but also to those based on widely-followed financial statement items.[5] Thus, a large deviation from average values for the more visible accounting numbers should cause underreaction. We show that this is indeed the case. Defining a comprehensive analog of *MAD* using several accounting variables related to operating performance (termed performance deviation index or *PDI*), we show that this fundamentals-based measure strongly predicts returns incremental to *MAD*, even in the most recent fifteen years of our sample.

In terms of magnitude, we find that extreme decile hedge portfolios formed on *MAD/PDI* stocks generate average returns of more than 13% per year. After adjusting for standard risk factors, the performance of *MAD/PDI* still exceeds 12%. This is about the same order of magnitude as the profitability of momentum in Jegadeesh and Titman (1993). Further, the breakeven levels of transaction costs for the rules are well above reasonable trading cost levels. The rules remain viable in the more recently developed five-factor model of Fama and French (2015), survive value-weighted portfolios, and also predict returns at the market and industry levels.

Our work relates to the extensive literature on behavioral biases applied to explain return anomalies. Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam

[5] Different categories of investors may anchor to different types of variables. For example, the "newswatchers" in Hong and Stein (1999) (who only consider news in forming demands) may anchor to accounting variables, whereas their "trend-chasers" (who only condition on market prices), could anchor to moving averages of prices. The assumption, here, as in Hong and Stein (1999), is that each class is capital constrained enough to not fully arbitrage the behavioral proclivity of the other class.

(1998), respectively, use the representativeness bias and overconfidence to explain value and momentum effects. Barberis and Huang (2001) argue that mental accounting can explain value effects. Barberis, Mukherjee, and Wang (2016) show that stocks whose past return distributions have higher prospect theory values earn, on average, lower subsequent returns. Our paper fits into this literature by proposing that the anchoring bias of Tversky and Kahneman (1974) accords with a remarkably robust trading strategy across prices as well as firm fundamentals. Specifically, *MAD* and *PDI* yield significant returns in periods of high and low sentiment, market volatility, and aggregate liquidity. Also, our paper complements important earlier work on technical indicators by Brock, LeBaron, and Lakonishok (1992) and Han, Yang, and Zhou (2013). These papers consider technical strategies mostly based on binary crossing rules. We spotlight a specific distance-based rule, relate it to the anchoring bias, and show that an analog of the rule is also profitable when applied to firm fundamentals.

This paper is organized as follows. Section 2 describes the data. Section 3 presents the cross-sectional relation between *MAD* and future returns. Section 4 relates the *MAD*-return relation to anchoring, and shows that a predictor based on deviations of firm fundamentals from their moving averages (i.e., *PDI*), also predicts returns. Section 5 explores whether profits on *MAD/PDI*-sorted portfolios survive reasonable transaction cost estimates and recently-proposed risk factors. Section 6 considers the aggregate relation between *MAD* and future market returns. Section 7 considers *MAD* in an international context, and Section 8 concludes.

2. The 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, stocks that do not record return observations for the previous 12 months, and stocks for which there are no available records to construct our controls for cross-sectional return predictors.

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 June 1977, when all accounting reports for 1976 are publicly available, and ends in October 2015. Altogether, we capture 806,485 monthly returns for 8,367 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 of average stock returns is formed as:

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

where MA(21) is the stock price moving average based on approximately the past one month (21 trading days) and MA(200) is the corresponding 200-day moving average. According to Brock, LeBaron, and Lakonishok (1992), MA(200) is a popular long-term moving average amongst investors using MA strategies. Further, MA(200) is the longest moving average employed by Han, Yang, and Zhou (2013).[6] We focus on the quantitative value of *MAD*, and also consider an *MAD* signal that is unity if *MAD* exceeds (falls below) specified thresholds. In computing moving averages, stock prices are adjusted for splits and dividend distributions.

To ensure that *MAD* does not merely capture well-established phenomena or other

[6] Our results are robust to considering an alternative long-term anchor, MA(250), which is the approximate annual moving average in terms of trading days. Since the price over a single day is a noisy proxy for deviations from the long-term, we average over the most recent prices for the numerator. Our results are robust to considering short-term moving averages ranging from 5 to 35 trading days.

technical trading rules, we control for 19 firm-level predictive characteristics that are described below. We also control for a binary signal denoted *MAS*, which records the value one if the current price exceeds the 200-day moving average and zero otherwise, the *MAD* signal (*MDS*) noted above, the *MACD* convergence/divergence measure (see Footnote 2), five 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 (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 (*TRND*) 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 (Haugen and Baker, 1996; Hu, 1997; Datar, Naik, and Radcliffe, 1998; Rouwenhorst, 1998; Chordia, Roll, and Subrahmanyam, 2011). The Amihud (2002) illiquidity measure (*ILLIQ*) is the monthly average of daily absolute return per dollar of daily trading volume. The 52-week high (*52HIGH*) captures the variable 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. We use *SUE* to control for the post-earnings announcement drift per Ball and Brown (1968) and Bernard and Thomas (1989, 1990). The variable representing analysts' upgrades-downgrades (*RUD*) is calculated as the number of upgrades minus downgrades divided by the total number of outstanding recommendations. *RUD* accounts for the potential effect of recommendation revisions (Stickel, 1992; Womack, 1996). Net stock issues (*NS*) controls for high returns following stock repurchases (Ikenberry, Lakonishok, and Vermaelen, 1995) and low returns following stock issues (Loughran and Ritter, 1995; Daniel and Titman, 2006; 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 Haugen and Baker (1996), 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 Fairfield, Whisenant, and Yohn (2003), Titman, Wei, and Xie (2004), and Xing (2008). Return on equity (*ROE*) 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, new operating assets, and credit risk. In particular, Novy-Marx (2013) argues that gross profits scaled by assets (*GP*) are associated with higher future returns, Sloan (1996) finds a negative relation between accruals (*Ac/A*) and returns, Chen, Novy-Marx, and Zhang (2011) show that return on assets (*ROA*) is positively associated with future stock returns, and Hirshleifer et al. (2004) argue that net operating assets scaled by total assets (*NOA*) are a strong negative predictor of returns. To account for the credit risk effect, we consider the Ohlson (1980) distress O-score (*DTRS*), as in Campbell, Hilscher, and Szilagyi (2008).

Panel A of Table 1 displays descriptive statistics for stock returns and control variables. Notably, there is large variability in profitability (*Y/B*), illiquidity (*ILLIQ*), and *MACD* relative to their means; however, these variables are not the focus of our analysis.

3. The *MAD*-Return Relation

In this section, we explore the ability of *MAD* to predict the cross-section of future stock returns. Panel B of Table 1 provides next months' average returns on ten portfolios sorted on *MAD*. The evidence indicates that returns increase nearly monotonically with *MAD* from 0.84% (bottom portfolio) to 1.92% (top portfolio). The hypothesis of equal means across extreme *MAD* deciles is strongly rejected (t = 3.62). Figure 1 displays average returns per *MAD* decile. Panel A depicts next months' average returns, while Panel B displays the average cumulative returns for months 2 through 6. The latter five-month horizon also delivers a return spread between the top and bottom *MAD* portfolios that is economically large (about 7%).

We next show that the *MAD*-return relation is a significant and robust phenomenon that is unexplained by short- and long-term reversals, intermediate-term momentum, or previously considered technical indicators. It exists at both the cross-section and aggregate and survives reasonable transaction costs. Notably, unlike the vast majority of market anomalies, the *MAD* effect is also robust in the long-leg of the trade in recent years, as well as across various states of the economy including high versus low investor sentiment, market volatility, and aggregate liquidity.

3.1 Cross-Sectional Regressions

We now employ the Fama and MacBeth (1973) cross-sectional regression setup. For each month, we regress monthly stock returns on *MAD*, the above-described predictive characteristics, the *MAS* and *MDS* binary signals, and past return instruments. Table 2 reports the slope coefficients for *MAD*, past returns for months 2 to 6 (*MOM*), the 52-week high price (*52HIGH*), and the trend variable (*TRND*) 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 *MAD*. Estimated slope coefficients for all other control variables are reported in Appendix B.

The dependent variable in the first test is the one-month-ahead return. In Table 2, the *MAD* coefficient is economically large at 2.79% and highly significant (t = 5.80). The *MOM* and *TRND* coefficients are also positive and highly significant. The *52HIGH* is positively associated with the future one-month return on a stand-alone basis. These results confirm George and Hwang (2004) and Han, Zhou, and Zhu (2016). However, *MAD* survives all of the controls.

For an investment horizon of 2-6 months, the *MAD* coefficient is especially large (11.54%) and highly significant (t = 8.98), even after accounting for *MOM*, *52HIGH*, and *TRND*, either individually, or all inclusive. The coefficients for the binary *MAS* and *MDS* are also indistinguishable from zero (see Appendix B) in the presence of *MAD*. The evidence thus suggests that our proposed *MAD* contains unique information vis-à-vis well-known predictive variables that employ past returns, prices, and trends. There also is strong significance for returns at the 7-12 month investment horizon (6.04%, t = 5.05). *MAD* is insignificant for the 13-24-month horizon.

We next examine the *MAD* effect for the recent 2001-2015 period. This period is especially important, as Schwert (2003), Chordia, Subrahmanyam, and Tong (2014), and McLean and Pontiff (2016) show that anomalies tend to attenuate and even disappear over time. Consistent with these studies, we demonstrate that over the 2001-2015 period, the momentum, 52-week high price, and trend effects all disappear (t=0.70, −1.26, and 0.45, respectively). In contrast, investment rules based on *MAD* produce a positive and significant coefficient (t = 2.80).

We also consider three specifications of four-factor models: the three Fama-French market, size, and value factors, along with either (i) the cross-sectional momentum of Jegadeesh and Titman (1993), (ii) the time-series momentum of Moskowitz, Ooi, and Pedersen (2012), or (iii) the trend factor of Han, Yang, and Zhou (2016). The results in Table 2 show that the *MAD* effect continues to obtain for factor-adjusted returns.

Thus far we have focused on the quantitative value of *MAD*. We now explore three time-invariant thresholds, equal to 0.1, 0.2, and 0.3. For each threshold γ, the variable *MAD Threshold* takes on the value unity if *MAD* is greater than $1+\gamma$, negative unity if *MAD* is smaller than $1-\gamma$, and zero otherwise. Considering these firm-specific thresholds offsets the common variation of stock-level *MAD* with the market. We find that *MAD Threshold* carries highly significant coefficients (t = 4.29, 6.04, and 5.19, for the 0.1, 0.2, and 0.3 thresholds, respectively). Moreover, the slope coefficient estimates increase with the threshold. Thus, higher thresholds are associated with higher investment returns in ways unrelated to momentum, 52-week high, various trend variables, or other technical rules.

We further analyze the predictive power of *MAD* across different states. Here, 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, and liquidity states (stratified by medians). 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. In Table 2, we confirm that, unlike momentum, the *MAD* effect is large and significant in all sentiment, volatility, and liquidity states.

To complete the analysis, we repeat the main regressions in Table 2 while controlling for dispersion in analyst forecasts, as in Diether, Malloy, and Scherbina (2002). These regressions are confined to stocks which are covered by at least two analysts in the I/B/E/S database and therefore are relegated to Appendix C. The *MAD* coefficient in those tests is large and significant indicating that the effect is also robust to forecast dispersion across analysts.

In sum, the evidence indicates that *MAD* is a strong and significant predictor of future returns. Unlike prominent anomalies that have attenuated during the most recent years, the *MAD* effect still stands out. It is not captured by simple moving average rules or the *MAD* signal. It is also left unexplained by well-known predictive characteristics that employ past returns, prices, and trends. The robustness of our proposed *MAD* during the entire sample period, in recent years, and in different states related to volatility, liquidity, and sentiment, distinguishes this variable from other predictors.

3.2 Portfolio Analysis

We next employ portfolio sorts to identify cross-sectional patterns in average stock returns. Table 3 reports next months' average returns for top 30%, mid 40%, and bottom 30% portfolios sorted on *MAD* and, independently, on *MOM*, *52HIGH*, and *TRND*. In all cases, top *MAD* portfolios yield average returns that are significantly higher than the bottom *MAD* ones. For example, for bottom trend stocks, top and bottom *MAD* portfolios demonstrate average returns of 1.11% and 0.12%, respectively. In addition, *MAD* positively interacts with past return and trend in its ability to predict next months' returns.

In Table 4, we report the results of double-sort analyses that address how *MAD* is related to the standard momentum effect of Jegadeesh and Titman (1993). Table 4 reports payoffs of 10

× 10 portfolios constructed by double sorts, either independently or in sequence, on *MAD* and on past returns for months −2 through −6 (*MOM*). The table summarizes investment payoffs for the ten top and ten bottom *MAD* portfolios. Consistent with the cross-sectional regression results reported in Table 2, the next month's return differential between the top and bottom *MAD* portfolios is consistently positive and significant. The results are even sharper for the intermediate investment horizons (months 2-6). Investment payoffs for months 7-12 reveal a weaker *MAD* effect. Notably, however, for the 2-6 investment horizon, momentum does not exhibit significant patterns across *MAD* deciles. The notion that the *MAD* effect is present in every momentum decile indicates that this phenomenon goes beyond traditional momentum.

Appendix D reports double-sort results for 15 other variables. Table D1 reports the results for *MAD* deciles further split into two portfolios based on the *MAD* signal (above and below one). Tables D2-D15 report payoffs of 10 × 10 portfolios constructed by double sorts on *MAD* and, in turn: (i) 52-week high price (*52HIGH*), (ii) trend (*TRND*), (iii) size (*ME*), (iv) book-to-market (*BE/ME*), (v) turnover (*TURN*), (vi) illiquidity (*ILLIQ*), (vii) volatility (*VOL*), (viii) previous month's return (R_{t-1}), (ix) past returns for months 7-12 ($R_{t-7:t-12}$), (x, xi) returns for months 13-24 ($R_{t-13:t-24}$) and for months 25-36 ($R_{t-25:t-36}$), (xii) standardized unexpected earnings (*SUE*), (xiii) return on equity (*ROE*), and (xiv) upgrades-downgrades (*RUD*). We implement independent and sequential sorts and examine various investment horizons.

As with momentum in Table 4, return differentials between top and bottom *MAD* portfolios are positive and mostly significant across all time horizons and all variables. Also, like momentum, for the 2-6 investment horizon, the trend variable does not exhibit significant patterns across *MAD* deciles. Altogether, the predictive characteristics we consider do not capture the *MAD* effect.

We next assess the annual alphas of five zero-cost strategies that employ the *MAD* variable. The first is the *MAD signal* strategy where all stocks with *MAD* greater than one (below one) are bought (sold). It is important to note that the *MAD signal* is not our major focus in the cross-section, as we pay special attention to the distance. Accordingly, in the second strategy, stocks in the top (bottom) *MAD* decile are bought (sold). The next three strategies are based on the fixed thresholds described earlier. In these strategies, stocks with *MAD* greater than one plus a fixed threshold are bought and all stocks with *MAD* smaller than one minus the same threshold are sold. A zero threshold corresponds to the *MAD signal*. We consider the three thresholds of 0.1, 0.2, and 0.3 and investment horizons that range from one to 24 months. 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).

Figure 2 displays the value of a $1 position invested at the end of June 1977 in either the buy portfolio or the sell portfolio per each of the five strategies. For perspective, the figure also displays a market proxy (the value-weighted CRSP index) that rises to $59.98 at the end of our sample period. The portfolios are rebalanced on a monthly basis. Strikingly, all buy portfolios largely outperform the market with terminal values of $324.36 (*MAD signal*), $2,066.46 (*MAD* decile), and $671.12, $2,115.81, and $4,158.35 for thresholds of 0.1, 0.2, and 0.3, respectively. In contrast, all sell portfolios uniformly lag the market with corresponding end values of $35.25, $15.30, $5.65, $2.04, and $0.39, respectively.

In Table 5, we summarize *MAD* payoffs and their significance for holding periods ranging from one to 24 months. Panel A provides annual alpha estimates from regressing top-minus-bottom portfolio payoffs on the three Fama-French factors. The alphas of the *MAD signal* strategy are all positive and significant. The *MAD* decile strategy yields substantially larger alphas ranging from 3.58% (t = 2.29) for the 24-month horizon to 15.13% (t = 4.75) for the three-month horizon. For the 0.1 threshold, alpha ranges between 5.48% (t = 4.96) for the 24-month horizon and 14.20% (t = 6.22) for the one-month horizon. The corresponding alphas for the 0.2 and 0.3 thresholds are 6.63% (t = 4.35), 20.48% (t = 7.26), 6.55% (t = 3.15), and 26.14% (t = 6.58). Remarkably, the *MAD* effect is present even after two years.

We next examine the profitability of long versus short legs of *MAD* rules. Stambaugh, Yu, and Yuan (2012) and Avramov et al. (2013) show that for most anomalies, short legs are more profitable than the corresponding long ones, as short-selling constraints impede arbitrage. Figure 2 shows, however, that top *MAD* stocks outperform the market. Panel B of Table 5 reports long-leg annual alpha estimates and shows that up to the one-year investment horizon, all five strategies deliver positive and significant alphas. The alphas are also significant in three (out of five) cases for the 18- and 24-month investment horizons. In the other two insignificant cases, the alphas are still positive, suggesting there are no long-run reversals. Collectively, the profitable long legs, the long-lasting effects, and the absence of future reversals distinguish *MAD* from other investment strategies that employ past returns and prices.

4. Anchoring and the *MAD* Effect

Why is the *MAD* effect so strong and robust? One possibility is that agents 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 agents overreact to *MAD* (i.e., the feedback trading is based purely on price moves and not on fundamentals), we should observe a long-run reversal of the *MAD* effect. In the results reported in Appendix B, we find no evidence of reversals for returns up to 36 months after portfolio formation based on *MAD*. In addition, the results in Table 5 show that portfolio payoffs do not reverse even after two years. Thus, the evidence accords with investor underreaction, rather than overreaction.

One possible rationale for underreaction is cognitive dissonance (CD). Antoniou, Doukas, and Subrahmanyam (2013) argue that CD emerges when news contradicts investors' sentiment, thereby slowing the diffusion of signals that oppose the direction of sentiment. Under CD, bottom *MAD* stocks are expected to be underpriced during high sentiment, while top *MAD* stocks are expected to be underpriced during low sentiment. While the latter phenomenon can be corrected by arbitrage buying, short-selling constraints should impede arbitraging of bottom *MAD* stocks under high sentiment, causing the *MAD* effect to be stronger during high sentiment periods. However, Table 2 demonstrates that the *MAD* effect delivers statistically indistinguishable payoffs across high and low sentiment states.

Hirshleifer and Teoh (2003) propose limited attention as an intriguing rationale for underreaction to new information (such as items higher up in the income statement relative to the bottom line, i.e., net income). It is hard to argue, however, that long-run moving averages of prices (and deviations from these baselines) represent new information relative to the much more salient, and easily available, current stock price. Thus, applying limited attention to explain *MAD* is challenging. Further, the preceding argument indicates that any explanation for *MAD* should involve a role for the seemingly irrelevant baseline (the long-run moving average). In the subsection below, we propose an explanation for the predictive power of the *MAD* that relies on the anchoring bias (Tversky and Kahneman, 1974).

4.1 Anchoring on Moving Averages of Prices

We explore the notion that agents rely on readily available but often irrelevant information to form anchors and then shift insufficiently from these estimates. What is a reasonable anchor? 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 supported by the work of Kaustia, Alho, and Puttonen (2008), who indicate that agents' estimates of future market performance in the European Union are influenced by whether they are given a historical estimate from a rising stock market (Sweden) or a falling one (Japan).

We thus conjecture that investors' anchors about future stock prices are set around the historical (200-day) moving average of prices. Investors underreact to the arrival of new information, so that low *MAD* stocks do not fully account for downside outcomes, while high *MAD* stocks do not fully reflect upside prospects. Thus, the anchoring bias accords with why high (low) *MAD* stocks predict higher (lower) returns. To develop an additional hypothesis, suppose that *MAD* is large positive. Then, further positive news that tends to move prices further away from the anchor should cause underreaction but negative news that tends to move prices towards the anchor should cause a more muted reaction. An analogous argument holds for negative *MAD*. These arguments are formalized within a simple setting described in Appendix H. Below, we provide empirical evidence supporting these arguments.

First, we examine the post-announcement drift (six months) following releases of three types of good news. Specifically, we consider positive earnings surprise announcements, first-time buy recommendations (that, is events where the first recommendation for a stock by any analyst is a buy), and dividend initiations. The hypothesis is that top *MAD* stocks underreact more in response to positive news. That is, top *MAD* stocks are expected to display a positive drift that is larger than that of bottom *MAD* stocks. In the same vein, we examine drift following negative earnings surprises, sell recommendation announcements, and seasoned equity issues.

The hypothesis here is that bottom *MAD* stocks underreact more to negative news. That is, bottom *MAD* stocks are expected to display more negative drift than top *MAD* stocks in response to negative news. We do not include dividend cancellations as a complement to positive dividend initiations because there are no top *MAD* stocks in our sample with canceled dividends.

In Figure 3, we examine positive news (i.e., positive earnings surprises, buy recommendations, and dividend initiations). Presented are average cumulative returns in excess of the market index. The left, middle, and right plots correspond to positive earnings surprises, buy recommendations, and dividend initiations, respectively. In Panel A (B), we focus on equal- (value-) weighted returns in excess of the CRSP index counterparts. Recommendations and earnings surprise data are from the Institutional Brokers' Estimate System (I/B/E/S) and dividend initiations and equity issues data are from Compustat - Capital IQ. We cumulate returns for six months (126 trading days) starting with closing prices one day after the event announcement. We consider stocks belonging to the top (bold line) versus the bottom (dashed line) *MAD* deciles. As conclusions are qualitatively similar using t-statistics versus Patell (1976) z-scores (the latter accounts for return compounding), we report only the former.

We first discuss the equally-weighted portfolios. The top *MAD* stocks exhibit a large and significant drift after positive earnings surprises (t = 4.61), but the corresponding drift for bottom *MAD* stocks is insignificant. The hypothesis of equal drifts across top and bottom *MAD* deciles is rejected (t = 2.37). Likewise, following buy recommendations, the top decile exhibits a large positive drift (t = 3.63), while the bottom one displays a negative drift. The hypothesis of equal drifts among the top and bottom deciles is again rejected (t = 7.67). A similar pattern emerges following dividend initiations, where the difference in returns across deciles after six months exceeds 5.85%. However, this difference is relatively noisy and insignificant, likely due to the small number of dividend initiation events (14 for bottom *MAD* and 17 for top *MAD*). For value-weighted portfolios, the top (bottom) *MAD* stocks exhibit significant positive (insignificant) drifts following positive earnings surprises and buy recommendations. The difference in returns following dividend initiations, albeit insignificant, reaches 14.75%. Across the board, the drift is considerably higher for the top *MAD* stocks, consistent with our conjecture.

We consider negative news releases (i.e., negative earnings surprises, first-time sell recommendations, and seasoned equity issues) in Figure 4. In the equally-weighted portfolios (Panel A), the top *MAD* stocks reveal small drifts that are not significantly different from zero, while the bottom *MAD* stocks reveal significantly negative drifts. The drifts of the top and bottom *MAD* stocks of value-weighted portfolios in Panel B are positive and negative, respectively, and the difference is significant for earnings surprises and equity issues.

For the most part, the results support the notion that for the top *MAD* stocks, positive events lead to substantial investor underreaction. Analogously, for the bottom *MAD* stocks, negative events invoke underreaction. These results accord with the anchoring rationale. In particular, for positive *MAD* stocks, investors anchor to the lower long-run moving average, thus underreacting to positive news, and vice versa.

Limits to arbitrage (short-selling constraints, viz. D'Avolio 2002) could possibly explain why *MAD*-based overvaluation cannot be easily arbitraged away. To explore this issue, in Figure 5 we plot the post-announcement drift for the bottom *MAD* stocks conditioning on high versus low institutional holdings, with the latter characterizing difficult-to-arbitrage stocks. Our hypothesis is that following negative events, bottom *MAD* stocks with lower institutional holdings should be associated with greater negative drift or greater overpricing.

Figure 5 compares the average cumulative excess return following negative events conditioning on above and below median intuitional holdings. The negative events include all the events in Figure 4, i.e., negative earnings surprises, sell recommendation announcements, and seasoned equity issues. Panel A (B) reports equal- (value)-weighted returns in excess of the CRSP index counterparts. In both panels, the more difficult-to-arbitrage stocks exhibit more negative drifts. The six-month returns on low holdings stocks are uniformly smaller than those in the other subsamples and the difference is significant (t = 7.67 and 2.25, respectively).

4.2 Anchoring on Moving Averages of Firm Fundamentals

We next consider the notion that if anchoring is indeed the cause of the *MAD* phenomenon, the predictability should also be discernible in other settings, in that different categories of investors could anchor on different types of financial variables. Thus, Hong and Stein (1999) consider two types of investors: "trend chasers," who condition only on past prices, and "newswatchers," who consider fundamental news. While the former category could anchor on past prices, the latter might do so on financial statement variables. This implies that the market could also underreact to large deviations of commonly followed accounting numbers from their average values.[7]

To investigate the preceding notion, we construct a Performance Deviation Index (*PDI*) from seven measures related to firms' operating performance: Cash and short-term investments (*Cash*), Retained Earnings, Operating Income, Sales, capital expenditures (*CAPEX*), Invested Capital, and Inventories, and an extended index that also considers income before extraordinary items (*IB*). A deviation is defined as the most recent quarterly release, if it exists in the previous six months, minus the mean in the preceding three quarters, scaled by total assets.[8] Each deviation is assigned a percentile relative to all stocks' deviations in the previous year (one

[7] The assumption here, as in other behavioral models such as Hong and Stein (1999), is that each category of investors faces limits to arbitrage (Shleifer and Vishny, 1997) that prevent the class from perfectly arbitraging the anchoring of the other class.
[8] Computing deviations of most recent two quarters' means relative to four quarter averages leads to substantively similar results.

minus percentile for invested capital and inventories). Deviations are then equally weighted to construct a monthly *PDI*. If the exact release date of the accounting reports within the month is not given, we assume a 90-day delay in release to guarantee data availability for investors. We present Fama-MacBeth regressions in Table 6 with an extensive set of controls (see Appendix E).

The results show that *PDI* and its extended version strongly and positively predict returns incremental to all of the controls. Indeed, all but two of *PDI*'s components predict returns individually as well. The *PDI*-based predictability prevails in regimes sorted by high versus low values of sentiment, volatility, and liquidity, and obtains in horizons exceeding one year, as well as in the recent 2001-2017 period. Indeed, its significance diminishes little in recent years. *PDI* also survives momentum controls. The third column of Table 6 includes both *PDI* and *MAD* in the regressions and shows that these variables do not subsume each other and thus are distinctly different predictors. *PDI* also survives the trend variable of Han, Zhou, and Zhu (2016). The statistical significance of *PDI* is strong, with *t*-statistics that exceed five for the monthly horizon. Overall, the results indicate that anchoring-based underreaction is a broader phenomenon in the cross-section of stock returns than just *MAD*.[9]

4.3 Do MAD and PDI Survive Recently Proposed Risk Factors?

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

[9] In contrast to our time-series approach to consider investors' reaction to firm fundamentals, Bartram and Grinblatt (2018) consider a cross-sectional approach. Specifically, they analyze whether a firm's mispricing can be identified by comparing the firm's price performance to that of a replicating portfolio of other firms with similar fundamentals.

persistent anomalies including market beta, net share issues, and volatility. We regress returns of the *PDI* and *MAD* long-short portfolios on the five Fama and French (2015) factors. Panel A of Table 7 reports the equal-weighted portfolio alphas for investment horizons of one, three, six, and 12 months. The alphas of the top-minus-bottom *PDI* and *MAD* portfolios and *MAD* threshold portfolios are all economically large and significant. Notably, the point estimate of the annualized *PDI* alpha based on next months' returns (15.5%) is materially higher than that for *MAD* (12.5%). For longer horizons, the *MAD* alphas are higher than the *PDI* ones.

In a recent paper, Hou, Xue, and Zhang (2017) argue that abnormal profits from investing in 64% of anomalies disappear when the impact of microcap stocks is mitigated by value weighting returns. Also, Fama and French (2015) note that the most serious challenges faced by asset pricing models are in small cap stocks. As noted Section 2, we exclude stocks with an 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 microcap stocks, it is still relevant to consider value-weighting. Accordingly, Panel B of Table 7 reports alphas for value-weighted portfolios. While these alphas tend to be smaller than those reported in Panel A, they are still economically large and significant. Note that the differences between equally-weighted and value-weighted portfolios decrease in the case of the 0.3 threshold as those portfolios are typically characterized by relatively smaller firms.

5. Properties of *MAD*/*PDI* portfolios

Do investment strategies that employ *MAD* and *PDI* survive reasonable transaction costs? We implement two schemes to investigate. In the first, we assess break-even transaction costs that eliminate average abnormal profits of our proposed zero-cost strategies described above. In the second, we consider risk and preferences directly. Specifically, we assess the cost that would equate the certainty equivalent return of the five strategies to that of a zero-cost market portfolio. The latter invests long in the CRSP value-weighted composite index and sells short 30-day Treasury bills. The certainty equivalent return is equal to the average return minus half times the variance times the relative risk aversion value. We set the risk aversion value equal to two, consistent with a large body of past work (see, e.g., Mehra and Prescott, 1985). For perspective, a risk aversion equal to unity is implied by log preferences. Also, for unit risk aversion, the certainty equivalent return coincides with the geometric average. Of course, break-even transaction costs diminish with increasing risk aversion.

Table 8 reports the two break-even cost estimates for the investment strategies described above. The figures in the table reflect the transaction costs multiplied by the portfolio average turnover (both long and short positions). The results show that the break-even costs increase with holding periods up to one year and then somewhat diminish. There are two effects at work. First, longer holding periods imply less trading and thus lower transaction costs. Second, as noted above, the *MAD* effect is most pronounced for holding periods of about six months. Up to six months, the two effects work in the same direction; beyond that, there is a tradeoff.

As also shown in Table 8, break-even costs increase with the threshold. Focusing on the one-month holding period, the cutoff costs are 234, 289, and 335 bps for the 0.1, 0.2, and 0.3 thresholds, respectively, compared to 161bps for the *MAD signal* strategy and 184 bps for the *MAD* decile strategy. [Recall that the *MAD signal* strategy is tantamount to a zero threshold.] The corresponding figures for the 12-month holding period are 698 and 667 for the *MAD signal* and decile, and 995, 1169, and 1245 for the thresholds, respectively.

Moving to our second scheme and a one-month horizon, the *MAD* decile portfolio returns withstand 27 bps. Considering the 0.1, 0.2, and 0.3 thresholds, the break-even costs are 78, 118, and 114 bps, respectively. The corresponding figures for the 12-month horizon are 222, 409, and 437 bps, respectively. Collectively, our evidence shows that trading strategies that employ *MAD* deliver payoffs that largely exceed reasonable transaction costs.

The break-even transaction costs for the *PDI* portfolio are also large, ranging from 199 to 506 bps in the first scheme and 128 to 441 bps in the second, and a holding period of up to six months. Indeed, for the most part, the reported break-even transaction costs are much larger than reasonable transaction costs. For perspective, 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.

For completeness, we also assess whether our *MAD/PDI* strategies deliver Sharpe ratios that are significantly higher than the Sharpe ratio of a market proxy, as in MacKinlay (1995). The results are reported in Appendix F. In brief, portfolios that employ the *MAD signal* or extreme *MAD*-based deciles produce Sharpe ratios that are not significantly greater than that of the value-weighted CRSP index. In contrast, the fixed thresholds and the *PDI*-based decile strategy yield Sharpe ratios that are significantly greater than that of the market index for investment horizons of up to one year.

Higher *MAD/PDI* stocks could be potentially riskier, thereby commanding higher required returns. While we do control for prominent common factors in Section 4.3, nevertheless, in Panel A of Table 8 we compare the risk profile of top versus bottom *MAD/PDI* decile portfolios. Results are reported for equally-weighted portfolios as those for value-weighted ones are qualitatively similar. The second column in Panel A reports the past 200-day mean standard deviation of daily stock returns. The average standard deviation for the top *MAD* portfolio is slightly higher than that for the bottom one. This relation is reversed in the third column. Similar relations are observed in *PDI* decile portfolios. We also report the loadings on the five Fama and French (2015) factors. We find that the loadings on market and value are significantly smaller for the top versus the bottom deciles. The loadings on operating profitability are indistinguishable across the deciles. The size and investment factor loadings are larger for the top *MAD* decile relative to the bottom and the differences are significant. In the case of *PDI*, the size and value factor loadings are significantly smaller for the top versus the bottom deciles. The market and investment factor loadings are indistinguishably different across the top and bottom deciles, while only the loading on operating profitability is larger for the top versus the bottom portfolio. Overall, the results support the notion that top *MAD/PDI* stocks are not distinctly riskier than equities.

Could gradual information diffusion cause the *MAD/PDI* effects? Hong and Stein (1999) and Hong, Lim, and Stein (2000) argue that past return effects are stronger among small cap stocks, as well as stocks that are less covered by analysts, possibly due to their higher information acquisition costs. Hou and Moskowitz (2005) suggest that market frictions may delay information diffusion for up to several weeks. Such delay is most pronounced for less visible, smaller cap, more volatile, and more illiquid stocks. We argue in Section 4 that MAD is unlikely to carry any fundamental information as it is based purely on past price histories. Nevertheless, we consider below whether such channels of gradual information diffusion provide explanatory power for *MAD/PDI*.

Tables D4, D6, and D7 in Appendix D show that the *MAD* effect is robust among all size, turnover, and illiquidity groups. We report in Panel B of Table 9 the average firm characteristics for the *MAD/PDI* groups and the various *MAD* thresholds. The mean size of firms in the top *MAD* decile is $1,664 million, which is much larger than the $6 million corresponding to the top decile of price delayed stocks, as reported by Hou and Moskowitz (2005). In addition, the highest *MAD* stocks are the most liquid and have the highest turnover. Next, the average number of analysts covering the top *MAD* stocks is 5.82 and the average share of institutional holdings is 0.37, while the corresponding values for top price-delayed stocks are 1.3 and 0.06. Finally, the O-score for the top *MAD* stocks is not markedly different from that for other *MAD* deciles suggesting that the *MAD* effect is not driven by credit risk. Comparing firm characteristics across *PDI* deciles at the bottom of the table also does not reveal clear patterns that could point to risks associated with *PDI*.

Overall, top *MAD/PDI* stocks are not considerably riskier or the most prone to gradual information diffusion or frictions. Further, modern, recently-proposed factors do not capture the *MAD/PDI* effect, even as they provide explanatory power for other cross-sectional patterns in average stock returns. The features that (i) risk factors are unable to capture the *MAD/PDI* effect, (ii) *MAD/PDI* portfolios are not riskier, and (iii) gradual information diffusion due to market frictions does not accord with the *MAD/PDI* effect, support the notion in Section 4 that the *MAD/PDI* effect is unrelated to risk or market frictions.

6. *MAD/PDI* and the Aggregate Equity Premium

Thus far, we have examined the predictive ability of *MAD/PDI* for the cross-section of average stock returns. Our major theme is that investors underweight information that is at odds with their anchoring reference, where the latter is either the long-run moving average of prices (*MAD*) or that of fundamentals (*PDI*). While Peng and Xiong (2006) argue that investors more effectively process market-wide information relative to firm-specific information, it is still worth investigating whether the *MAD/PDI* effect applies at the aggregate level. Accordingly, we examine whether *MAD/PDI* constructed using the market index and industry portfolios can time the market.[10]

We consider market-timing strategies that are similar to those proposed by Moskowitz, Ooi, and Pedersen (2012). In the *MAD signal* strategy, investors buy the market portfolio if *MAD* exceeds one and hold Treasury bills otherwise. In the *MAD threshold* strategy, investors buy if *MAD* exceeds one plus a threshold and hold Treasury bills otherwise. We examine thresholds of 0.025 and 0.05, which are lower than those used for individual stocks (0.1, 0.2, and 0.3). This is because the volatility of *MAD* at the aggregate level is considerably lower than that of single stocks. Put another way, high enough thresholds induce a position that mostly invests in Treasury bills. The threshold-based equity position is scaled by $1/e$ while $1-1/e$ is invested in Treasury bills, where e denotes the ratio of the number of months when *MAD* is above one plus a threshold, to the number of months when *MAD* is above one, calculated over a rolling window. The computation begins at the start of the sample, using available months up to 60 months for the window, and thereafter stays constant at 60 months. This scaling uses available data in real time to equate the average exposure of our zero-cost portfolios to the market across the employed strategies.

Table 10 reports the annualized market alphas for the value-weighted composite index

[10] The analysis at the aggregate level is essentially an analysis of the *MAD/PDI* effect in a time series setting, which is analogous to the time-series momentum analyzed in Moskowitz, Ooi, and Pedersen (2012).

(first test), 12 industry portfolios,[11] and an all-industry portfolio. With the all-industry portfolio, we test the joint significance of the predictive ability of *MAD*. In particular, each industry-level trading strategy invests in the corresponding industry or the risk-free rate depending upon *MAD*. In the all-industry portfolio, we equal weight the industry-level trading strategies. We find that the alpha of the *MAD signal* strategy is positive and significant for the entire sample period, as well as for the 2001-2015 period. The alphas for the recent years range from five to seven percent, and both the alpha and the *t*-statistic increase with the threshold. The pattern in individual industry portfolios, as well as that in the all-industry portfolio is stronger for the entire sample period, but the all-industry portfolio alphas are all strongly significant and also yield alphas in the 5-7% range during recent years. In unreported tests, we uncover similar patterns using equally weighted industry portfolios. In sum, the *MAD* effects work at the market and industry levels, in addition to the cross-section.

We apply the same signal and threshold procedures to the value-weighted *PDI* index. The results are presented in the last two columns of Table 10. The market and all-industry portfolios yield positive alphas in the 2-4% range, which are significant at the 1% level or less. The alphas of specific industry portfolios are mostly positive but not consistently significant. The less sharp results for *PDI* are expected as the aggregate *PDI* index is not directly disseminated to investors and has to be computed from firm fundamentals. This makes it less likely that investors would anchor on the aggregate index.

We have thus far exclusively focused on U.S. equity markets. In what follows, we study the predictive power of *MAD* in a cross-country setting to provide further out-of-sample evidence supportive of our preceding results.

[11] The industries are defined as in Ken French's website at goo.gl/dZwSEB.

7. International Analysis

In this section, we evaluate 37 international equity markets. Descriptive statistics for these markets are reported in Appendix G. Due to data availability, the international analysis focuses on the more recent years starting from 2001. We focus on *MAD* and not *PDI*. As we pointed out above, it is unlikely investors would anchor on aggregate *PDI* since it is not readily available in real time; this would particularly be the case in developing stock markets with less reliable dissemination of accounting data to investors.

We consider all available countries in the Wharton Research Data Services (WRDS) database, excluding Greece and the Czech Republic for which data are incomplete. The risk-free rate corresponds to the Treasury-bill rate published by the International Monetary Fund (IMF). In the few cases where these rates are missing, we use the market interest rate and the deposit rate for three-month periods, in that order. We start with Fama-MacBeth cross-country regressions. We regress monthly country returns on previous months' *MAD*s and past returns corresponding to international momentum (see, e.g., Rouwenhorst, 1998; Hou, Karolyi, and Kho, 2011). We also control for the *MAS* and *MDS* signals. Table 11 reports the coefficient estimates. For 1-24-month investment horizons and raw returns, *MAD* is uniformly positive and mostly significant.

To account for systematic influences, we adjust returns using the international CAPM as well as the global versions of the Fama-French and momentum factors. Results are presented in the last few rows of Table 11. Most coefficients remain significant. Notably, when all factor controls are included, the *MAD* coefficient is statistically significant for every horizon at the 5% level or less. Altogether, the cross-country regression results indicate that the *MAD* effect extends beyond U.S. markets. Specifically, in the cross-section, countries with higher *MAD* yield reliably higher average returns.

We next examine whether *MAD* can be employed to time international markets. We again implement market-timing strategies that buy the market portfolio if *MAD* is above one plus a threshold and holds Treasury bills otherwise, where the *MAD signal* amounts to a zero threshold. Table 12 reports the alpha estimates obtained from the resulting strategy. The evidence provides reliable support for the ability of *MAD* to generate abnormal profits. In particular, with a threshold of 0.05, the market alpha is positive for all 38 economies we examine, and it is significant at least at the 10% level for 32 economies. Moreover, for the most part, alpha tends to increase with the *MAD* threshold.

We test the joint significance of the predictive ability of the *MAD* effect. In particular, each country-level trading strategy invests in the corresponding market or the risk-free rate depending upon *MAD*. Such a strategy produces a time series of country-level investment returns, as shown in Table 12. Then, an all-inclusive trading strategy invests in the country-level trading strategies either in equal or value weights where "value" reflects the overall market capitalization of a particular equity market. The value-weighted strategy, of course, is tilted towards the more developed economies. We assess the investment payoffs of the all-inclusive strategies using the alpha with respect to the global market portfolio. The results are reported at the bottom of Table 12. The alphas are large (8.11% - 12.28% equal-weighted and 6.42% - 9.81% value-weighted) and highly significant (t = 4.98 - 6.11 and 3.92 - 4.61, respectively). Thus, *MAD* is a statistically and economically significant predictor of market equity return across our 38 economies.

In sum, the international evidence reinforces the notion that *MAD* is a strong predictor of returns. High *MAD* countries considerably outperform low *MAD* countries, and *MAD* is a phenomenon incremental to the widely explored international momentum strategy. From a time-series perspective, market timing using *MAD* yields material returns in the U.S. and most other countries. Aggregating over all markets using equal and value weights generates trading strategies that overall produce material reward-to-risk ratios.

8. Conclusion

We shed new light on equity return predictability by showing that the distance between short- and long-run moving averages of prices (that we term *MAD*) is a surprisingly strong predictor of equity returns and it survives a host of controls, including standard momentum, the 52-week high, and a comprehensive set of other cross-sectional return predictors. Versions of this rule also yield supernormal profits at the market and industry levels and in cross-country contexts.

Since profits from the rule do not reverse in the long-run, they indicate investor underreaction, as opposed to continuing overreaction. We propose that the *MAD* effect occurs because investors are overly anchored to the long-term average and update beliefs insufficiently in the light of new information. We test a specific implication of the anchoring hypothesis: Following a large positive *MAD*, positive news that moves prices further away from the anchor should cause underreaction, but negative news that moves prices towards the anchor should result in a more muted reaction (and analogously for large negative *MAD*). Supporting this notion, we find that there is greater underreaction to positive (negative) earnings announcements and first-time buy (sell) recommendations by analysts following a large positive (negative) *MAD*.

We provide another new result; that anchoring goes beyond stock prices and extends to firm fundamentals. Specifically, stock returns are cross-sectionally predictable from a comprehensive measure that captures deviation of widely-followed accounting items from their preceding averages. This predictability is incremental to *MAD* and is about equally as strong as *MAD* in terms of economic and statistical significance.

Our work suggests avenues for future research. First, it is worth considering whether the profitability we document depends on the extent to which there is material public information available on companies, which, in turn, depends on disclosure requirements across countries. Second, it would be interesting to investigate whether there are cross-effects; i.e., whether stock prices underreact to *MAD* and accounting-based analogs of other stocks in the same industry. These and other topics are left for future research.

References

Amihud, Y., 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31-56.

Antoniou, C., J. Doukas, and A. Subrahmanyam, 2013, Cognitive dissonance, sentiment, and momentum, *Journal of Financial and Quantitative Analysis* 48, 245-275.

Appel, G., 2005, *Technical analysis: power tools for active investors*. FT Press, New York, NY.

Ariely, D., G. Loewenstein, and D. Prelec, 2003, "Coherent arbitrariness": Stable demand curves without stable preferences, *Quarterly Journal of Economics* 118, 73-106.

Avramov, D., S. Cheng, and A. Hameed, 2016, Time-varying liquidity and momentum profits, *Journal of Financial and Quantitative Analysis* 51, 1897-1923.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov, 2013, Anomalies and financial distress, *Journal of Financial Economics* 108, 139-159.

Baker, M., and J. Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645-1680.

Ball, R., and P. Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159-178.

Banz, R., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.

Barberis, N., and M. Huang, 2001, Mental accounting, loss aversion, and individual stock returns, *Journal of Finance* 56, 1247-1292.

Barberis, N., A. Mukherjee, and B. Wang, 2016, Prospect theory and stock returns: An empirical test, *Review of Financial Studies* 29, 3068-3107.

Barberis, N., A. Shleifer, and R. Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Bartram, S., and M. Grinblatt, 2018, Agnostic fundamental analysis works, *Journal of Financial Economics* 128, 125-147.

Bernard, V., and J. Thomas, 1989, Post-earnings-announcement drift: delayed price response or risk premium?, *Journal of Accounting Research* 27, 1-36.

Bernard, V., and J. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305-340.

Brock, W., J. Lakonishok, and B. LeBaron, 1992, Simple technical trading rules and the stochastic properties of stock returns, *Journal of Finance* 47, 1731-1764.

Campbell, J., J. Hilscher, and J. Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899-2939.

Cen, L., G. Hilary, and J. Wei, 2013, The role of anchoring bias in the equity market: Evidence from analysts' earnings forecasts and stock returns, *Journal of Financial and Quantitative Analysis* 48, 47-76.

Chen, L., R. Novy-Marx, and L. Zhang, 2011, An alternative three-factor model, working paper, University of Rochester.

Chincarini, L., and D. Kim, 2009, *Quantitative Equity Portfolio Management: An Active Approach to Portfolio Construction and Management*. New York, NY: McGraw-Hill.

Chordia, T., R. Roll, and A. Subrahmanyam, 2010, Recent trends in trading activity and market quality, *Journal of Financial Economics* 101, 243-263.

Chordia, T., A. Subrahmanyam, and Q. Tong, 2014, Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?, *Journal of Accounting and Economics* 58, 41-58.

Cohen, R., P. Gompers, and T. Vuolteenaho, 2002, Who underreacts to cash-flow news? Evidence from trading between individuals and institutions, *Journal of Financial Economics* 66, 409-462.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, *Journal of Finance* 53, 1839-1885.

Daniel, K., and S. Titman, 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605-1643.

Datar, V., N. Naik, and R. Radcliffe, 1998, Liquidity and stock returns: An alternative test, *Journal of Financial Markets* 1, 203-219.

D'Avolio, G., 2002, The market for borrowing stock, *Journal of Financial Economics* 66, 271-306.

De Long, B., A. Shleifer, L. Summers, and R. Waldmann, 1990, Positive feedback investment strategies and destabilizing rational speculation, *Journal of Finance* 45, 379-395.

DeBondt, W., and R. Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793-805.

Diether, K., C. Malloy, and A. Scherbina, 2002, Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113-2141.

Fairfield, P., S. Whisenant, and T. Yohn, 2003, Accrued earnings and growth: Implications for future profitability and market mispricing, *Accounting Review* 78, 353-371.

Fama, E., and K. French, 1992, The cross section of expected stock returns, *Journal of Finance* 47, 427-466.

Fama, E., and K. French, 1993, Common risk factors in the returns of stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, E., and K. French, 2006, Profitability, investment and average returns, *Journal of Financial Economics* 82, 491-518.

Fama, E., and K. French, 2008, Dissecting anomalies, *Journal of Finance* 63, 1653-1678.

Fama, E., and K. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1-22.

Fama, E., and K. French, 2016, Dissecting anomalies with a five-factor model, *Review of Financial Studies* 29, 69-103.

Fama, E., and J. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Festinger, L., 1957, *A Theory of Cognitive Dissonance*, Stanford University Press, Stanford, CA.

George, T., and C. Hwang, 2004, The 52-week high and momentum investing, *Journal of Finance* 59, 2145-2176.

George, T., C. Hwang, and Y. Li, 2015, Anchoring, the 52-week high and post earnings announcement drift, working paper, University of Houston.

Han, Y., K. Yang, and G. Zhou, 2013, A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis* 48, 1433-1461.

Han, Y., G. Zhou, and Y. Zhu, 2016, A trend factor: Any economic gains from using information over investment horizons? *Journal of Financial Economics* 122, 352-75.

Haugen, R., and N. Baker, 1996, Commonality in the determinants of expected stock returns, *Journal of Financial Economics* 41, 401-439.

Hirshleifer, D., K. Hou, S. Teoh, and Y. Zhang, 2004, Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics* 38, 297-331.

Hong, H., T. Lim, and J. Stein, 2000, Bad news travels slowly: Size, analyst coverage and the profitability of momentum strategies, *Journal of Finance* 55, 265-296.

Hong, H., and J. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143-2184.

Hou, K., A. Karolyi, and B. Kho, 2011, What factors drive global stock returns?, *Review of Financial Studies* 24, 2527-2574.

Hou, K., and T. Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns, *Review of Financial Studies* 18, 981-1020

Hou, K., C. Xue, and L. Zhang, 2015, Digesting anomalies: An investment approach, *Review of Financial Studies* 28, 650-705.

Hou, K., C. Xue, and L. Zhang, 2017, Replicating anomalies, *NBER Working Paper w23394*.

Hu, S., 1997, Trading turnover and expected stock returns: The trading frequency hypothesis and evidence from the Tokyo Stock Exchange, working paper, National Taiwan University.

Ikenberry, D., J. Lakonishok, and T. Vermaelen, 1995, Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181-208.

Jegadeesh, N., 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Kaplanski, G., H. Levy, C. Veld, and Y. Veld-Merkoulova, 2016. Past returns and the perceived Sharpe ratio, *Journal of Economic Behavior & Organization* 123, 149-167.

Kaustia, M., E. Alho, and V. Puttonen, 2008. How much does expertise reduce behavioral biases? The case of anchoring effects in stock return estimates, *Financial Management* 37, 391-412.

Korajczyk, R. and R. Sadka, 2004, Are momentum profits robust to trading costs?, *Journal of Finance* 59, 1039-1082.

Lo, A., 2002, The statistics of Sharpe ratios, *Financial Analysts Journal* 58, 36-52

Lo, A., and J. Hasanhodzic, 2009, *The Heretics of Finance: Conversations with Leading Practitioners of Technical Analysis*. New York, NY: Bloomberg Press.

Lo, A., and C. MacKinlay, 1988, Stock market prices do not follow random walks: Evidence from a simple specification test, *Review of Financial Studies* 1, 41-66.

Lo, A., H. Mamaysky, and J. Wang, 2000, Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation, *Journal of Finance* 55, 1705-1770.

Loughran, T., and J. Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23-51.

MacKinlay, A.C., 1995, Multifactor models do not explain deviations from the CAPM, *Journal of Financial Economics* 38, 3-28.

McLean, D., and J. Pontiff, 2016, Does academic research destroy stock return predictability?, *Journal of Finance* 71, 5-32.

Mehra R, and E. Prescott, 1985, The equity premium: A puzzle, *Journal of Monetary Economics* 15, 145-61.

Moskowitz, T., Y. Ooi, and L. Pedersen, 2012, Time series momentum, *Journal of Financial Economics* 104, 228-250.

Novy-Marx, R., 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1-28.

Novy-Marx, R., and M. Velikov, 2016, A taxonomy of anomalies and their trading costs, *Review of Financial Studies* 29, 104-147.

Ohlson, J., 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research* 18, 109-131.

Patell, J., 1976, Corporate forecasts of earnings per share and stock price behavior: Empirical test, *Journal of Accounting Research* 14, 246-276.

Peng, L., and W. Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563-602.

Pontiff, J., and A. Woodgate, 2008, Share issuance and cross-sectional returns, *Journal of Finance* 63, 921-945.

Reinganum, M., 1981, Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values, *Journal of Financial Economics* 9, 19-46.

Rouwenhorst, G., 1998, International momentum strategies, *Journal of Finance* 53, 267-284.

Schwert, W., 2003, Anomalies and market efficiency, *Handbook of the Economics of Finance* 1 939-974.

Shleifer, A., and R. Vishny, 1997. The limits of arbitrage. *Journal of Finance* 52, 35-55.

Shumway, T., 1997, The delisting bias in CRSP data, *Journal of Finance* 52, 327-340.

Sloan, R., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *Accounting Review* 71, 289-315.

Stambaugh, R., J. Yu, and Y. Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288-302.

Stickel, S., 1992, Reputation and performance among security analysts, *Journal of Finance* 47, 1811-1836.

Titman, S., J. Wei, and F. Xie, 2004, Capital investments and stock returns, *Journal of Financial and Quantitative Analysis* 39, 677-700.

Tversky, A. and D. Kahneman, 1974, Judgment under uncertainty: Heuristics and biases, *Science* 185, 1124-1131.

Wang, K., and J. Xu. 2015, Market volatility and momentum, *Journal of Empirical Finance* 30, 79-91.

Welch, I., 2000, Views of financial economists on the equity premium and other issues, *Journal of Business* 73, 501-537.

Womack, K., 1996, Do brokerage analysts' recommendations have investment value?, *Journal of Finance* 51, 137-167.

Xing, Y., 2008, Interpreting the value effect through the Q-theory: An empirical investigation, *Review of Financial Studies* 21, 1767-1795.

Table 1. Descriptive statistics

Panel A displays descriptive statistics for stock returns and firm characteristics defined in Appendix A. Panel B reports next months' average returns for ten portfolios sorted on the moving average distance, *MAD*. The symbols *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample is from June 1977 to October 2015.

Panel A. Economic Variables

Variable	Mean	Standard Deviation
Monthly Return (*R*)	0.012	0.133
Log Size (*ME*)	12.774	1.959
Book-to-Market (*BE/ME*)	0.643	0.495
Trend (*TRND*)	0.253	0.112
Idiosyncratic Volatility (*IVOL*)	0.110	0.059
Turnover (*TURN*)	0.123	0.215
Illiquidity (*ILLIQ*)	0.962	8.871
52-Week High Price (*52HIGH*)	0.789	0.179
Standardized Unexpected Earnings (*SUE*)	0.104	1.366
Recommendation Upgrade-Downgrade (*RUD*)	−0.043	0.252
Net Stock Issues (*NS*)	0.031	0.135
Assets Growth (*dA/A*)	0.092	0.233
Profitability (*Y/B*)	0.010	14.644
Investment-to-Assets (*I/A*)	0.092	0.226
Gross Profitability Premium (*GP*)	0.388	0.268
Accruals (*Ac/A*)	−0.029	0.088
Return on Assets (*ROA*)	0.038	0.131
Return on Equity (*ROE*)	0.020	1.37
Net Operating Assets (*NOA*)	0.680	0.441
Distress O-Score (*DTRS*)	−0.013	0.091
Moving Average Distance *(MAD)*	1.050	0.210
Moving Average Convergence/Divergence (*MACD*)	0.054	91.610

Panel B. The *MAD*-Return Relation

	1 (bottom)	2	3	4	*MAD* Decile 5	6	7	8	9	10 (top)	Top-minus-bottom
Average Return (%)	0.84	1.04	1.14	1.17	1.20	1.28	1.30	1.27	1.50	1.92	1.09***

Table 2. Cross-sectional regressions

The table reports average slopes (multiplied by 10^4) and their t-values (in parentheses) obtained from monthly cross-sectional regressions. The dependent variable is the stock return over (i) the next month, (ii) months 2-6, (iii) months 7-12, and (iv) months 13-24. The analysis is implemented for the entire sample period (June 1977 to October 2015), for the most recent period (2001-2015), and for various market states: (a) positive versus negative sentiment per Baker and Wurgler (2006), (b) below versus above median previous months' market volatility, and (c) below versus above median previous months' market illiquidity per Amihud (2002). Risk-adjusted excess returns are based on the three Fama-French factors, along with one of three momentum factors: cross-sectional momentum, time series momentum, and the trend factor of Han, Zhou, and Zhu (2016). *MAD* and the control variables are defined in Appendix A. *MAD Threshold* = γ is a variable that records the value one if *MAD* is greater than 1+γ, negative one if
and 1% levels, respectively.

Dependent variable	*MAD*	*MOM*	*52HIGH*	*TRND*	Averaged R^2
R_{t+1}	2.79***	0.40***	−1.02***	28.15***	0.10
	(5.80)	(3.75)	(−3.39)	(7.77)	
$R_{t+2:t+6}$	11.54***	−0.15	0.68	−12.36	0.10
	(8.98)	(−0.53)	(1.02)	(−0.70)	
$R_{t+7:t+12}$	6.04***	−2.16***	−0.51	−10.18	0.09
	(5.05)	(−7.49)	(−0.75)	(−1.06)	
$R_{t+13:t+24}$	−0.04	−1.12**	−2.18**	−2.80	0.09
	(−0.02)	(−2.45)	(−2.08)	(−0.18)	
R_{t+1} for 2001−2015	1.98***	0.12	−0.68	3.25	0.09
	(2.80)	(0.70)	(−1.26)	(0.45)	
Excess R_{t+1} adjusted to FF &					
Cross−Sectional Momentum	2.41***	0.36***	−0.75***	27.19***	0.07
	(5.78)	(3.70)	(−3.28)	(7.77)	
Time−Series Momentum	2.33***	0.37***	−0.75***	27.15***	0.07
	(5.58)	(3.69)	(−3.26)	(7.74)	
Trend	2.08***	0.42***	−0.68***	27.81***	0.07
	(4.79)	(4.23)	(−2.95)	(7.79)	
R_{t+1}					
MAD Threshold = 0.1	0.23***	0.56***	−0.87***	30.88***	0.09
	(4.29)	(5.26)	(−2.78)	(9.11)	
MAD Threshold = 0.2	0.44***	0.52***	−0.92***	30.52***	0.09
	(6.04)	(4.96)	(−3.00)	(8.91)	
MAD Threshold = 0.3	0.51***	0.57***	−0.78**	30.63***	0.09
	(5.19)	(5.35)	(−2.56)	(9.05)	
R_{t+1}					
High Sentiment	2.92***	0.56***	−0.61*	28.75***	0.09
	(5.21)	(4.56)	(−1.75)	(5.94)	
Low Sentiment	2.50***	0.13	−1.72	27.10***	0.11
	(2.87)	(0.64)	(−3.14)	(5.15)	
Low Volatility	3.32***	0.31**	−0.50	33.24***	0.10
	(5.01)	(2.12)	(−1.44)	(8.03)	
High Volatility	2.23***	0.49***	−1.51***	23.31***	0.10
	(3.28)	(3.14)	(−3.14)	(3.99)	
High liquidity	2.63***	0.30**	−0.94**	13.843**	0.09
	(4.15)	(2.25)	(−2.03)	(2.42)	
Low liquidity	2.90***	0.51***	−1.10***	43.62***	0.11
	(4.06)	(3.01)	(−2.96)	(10.72)	

Table 3. The interaction between *MAD* and momentum, 52-week high price, and price trend

The table reports next months' average returns (*R*) on top 30%, mid 40%, and bottom 30% portfolios corresponding to 3 × 3 sorts on *MAD* and, independently, on momentum (*MOM*), 52-week high price (*52HIGH*), and price trend (*TRND*), as defined in Appendix A. The sample is from June 1977 to October 2015. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

MOM	***MAD***	***R* (%)**	***52HIGH***	***MAD***	***R* (%)**	***TRND***	***MAD***	***R* (%)**
Bottom	Bottom	0.75	Bottom	Bottom	0.98	Bottom	Bottom	0.12
	Top	1.19		Top	1.52		Top	1.11
	Diff.	0.44**		Diff.	0.54**		Diff.	0.99***
Mid	Bottom	1.21	Mid	Bottom	0.97	Mid	Bottom	1.13
	Top	1.54		Top	1.70		Top	1.51
	Diff.	0.33*		Diff.	0.73***		Diff.	0.38**
Top	Bottom	1.15	Top	Bottom	0.16	Top	Bottom	1.62
	Top	1.78		Top	1.48		Top	2.09
	Diff.	0.63**		Diff.	1.36***		Diff.	0.47**

Table 4. ***MAD*** **versus Momentum**

The table reports the average portfolio returns for the next month, months 2 through 6, and months 7 through 12. "Largest" (L.) and "Smallest" (S.) portfolios correspond to 10 × 10 portfolios sorted sequentially and independently, first on *MAD* and then on past returns for months −2 through −6. The sample is from June 1977 to October 2015. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

		MOM **($R_{t-2:t-6}$)**										
	MAD	**Smallest**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Largest**	**Diff.**
R_{t+1}	Smallest	0.42	0.89	0.66	0.75	0.95	1.27	1.04	1.00	1.22	0.98	0.56*
	Largest	1.48	1.70	1.96	2.12	1.83	1.98	2.08	2.09	2.20	2.42	0.94***
	Diff.	1.06**	0.81**	1.30***	1.37***	0.88**	0.71*	1.04**	1.09***	0.98***	1.44***	
Sorted	S.	0.45	0.76	0.72	0.79	1.43	0.97	0.75	1.10	0.85	1.05	0.60**
independently	L.	1.24	1.46	1.80	1.87	2.10	1.81	2.27	1.92	1.97	2.15	0.91***
	Diff.	0.79**	0.70*	1.08***	1.08**	0.67	0.84**	1.52***	0.82**	1.12***	1.10***	
$R_{t+2:t+6}$	S.	2.62	3.06	3.65	3.57	4.19	3.87	3.27	3.43	3.29	2.87	0.25
	L.	8.16	9.62	9.31	9.95	10.11	9.85	10.13	9.17	8.45	8.32	0.16
	Diff.	5.54***	6.56***	5.66***	6.38***	5.92***	5.98***	6.86***	5.74***	5.16***	5.45***	
Sorted	S.	2.23	3.35	3.81	3.53	4.20	3.23	3.40	3.20	2.94	2.79	0.56
independently	L.	7.81	8.96	9.48	9.65	9.67	8.98	9.05	9.74	9.48	7.92	0.11
	Diff.	5.58***	5.61***	5.67***	6.12***	5.47***	5.75***	5.65***	6.54***	6.54***	5.13***	
$R_{t+7:t+12}$	S.	8.05	6.63	7.32	6.39	7.09	5.77	5.05	4.64	5.08	3.71	−4.34***
	L.	12.93	11.15	10.57	11.04	9.61	10.53	9.81	8.87	8.89	6.64	−6.29***
	Diff.	4.88***	4.52***	3.25***	4.65***	2.52**	4.76***	4.76***	4.23***	3.81***	2.93***	

Table 5. Annual alphas of *MAD* portfolios

The table reports annual alphas (in %) and their *t*-values (in parentheses) obtained from regressing monthly zero-cost portfolio returns on the three Fama-French factors. Panel A reports long positions in top *MAD* stocks, along with short positions in bottom *MAD* stocks. Panel B focuses exclusively on the long leg of the trade. Annual alphas are obtained by multiplying monthly alphas by 12 (no compounding). The *MAD* signal strategy takes long (short) positions in positive (negative) *MAD* stocks. The *MAD* decile strategy takes long (short) positions in the top (bottom) *MAD* decile. The *MAD* threshold strategies take long (short) positons in stocks with *MAD* greater than (smaller than) or equal to 1 plus (minus) a threshold of 0.1, 0.2, or 0.3. Portfolios are constructed by equally weighting stocks. Portfolios with different time horizons are equal-weighted. The sample is from June 1977 to October 2015. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	Holding Period (months)					
Portfolio Strategy	**1**	**3**	**6**	**12**	**18**	**24**
A. Long-Short Equities						
MAD Signal	6.87***	6.69****	6.41****	4.95***	3.24***	2.61***
(long *MAD* > 1, short *MAD* ≤ 1)	(4.40)	(4.64)	(4.90)	(4.98)	(3.89)	(3.62)
MAD Decile	15.10***	15.13***	13.93***	9.11***	4.94***	3.58**
(long Top, short Bottom)	(4.27)	(4.75)	(4.78)	(4.08)	(2.65)	(2.29)
MAD Threshold = 0.10	14.20***	14.16***	13.23***	10.06***	6.99***	5.48***
(long *MAD* ≥ 1.1, short *MAD* ≤ 0.9)	(6.22)	(6.81)	(6.92)	(6.71)	(5.50)	(4.96)
MAD Threshold = 0.20	19.97***	20.48***	18.31***	13.45***	8.69***	6.63***
(long *MAD* ≥ 1.20, short *MAD* ≤ 0.8)	(6.46)	(7.26)	(7.12)	(6.51)	(4.92)	(4.35)
MAD Threshold = 0.30	25.41***	26.14***	23.16***	15.76***	9.46***	6.55***
(long *MAD* ≥ 1.30, short *MAD* ≤ 0.7)	(5.62)	(6.58)	(6.70)	(5.57)	(3.91)	(3.15)
B. Long Equities, Short T-bills						
MAD Signal	3.37***	3.42***	3.35***	2.67***	1.92***	1.87***
(long *MAD* > 1, short T-bills)	(4.26)	(4.76)	(5.16)	(4.73)	(3.39)	(3.12)
MAD Decile	8.92***	7.82***	6.54***	3.48***	1.38	1.07
(long Top, short T-bills)	(5.20)	(5.34)	(5.09)	(3.36)	(1.45)	(1.12)
MAD Threshold = 0.10	5.47***	5.21***	4.81***	3.50***	2.37***	2.04***
(long *MAD* ≥ 1.1, short T-bills)	(5.00)	(5.31)	(5.53)	(4.98)	(3.54)	(2.95)
MAD Threshold = 0.20	8.65***	7.13***	5.89***	3.83***	2.11**	1.59*
(long MAD ≥ 1.20, short T-bills)	(6.05)	(5.39)	(5.08)	(4.18)	(2.50)	(1.90)
MAD Threshold = 0.30	10.52***	7.83**	6.34**	3.62***	1.38	0.72
(long *MAD* ≥ 1.30, short T-bills)	(5.55)	(4.41)	(4.15)	(3.02)	(1.29)	(0.70)

Table 6. Cross-sectional regressions: considering widely-followed accounting characteristics

The table reports average slopes (multiplied by 10^4) and their *t*-values (in parentheses) obtained from monthly cross-sectional regressions. The dependent variable is the stock return for the next month, months 2-6, 7-12, and 13-24. High and low sentiment, liquidity, and volatility states are defined as in Table 2. The variables are defined in Appendix A and the slopes corresponding to the control variables are given in Appendix E. The sample is from June 1977 to October 2017, whereas the Baker and Wurgler sentiment data is up to 2015. Portfolios with different time horizons are equal-weighted. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	R_{t+1}											$R_{t+2:t+6}$	$R_{t+7:t+12}$	$R_{t+13:t+24}$
						Sentiment		Liquidity		Volatility				
		PDI	*PDI* & *MAD*	Extended *PDI*	2001-2017	Low	High	Low	High	Low	High			
Performance Deviation Index (*PDI*)		2.24*** (14.22)	2.21*** (14.11)	1.98*** (13.03)	1.89*** (7.43)	2.30*** (7.60)	2.32*** (12.34)	2.36*** (10.77)	2.11*** (9.39)	1.85*** (9.68)	2.62*** (10.60)	2.93*** (7.94)	3.28*** (7.94)	2.50*** (3.40)
Cash	1.57*** (4.57)													
Operating Income	2.00* (1.90)													
Retained Earnings	0.88* (1.91)													
CAPEX	1.49*** (2.72)													
Invested Capital	−1.59*** (−6.41)													
Inventories	−4.18*** (−7.12)													
Sales	1.14*** (3.34)													
IB	0.47 (0.50)													
MAD			2.54*** (5.45)											
SUE	0.21*** (12.93)	0.20*** (12.14)	0.20*** (12.01)	0.19*** (11.73)	0.08*** (3.69)	0.23*** (7.15)	0.20*** (10.68)	0.27*** (11.60)	0.13*** (5.81)	0.22*** (9.79)	0.18*** (7.45)	0.23*** (5.52)	−0.09** (−2.09)	0.49*** (8.47)
SURGE	0.24*** (12.68)	0.20*** (11.17)	0.19*** (10.74)	0.20*** (11.17)	0.16*** (6.17)	0.20*** (5.93)	0.20*** (9.52)	0.23*** (8.34)	0.18*** (7.47)	0.21*** (8.75)	0.19*** (7.14)	0.59*** (13.37)	0.05 (0.87)	0.70*** (8.41)
MOM	0.73*** (4.89)	0.72*** (4.85)	0.23*** (2.20)	0.72*** (4.80)	0.38 (1.56)	0.47* (1.78)	0.90*** (4.96)	0.73*** (3.47)	0.72*** (3.38)	0.56*** (2.86)	0.89*** (3.94)	3.05*** (8.39)	1.33*** (3.60)	−1.83*** (−3.25)
TRND	31.20*** (9.45)	31.32*** (9.60)	28.03*** (8.12)	31.28*** (9.57)	6.57 (1.17)	30.78*** (5.93)	34.31*** (7.65)	45.85*** (11.66)	16.84*** (3.35)	26.06*** (5.89)	36.60*** (7.66)	8.00 (1.15)	0.66 (0.07)	11.35 (0.76)
Average R^2	0.10	0.09	0.10	0.09	0.09	0.10	0.09	0.09	0.09	0.09	0.10	0.10	0.09	0.09

Table 7. Do anchor effects survive the modern five factor model?

The table reports annual alphas (in %) and their *t*-values (in parentheses) obtained from regressing monthly zero-cost portfolio returns on zero cost factor mimicking portfolios corresponding to the Fama and French (2015) five-factor model. Annual alphas are obtained by multiplying monthly alphas by 12 (no compounding). The variables are defined in Appendix A. The *PDI* and *MAD* strategies respectively take long (short) positions in *PDI* or *MAD* top (bottom) decile stocks. The *MAD* threshold strategies take long (short) positons in stocks with *MAD* greater than (smaller than) or equal to 1 plus (minus) a threshold. Portfolios with different time horizons are equally weighted. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	PDI	***MAD***	***MAD Threshold***		
Horizon	**Top-minus-Bottom Deciles**	**Top-minus-Bottom Deciles**	**0.10**	**0.20**	**0.30**
		A. Equally Weighted Portfolios			
1-Month	15.49***	12.51***	12.15***	17.78***	22.24***
	(13.10)	(3.46)	(5.21)	(5.60)	(4.79)
3-Months	10.98***	12.64***	12.38***	18.53***	23.63***
	(10.54)	(3.87)	(5.82)	(6.41)	(5.78)
6-Months	5.89***	11.60***	11.75***	16.66***	21.03***
	(6.40)	(3.88)	(5.99)	(6.30)	(5.90)
12-Months	4.08***	7.82***	9.19***	12.23***	13.84***
	(5.35)	(3.40)	(5.97)	(5.75)	(4.76)
		B. Value Weighted Portfolios			
1-Month	9.60***	9.97**	7.43**	15.85***	22.45***
	(4.91)	(2.15)	(2.39)	(3.83)	(3.74)
3-Months	7.06***	9.50***	7.41***	17.18***	26.45***
	(4.07)	(2.31)	(2.62)	(4.54)	(5.27)
6-Months	4.14***	9.95***	8.54***	16.30***	23.45***
	(2.82)	(2.72)	(3.33)	(4.82)	(5.50)
12-Months	4.13***	8.05***	8.45***	12.90***	16.41***
	(3.34)	(2.72)	(4.07)	(4.56)	(4.72)

Table 8. Break-even transaction costs

The table reports two break-even transaction costs: (i) transaction costs that would zero out average abnormal returns (alpha) on zero-cost portfolios reported in Table 4, and (ii) transaction costs that equate the certainty equivalent return of such zero-cost portfolios to that of the zero-cost market portfolio (long CRSP value-weighted composite index and short 30-day Treasury bills). The variables are defined in Appendix A. Certainty equivalent return = mean return minus 0.5 × risk aversion coefficient × variance, where the risk-aversion value is two. The sample is from June 1977 to October 2015. The notation na represents the case where the strategy does not deliver a positive certainty equivalent return.

		Holding Period (months)					
Portfolio Strategy		**1**	**3**	**6**	**12**	**18**	**24**
MAD Signal	(i)	161	236	452	698	686	736
(long *MAD* > 1, short *MAD* ≤ 1)	(ii)	na	na	na	na	na	na
MAD Decile	(i)	184	277	510	667	542	524
(long Top, short Bottom)	(ii)	27	68	129	10	na	na
MAD Threshold = 0.10	(i)	234	350	654	995	1036	1084
(long *MAD* ≥ 1.1, short *MAD* ≤ 0.9)	(ii)	78	136	246	222	na	na
MAD Threshold = 0.20	(i)	289	445	796	1169	1133	1153
(long *MAD* ≥ 1.20, short *MAD* ≤ 0.8)	(ii)	118	212	376	409	28	na
MAD Threshold = 0.30	(i)	335	516	915	1245	1121	1036
(long *MAD* ≥ 1.30, short *MAD* ≤ 0.7)	(ii)	114	233	443	437	na	na
PDI Decile	(i)	199	218	249	341	379	506
(long Top, short Bottom)	(ii)	128	114	441	na	na	na

Table 9. Risk and characteristic profiles of *MAD/PDI* portfolios

Panel A reports various risk measures for the top *MAD/PDI* decile, the bottom *MAD/PDI* decile, and top-minus-bottom equally-weighted portfolios. Panel B reports average firm characteristics for *MAD/PDI* decile portfolios. The second column in Panel A reports the past 200-day mean standard deviation (STD) of daily stock returns. The third column reports the standard deviation of portfolio monthly returns. Subsequent columns report loadings and their *t*-values (in parentheses) obtained from regressing portfolio monthly excess returns on zero-cost factor mimicking portfolios corresponding to Fama and French's (2015) five-factor model. Panel B reports various characteristics of *MAD/PDI* decile or *MAD threshold* portfolios. The firm variables are defined in Appendix A. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Risk of *MAD* and *PDI* Portfolios

	Stock Mean	***Portfolio***	**Five-Factor Model**					
Portfolio	***200-Day STD***	***Monthly STD***	***Intercept***	***Market***	***Size***	***HML***	***RMW***	***CMA***
Top *MAD* Decile	17.03	7.18	1.24***	0.98***	1.09***	−0.42***	−0.28***	0.26**
			(8.49)	(27.74)	(20.77)	(−6.13)	(−4.29)	(2.40)
Bottom *MAD* Decile	16.03	7.86	0.20	1.23***	0.69***	0.35***	−0.38***	−0.55***
			(1.04)	(26.60)	(10.04)	(3.87)	(−4.44)	(−4.09)
(Equal Slopes *t*-test)			(4.30)***	(−4.43)***	(4.55)***	(−6.79)***	(0.95)	(4.77)***
Top−minus-Bottom		6.45	1.04***	−0.26***	0.40***	−0.77***	0.10	0.81***
			(3.46)	(−3.56)	(3.66)	(−5.46)	(0.76)	(3.83)
Top *PDI* Decile	13.94	5.36	1.13***	0.98***	0.75***	−0.01	0.14***	0.01
			(15.58)	(55.48)	(28.95)	(−0.43)	(4.14)	(0.15)
Bottom *PDI* Decile	13.19	5.83	−0.17**	0.97***	0.87***	0.09***	−0.22***	−0.04
			(−2.15)	(51.39)	(31.17)	(2.57)	(−6.31)	(−0.71)
(Equal Slopes *t*-test)			(12.22)***	(0.46)	(−2.94)***	(−2.17)**	(7.44)***	(0.62)
Top−minus-Bottom		2.26	1.29***	0.01	−0.11***	−0.11**	0.36***	0.05
			(13.10)	(0.49)	(−3.15)	(−2.33)	(7.97)	(0.66)

Panel B. Characteristics of *MAD* and *PDI* Portfolios

Decile	**Market Cap ($ million)**	***BE/ME***	***TURN***	***ILLIQ***	***IVOL***	***O-Score***	**Share of Institutional Holdings**	**Number of Analysts**
Bottom *MAD*	1,187	0.84	0.18	1.30	0.13	−0.015	0.37	4.69
2	2,324	0.77	0.12	1.24	0.11	−0.014	0.39	4.61
3	3,022	0.73	0.10	1.16	0.10	−0.013	0.41	4.63
4	3,493	0.71	0.09	1.12	0.10	−0.012	0.39	4.69
5	3,784	0.67	0.09	0.97	0.10	−0.012	0.41	4.77
6	3,948	0.63	0.09	0.85	0.10	−0.012	0.40	4.86
7	3,930	0.60	0.10	0.81	0.10	−0.011	0.40	4.91
8	3,744	0.55	0.11	0.80	0.10	-0.012	0.40	4.91
9	3,059	0.51	0.13	0.70	0.12	−0.013	0.40	4.70
Top *MAD*	1,664	0.42	0.22	0.68	0.15	−0.013	0.37	3.55
MAD < 0.7	1,249	0.90	0.27	0.88	0.15	−0.014	0.43	5.94
MAD < 0.8	1,348	0.85	0.21	1.12	0.14	−0.014	0.41	5.23
MAD < 0.9	1,698	0.81	0.16	1.25	0.12	−0.014	0.40	4.78
MAD > 1.1	2,761	0.50	0.15	0.67	0.12	−0.012	0.39	4.47
MAD > 1.2	1,905	0.45	0.19	0.62	0.14	−0.013	0.38	3.89
MAD > 1.3	1,439	0.40	0.24	0.57	0.16	−0.013	0.36	3.37
Bottom *PDI*	1,528	0.70	0.13	1.24	0.12	−0.012	0.37	4.01
2	2,450	0.70	0.12	1.01	0.11	−0.011	0.38	4.38
3	2,943	0.70	0.12	0.96	0.11	−0.011	0.40	4.58
4	3,267	0.69	0.11	0.87	0.11	−0.010	0.40	4.68
5	3,357	0.66	0.12	0.92	0.11	−0.011	0.41	4.86
6	3,451	0.64	0.12	0.89	0.11	−0.012	0.40	4.82
7	3,565	0.62	0.12	0.91	0.11	−0.013	0.40	4.86
8	3,686	0.60	0.12	0.88	0.11	−0.014	0.40	4.87
9	3,250	0.57	0.13	0.91	0.11	−0.015	0.40	4.76
Top *PDI*	2,693	0.55	0.14	1.04	0.12	−0.017	0.39	4.52

Table 10. Market timing strategies at the market and industry levels

The table reports the annual alphas (in %) and their *t*-values (in parentheses) obtained from regressing *MAD* (*PDI*) portfolio monthly excess returns on the market factor. Annual alpha is obtained by multiplying monthly alpha by 12. There are two portfolio strategies. The *MAD* (*PDI*) signal strategy buys the industry index each month if *MAD* > 1 (*PDI* > 0.5) and holds Treasury bills otherwise. The *MAD* threshold strategy buys (1/*e* ×(industry index) − (1−1/*e*) × Treasury bills) if *MAD*/*PDI* > 1 + threshold, and holds Treasury bills otherwise. The equity exposure scale factor *e* = (number of months for which *MAD* > 1 + threshold) / (number of months for which *MAD* > 1) over a rolling window that uses as many months of data as are available from the first to the 60th month after the start of the sample period, and thereafter is held constant at 60 months (the same applies for *PDI* with 0.5 + threshold instead of 1+ threshold). The procedure ensures that the average exposure to the market over the sample period is the same across strategies. The market portfolio is the all-stock value-weighted composite index. In the last row, we test joint significance by equally weighting industry *MAD* (*PDI*) timing portfolios. Industry index *PDI* is the value-weighted *PDI* of the stocks belonging to the particular industry. The *PDI* computation period starts in 1977 and the threshold is 0.0125 which is equivalent to the first *MAD* threshold of 0.025. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	***MAD* 1927-2015**			***MAD* 2001-2015**			***PDI***	
Industry	**Signal**	**Threshold**		**Signal**	**Threshold**		**Signal**	**Threshold**
Portfolio		**0.025**	**0.05**		**0.025**	**0.05**		
Market	2.88***	4.54***	5.67***	4.90**	5.88***	7.00***	3.20***	3.45***
	(2.85)	(3.97)	(4.08)	(2.52)	(2.64)	(2.74)	(2.66)	(2.61)
NoDur	2.89***	4.91***	7.64***	6.39***	6.74***	6.40*	5.54***	6.67***
	(2.87)	(4.24)	(4.88)	(3.22)	(2.77)	(1.96)	(3.85)	(4.09)
Durbl	2.99*	4.72***	7.27***	4.15	6.38	8.23*	0.95	1.53
	(1.90)	(2.79)	(3.78)	(1.18)	(1.59)	(1.75)	(0.50)	(0.69)
Manuf	3.09**	3.63***	4.25***	4.78*	4.87	9.85***	3.16**	3.10*
	(2.47)	(2.63)	(2.67)	(1.76)	(1.63)	(2.68)	(2.04)	(1.75)
Enrgy	4.54***	5.40***	4.72**	6.29	8.51**	4.67	4.18*	7.44***
	(3.14)	(3.39)	(2.39)	(1.63)	(2.07)	(1.02)	(1.93)	(2.57)
Chems	3.17***	4.14***	5.18***	5.13**	5.18**	5.77**	0.45	1.16
	(2.61)	(3.05)	(3.34)	(2.30)	(2.05)	(1.98)	(0.35)	(0.75)
BusEq	2.29	4.29**	5.62***	2.62	4.39	4.65	−1.45	−0.37
	(1.49)	(2.52)	(2.98)	(0.93)	(1.53)	(1.39)	(−0.99)	(−0.14)
Telcm	4.01***	6.66***	9.20***	6.18***	7.52***	9.32***	0.11	1.34
	(3.72)	(5.38)	(5.69)	(2.57)	(2.81)	(3.18)	(0.08)	(0.83)
Utils	3.90***	5.73***	5.92***	7.12***	5.92*	3.79	2.04**	5.05**
	(3.08)	(4.09)	(3.80)	(2.66)	(1.90)	(1.04)	(2.13)	(2.45)
Shops	1.80	3.64**	6.46***	0.70	4.57*	7.53**	−1.09	−1.12
	(1.43)	(2.53)	(3.74)	(0.30)	(1.74)	(2.28)	(−0.77)	(−0.69)
Hlth	4.68***	5.31***	7.31***	2.91	3.93	6.47*	1.01	0.18
	(3.66)	(3.67)	(4.19)	(1.23)	(1.45)	(1.95)	(0.61)	(0.10)
Money	2.50*	5.06***	7.47***	3.48	3.24	3.17	1.74	4.93**
	(1.96)	(3.49)	(4.48)	(1.43)	(1.17)	(0.95)	(1.02)	(2.08)
Other	2.04	3.48**	4.61***	5.32**	6.39**	6.43**	1.82	3.73**
	(1.58)	(2.44)	(2.66)	(2.27)	(2.56)	(2.08)	(1.11)	(2.12)
All-	3.13***	4.71***	6.27***	5.03***	6.08***	6.78***	1.86***	2.80***
Industry	(3.81)	(5.15)	(5.83)	(3.14)	(3.29)	(3.13)	(2.68)	(3.26)

Table 11. International perspectives: Cross-country regressions

The table provides average slopes (multiplied by 10^4) and their t-ratios (in parentheses) from monthly cross-country regressions. The dependent variable is returns or risk-adjusted returns for next month, months 2-6, 7-12, and 13-24. Cross-sectional regressions consider raw payoffs, returns adjusted with respect to the global market, and returns adjusted with respect to the Fama-French and momentum global factors. The control variables are past 12-month returns ($R_{t\text{-}1:t\text{-}12}$); the *MAD* signal (*MDS*), which is equal to 1 if *MAD* > 1 and zero otherwise; and the *MA* signal (*MAS*), which is equal to 1 if current index price > index price 200-day moving average, and zero otherwise. The sample is from January 2001 to November 2015 and the data cover 38 markets. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	**Investment Horizon**	***MAD***	***MDS***	***MAS***	***Int. Momentum*** **($R_{t\text{-}1:t\text{-}12}$)**	**Averaged R^2**
Raw Returns	R_{t+1}	4.84**	−0.35	−0.62*	0.03	0.23
		(2.37)	(−1.15)	(−1.94)	(0.03)	
	$R_{t+2:t+6}$	10.62**	−0.83	−1.18	5.82**	0.24
		(1.97)	(−1.01)	(−1.47)	(2.45)	
	$R_{t+7:t+12}$	11.72	−1.66	−0.85	8.89***	0.23
		(1.61)	(−1.56)	(−0.86)	(3.57)	
	$R_{t+13:t+24}$	31.32***	−2.74	−8.07*	4.01	0.23
		(3.16)	(−1.35)	(−1.89)	(1.05)	
Returns Adjusted by International CAPM	R_{t+1}	5.18**	−0.37	−0.67**	0.64	0.23
		(2.51)	(−1.24)	(−2.20)	(0.67)	
	$R_{t+2:t+6}$	20.26***	−1.23	−1.67**	4.69**	0.23
		(3.74)	(−1.56)	(−2.20)	(2.01)	
	$R_{t+7:t+12}$	8.94	−2.22**	−0.24	9.00***	0.23
		(1.26)	(−2.30)	(−0.24)	(3.55)	
	$R_{t+13:t+24}$	31.32***	−2.74	−8.07*	4.01	0.23
		(3.16)	(−1.35)	(−1.89)	(1.05)	
Returns Adjusted to Fama-French-Momentum Global Factors	R_{t+1}	5.60***	−0.31	−0.68**	0.47	0.23
		(2.80)	(−0.99)	(−2.28)	(0.52)	
	$R_{t+2:t+6}$	21.10***	−1.13	−1.46*	3.28	0.23
		(3.84)	(−1.46)	(−1.93)	(1.42)	
	$R_{t+7:t+12}$	13.90**	−2.13**	−0.50	5.47**	0.22
		(1.96)	(−2.17)	(−0.50)	(2.24)	
	$R_{t+13:t+24}$	20.85**	−2.43	−8.03**	6.72*	0.22
		(2.24)	(−1.27)	(−2.07)	(1.89)	

Table 12. Market timing strategies for various economies

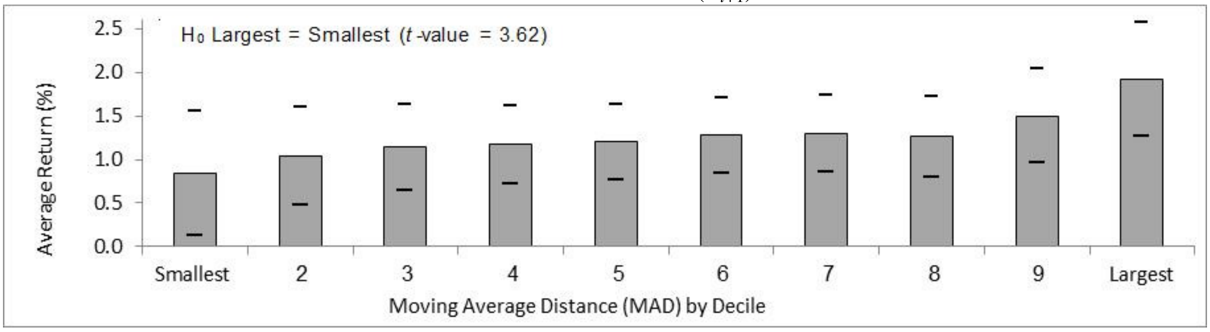
The table reports the annual alphas (in %) and their *t*-values (in parentheses) obtained from regressing *MAD* portfolios' monthly excess returns on the corresponding market factor. The annual alpha is the monthly alpha times 12. The signal strategy buys the market index each month if *MAD* > 1 and holds T-bills otherwise. The *MAD* strategy buys (1/*e* × (market index) − (1−1/*e*) × T-bills) if *MAD* > 1 + threshold, and holds T-bills otherwise. The equity exposure scale factor *e* = (number of months for which *MAD* > 1 + threshold) / (number of months for which *MAD* > 1) over a rolling window that uses as many months of data as are available from the first to the 60th month after the start of the sample period, and thereafter is held constant at 60 months. The procedure ensures that the average exposure to the market over the sample period is the same across strategies. The global portfolio includes equal- or value-weighted aggregated *MAD* timing portfolios, where "value" corresponds to the total annual market capitalization of listed companies as per the World Bank. The sample period is from January 2001 to November 2015. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	Signal	Threshold			Signal	Threshold	
Market		**0.025**	**0.05**	**Market**		**0.025**	**0.05**
U.S.	4.90**	6.10***	7.57***	Japan	0.96	2.77	1.38
	(2.52)	(2.71)	(2.88)		(0.42)	(0.94)	(0.36)
Australia	3.70**	4.85**	9.34***	Malaysia	1.93	5.23**	6.38**
	(2.20)	(2.39)	(3.50)		(1.03)	(2.13)	(2.18)
Austria	5.48**	8.54***	13.03***	Mexico	2.85	4.00	7.68***
	(2.17)	(3.01)	(3.03)		(1.29)	(1.57)	(2.59)
Belgium	8.53***	11.55***	13.09***	Netherlands	7.16***	6.16**	8.95***
	(3.97)	(4.70)	(4.45)		(3.24)	(2.46)	(2.80)
Brazil	−1.90	−1.32	1.46	Norway	4.71*	4.77*	6.65**
	(−0.71)	(−0.40)	(0.37)		(1.81)	(1.78)	(2.31)
Chile	4.18**	6.61***	8.50***	New Zealand	1.62	1.15	9.49*
	(2.28)	(2.64)	(2.71)		(1.08)	(0.61)	(1.89)
China	6.57*	15.74***	17.61***	Philippines	5.38**	5.77*	7.57**
	(1.83)	(3.03)	(3.01)		(2.18)	(1.92)	(2.28)
Columbia	3.43	0.26	10.13**	Poland	6.59**	6.93**	8.16**
	(1.23)	(0.03)	(2.08)		(2.40)	(2.07)	(2.05)
Denmark	10.76***	10.54***	11.54***	Portugal	5.35**	7.97***	8.00**
	(4.85)	(4.54)	(4.63)		(2.36)	(3.09)	(2.29)
Egypt	7.80***	15.59***	17.03***	Singapore	6.62***	6.05**	5.10*
	(2.58)	(3.21)	(3.39)		(2.83)	(2.40)	(1.80)
Finland	4.86	5.83	9.86**	South Africa	4.43**	5.67**	7.84**
	(1.53)	(1.58)	(2.05)		(2.21)	(2.18)	(2.33)
France	5.30**	9.16***	7.83***	South Korea	0.79	3.40	3.88
	(2.51)	(4.03)	(2.91)		(0.28)	(0.89)	(0.98)
Germany	4.62*	5.53**	6.39**	Spain	2.75	7.36***	11.91***
	(1.95)	(2.18)	(2.31)		(1.17)	(2.72)	(3.24)
Hong Kong	4.53	4.67	5.66*	Sweden	9.92***	9.90***	9.91***
	(1.64)	(1.52)	(1.65)		(4.21)	(3.97)	(3.68)
Hungary	3.20	6.00	8.34	Switzerland	6.00***	5.87***	8.81***
	(1.07)	(1.64)	(1.39)		(3.34)	(2.65)	(3.45)
India	2.48	4.35	9.66**	Taiwan	0.86	2.56	3.12
	(0.71)	(1.12)	(1.97)		(0.30)	(0.78)	(0.86)
Indonesia	5.82*	7.06**	10.72**	Thailand	0.55	2.49	7.86
	(1.91)	(2.18)	(2.30)		(0.19)	(0.72)	(1.40)
Ireland	6.70**	7.59***	8.13**	Turkey	3.64	5.02	5.78
	(2.55)	(2.73)	(2.54)		(0.81)	(1.02)	(1.02)
Italy	4.15*	6.22**	6.60**	U.K.	3.74**	6.60***	14.27***
	(1.82)	(2.40)	(1.97)		(2.06)	(3.20)	(2.82)
Global Equal	8.11***	9.94***	12.28***	Global Value	6.42***	9.85***	9.81***
Weighted	(4.98)	(5.68)	(6.11)	Weighted	(3.92)	(4.83)	(4.61)

Figure 1. Average returns and the moving average distance (*MAD*)

The charts depict future average returns on ten portfolios sorted on *MAD*. The sample period is from June 1977 to October 2015. The dashed lines represent 95% confidence intervals.

Panel A. Next Month (R_{t+1})



Panel B. Months 2-6 ($R_{t+2:t+6}$)

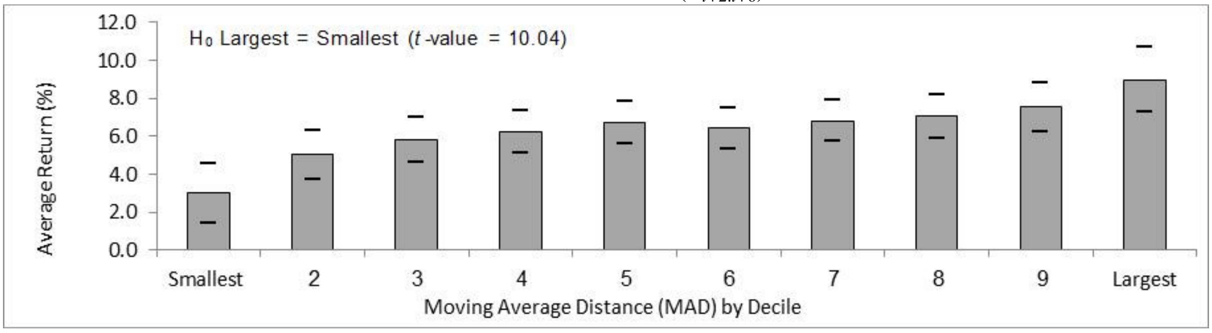


Figure 2. ***MAD*** **investing**

The figure depicts the value of $1 invested each month for the next month in buy and sell portfolios corresponding to five *MAD* strategies. The *MAD* signal strategy buys (sells) all stocks with *MAD* greater (smaller) than one. The *MAD* decile strategy buys (sells) the top (bottom) *MAD* deciles. The *MAD* threshold strategies buy (sell) stocks with *MAD* greater (smaller) than or equal to one plus (minus) a threshold. We consider three thresholds of 0.1, 0.2, and 0.3. The all-market return reflects the CRSP value-weighted composite index. Gray bars represent NBER-defined recessions.

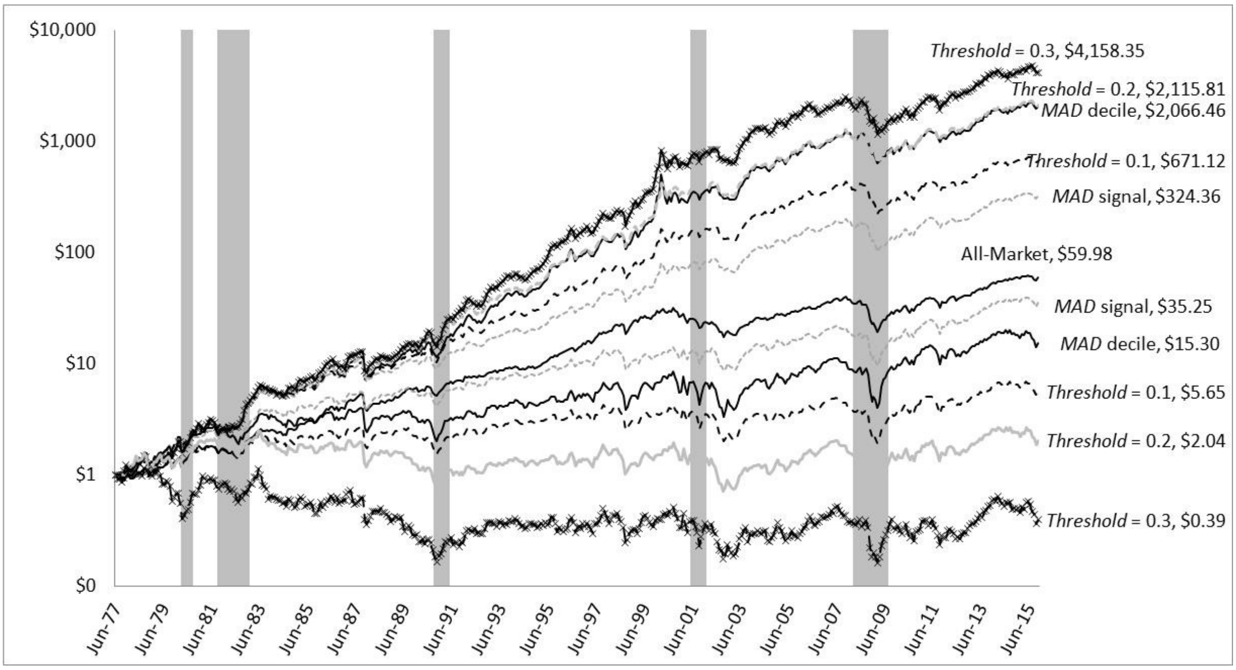
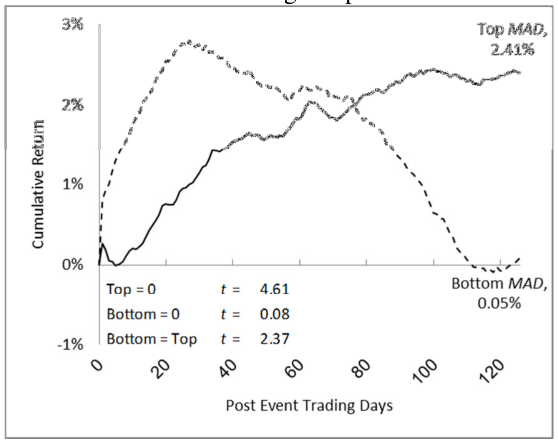


Figure 3. Positive news: Cumulative excess returns and *MAD*

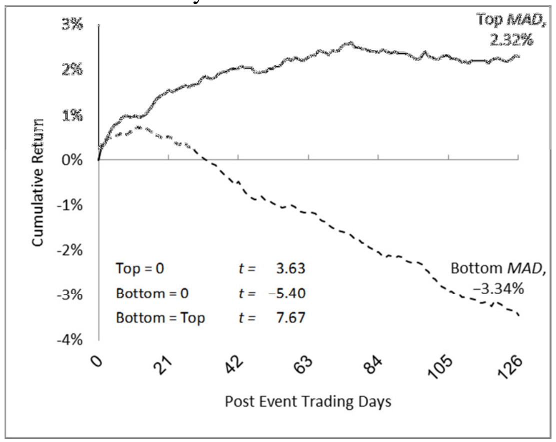
The figure depicts the cumulative excess returns post positive earnings surprises, first-time buy recommendation announcements, and dividend initiations. Portfolios consist of top and bottom *MAD* stocks at the end of the month prior to earnings, recommendations, or dividend initiation announcements. Equal- and value-weighted returns are in excess of the CRSP equally- and value-weighted composite index, respectively. The sample period for earnings surprises is from June 1977 to October 2015. The sample periods for analyst recommendations and dividend initiations are from 1992 and 2002, respectively, to October 2015.

Panel A. Equally-Weighted Portfolios

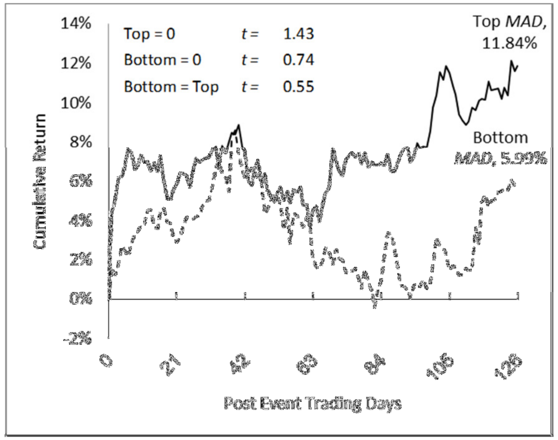
Positive earnings surprises



Buy recommendations

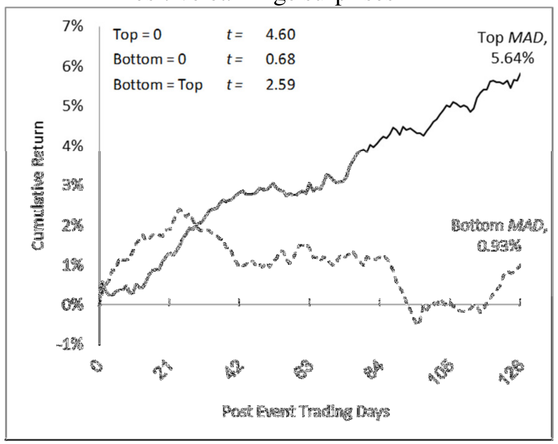


Dividend initiations

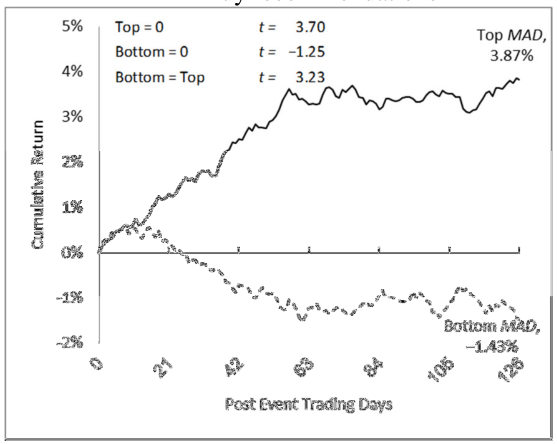


Panel B. Value-Weighted Portfolios

Positive earnings surprises



Buy recommendations



Dividend initiations

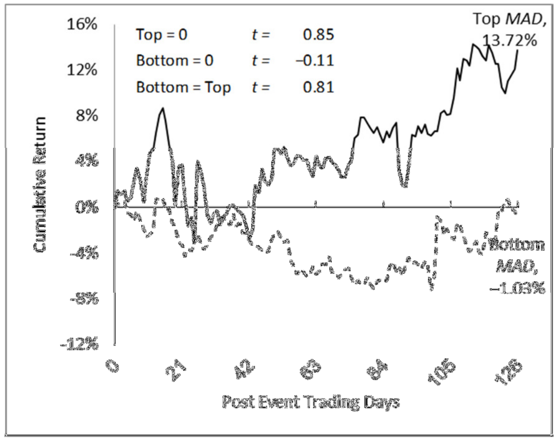
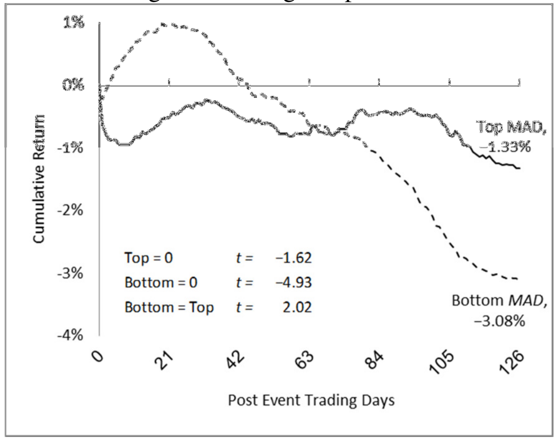


Figure 4. Negative news: Cumulative excess returns and *MAD*

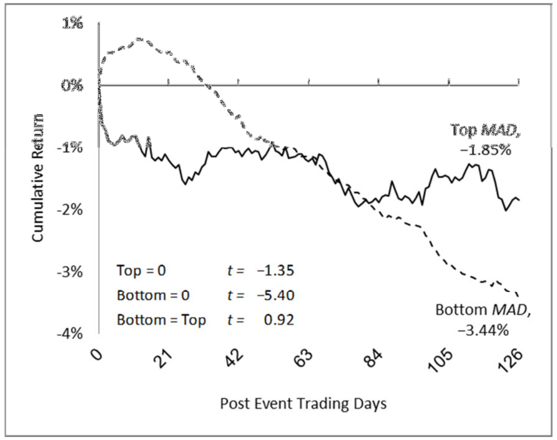
The figure depicts the cumulative excess returns post negative earnings surprises, first-time sell recommendation announcements, and seasoned equity issues (SEOs). Portfolios consist of top and bottom *MAD* stocks at the end of the month prior to earnings, recommendation, or SEO announcements. Equal- and value-weighted returns are in excess of the CRSP equally- and value-weighted composite index, respectively. The sample period for earnings surprises is from June 1977 to October 2015. The sample periods for analyst recommendations and dividend initiations are from 1992 and 2002, respectively, to October 2015.

Panel A. Equally-Weighted Portfolios

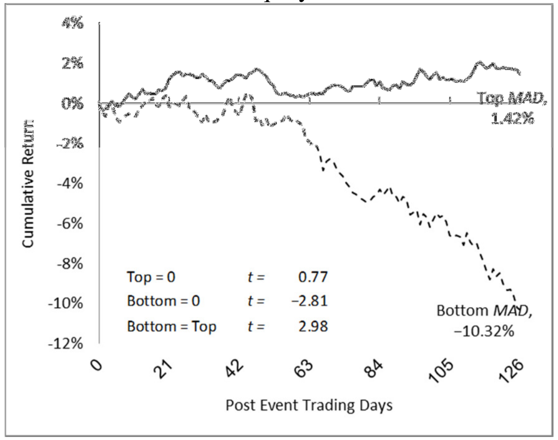
Negative earnings surprises



Sell recommendations

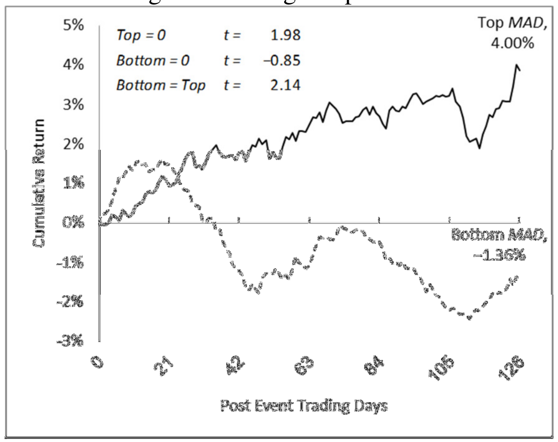


Seasoned equity issues

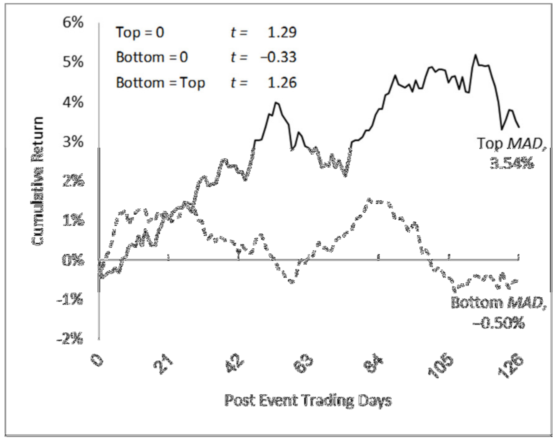


Panel B. Value-Weighted Portfolios

Negative earnings surprises



Sell recommendations



Seasoned equity issues

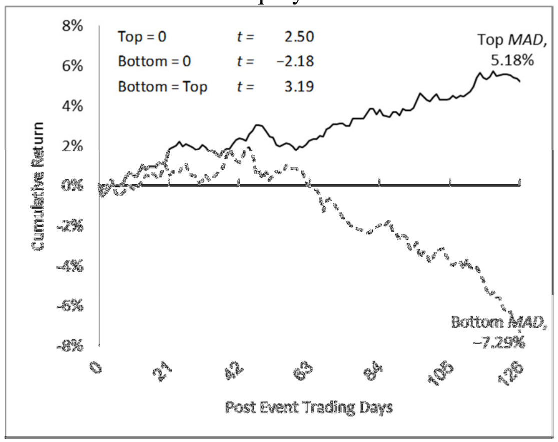
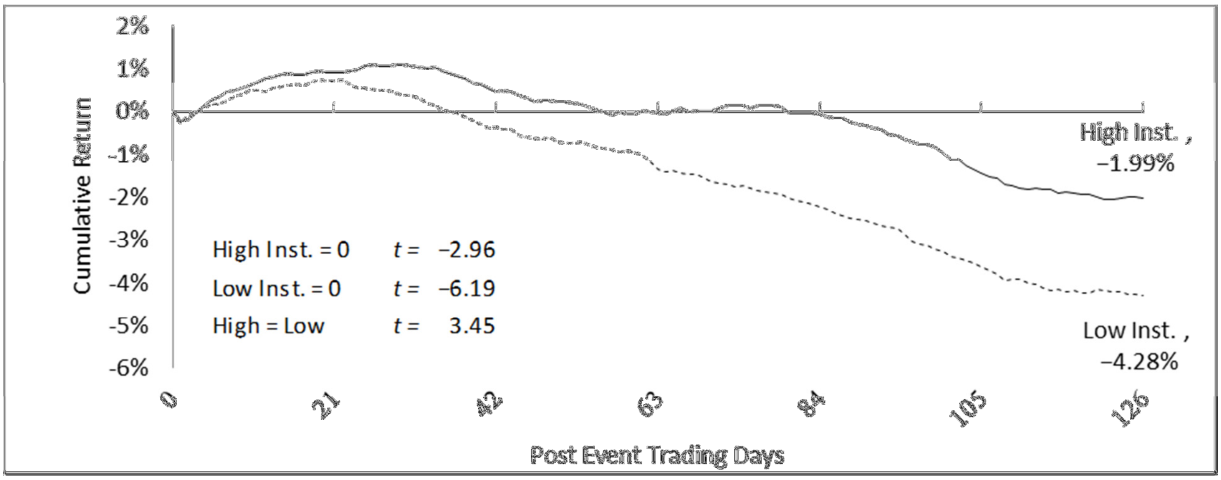


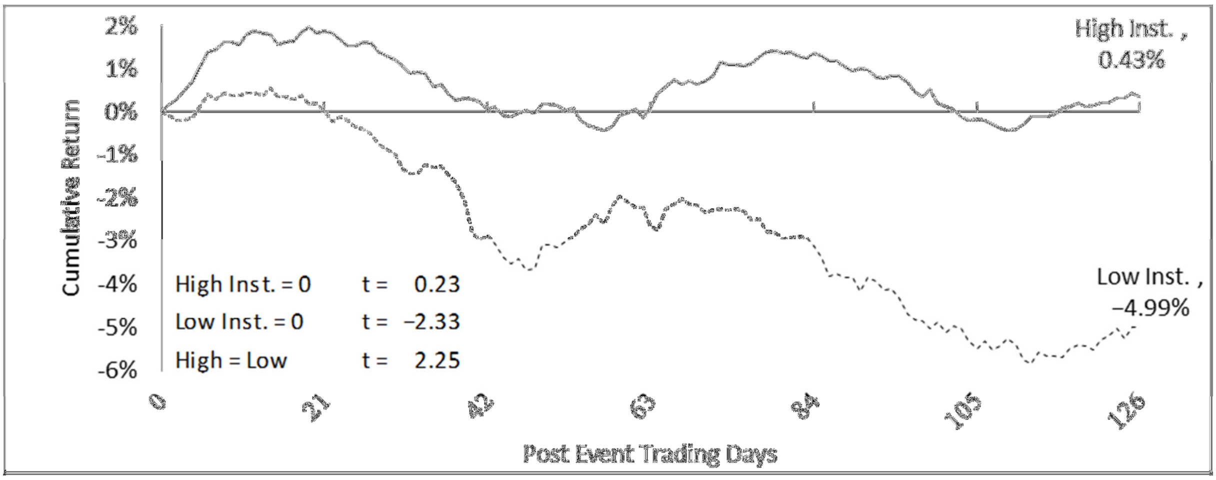
Figure 5. Cumulative excess returns, *MAD*, and short-sale constraints

The figure depicts cumulative excess returns post negative events. Negative events consist of earnings surprises, sell recommendation announcements, and seasoned equity issues. Portfolios consist of bottom *MAD* decile stocks at the end of the month prior to the events. Stocks are further classified based on median institutional holdings. Returns are measured in excess of the CRSP equal- or value-weighted composite index. The sample period for earnings surprises is from June 1977 to October 2015. The sample periods for analyst recommendations and dividend initiations are from 1992 and 2002, respectively, to October 2015.

Panel A. Equally-Weighted Portfolios



Panel B. Value-Weighted Portfolios



Appendix A. Variable Definitions

Moving Average Distance (*MAD*) = 21-day moving average/200-day moving average of stock prices.

MAD Signal (*MDS*) = a dummy variable that is equal to one if *MAD* > 1, and zero otherwise.

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

MAD Threshold = A three-level variable that is equal to one if *MAD* > 1 plus a threshold, negative one if *MAD* < 1 minus the threshold, and zero otherwise.

Moving Average Convergence/Divergence (*MACD*) = the nine-day exponential moving average of the difference between 26-day and 12-day exponential moving averages of stock price.

Performance Deviation Index (*PDI*) = equally weighted average of seven fundamental deviation measures related to firm's operating performance: Cash and short-term investments (*Cash*), Retained Earnings, Operating Income, Sales, capital expenditures (*CAPEX*), Invested Capital, and Inventories, while the extended index also considers income before extraordinary items (*IB*). Deviation is defined as the most recent quarterly release, if it exists during the previous six months, minus the mean in the preceding three quarters, scaled by total assets. Each deviation is assigned a percentile value relative to all stocks' deviations in the previous year (one minus the percentile for invested capital and inventories). Deviations are equally weighted to obtain the *PDI* measure. If the exact release date of the accounting reports within the month is not given, we assume a 90-day delay in release to guarantee data availability for investors.

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

Momentum (*MOM*) = stock return over the past 2-6 months.

Four additional past return control variables are over one month ($R_{t\text{-}1}$), months 7-12 ($R_{t\text{-}7:t\text{-}12}$), months 13-24 ($R_{t\text{-}13:t\text{-}24}$), and months 25-36 ($R_{t\text{-}25:t\text{-}36}$)

52-Week High Price (*52HIGH*) = 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 (*TRND*) = 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 average.

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*) = monthly 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.

Recommendation Upgrade-Downgrade (*RUD*) = (number of recommendation upgrades minus downgrades)/total number of outstanding recommendations.

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 (*DTRS*) = 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/quarterly lagged book equity, as in Hou, Xue, and Zhang (2015).

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.

Monthly Volatility (*VOL*) = standard deviation of daily returns over past 21 trading days.

Appendix B. Slope estimates for control variables included in the cross-section regressions of Table 2

Dependent variable	*MDS*	*MAS*	*MACD*	*ME*	*BE/ME*	R_{t-1}	$R_{t-7:t-12}$	$R_{t-13:t-24}$	$R_{t-25:t-36}$	*IVOL*	*TURN*	*ILLIQ*	*SUE*	*RUD*	*NS*	*dA/A*	*Y/B*	*I/A*	*GP*	*Ac/A*	*ROA*	*ROE*	*NOA*	*DTRS*
R_{t+1}	0.17***	−0.19***	0.07	−0.09***	0.33***	−2.47***	−0.52**	−0.00	−0.08	−3.27***	−0.98*	−0.04***	0.27***	0.14	−0.40	0.32**	0.15*	0.11	0.33**	−0.74***	1.54***	1.57***	−0.53***	0.78
	(2.68)	(−2.74)	(1.63)	(−3.39)	(4.52)	(−7.13)	(−2.15)	(−0.03)	(−1.30)	(−2.98)	(−1.71)	(−4.32)	(15.354)	(1.51)	(−1.56)	(2.20)	(1.79)	(0.73)	(2.47)	(−2.73)	(3.81)	(4.61)	(−5.31)	(1.56)
$R_{t+2:t+6}$	−0.04	0.22	−0.13**	−0.33***	1.32***	0.99	−1.50**	−0.02	0.26*	−2.98	−11.67***	−0.04	0.44***	0.35**	−2.26***	0.97**	0.54***	0.49	1.82***	−4.10***	3.13***	5.64***	−1.63***	3.91***
	(−0.26)	(1.31)	(−1.81)	(−4.95)	(6.67)	(1.06)	(−2.27)	(−0.12)	(1.75)	(−1.10)	(−9.02)	(−1.59)	(9.64)	(2.47)	(−3.85)	(2.56)	(2.94)	(1.44)	(5.46)	(−5.95)	(3.48)	(5.22)	(−5.74)	(3.80)
$R_{t+7:t+12}$	0.44***	0.62***	−0.01	−0.21***	1.61***	1.83**	−2.04***	−0.37*	0.20	−5.38*	−9.13***	0.01	−0.02	0.07	−3.53***	0.84**	0.51**	0.76*	2.14***	−5.75***	2.04**	−1.27	−1.77***	2.85**
	(2.82)	(3.77)	(−0.17)	(−2.99)	(5.14)	(2.00)	(−3.19)	(−1.89)	(1.26)	(−1.84)	(−6.79)	(0.29)	(−0.48)	(0.35)	(−5.21)	(2.11)	(2.19)	(1.71)	(5.54)	(−7.13)	(1.81)	(−1.54)	(−5.41)	(2.21)
$R_{t+13:t+24}$	0.64**	0.56**	−0.11	−0.12	3.80***	−0.61	−2.41**	−0.22	−0.34	9.20	−12.10***	−0.01	0.72***	−0.09	−2.53*	3.22***	0.52*	3.65***	2.43***	−11.40***	−1.64	−3.21**	−4.08***	2.67
	(2.04)	(1.77)	(−0.51)	(−0.99)	(6.85)	(−0.39)	(−2.14)	(−0.58)	(−1.25)	(1.63)	(−5.80)	(−0.14)	(11.07)	(−0.20)	(−1.90)	(3.96)	(1.77)	(4.45)	(3.45)	(−7.53)	(−0.73)	(−1.89)	(−7.58)	(0.93)
R_{t+1} for	0.20**	−0.21**	−0.09	−0.10***	0.16	−1.81***	−0.39	−0.04	−0.10	−2.03*	−0.84***	−0.04**	0.16***	−0.03	−0.68*	0.12	−0.02	−0.11	0.33	0.01	1.20**	0.10	−0.19	1.47
2001-2015	(2.32)	(−2.32)	(−0.39)	(−2.77)	(1.38)	(−3.65)	(−1.11)	(−0.42)	(−1.22)	(−1.66)	(−2.64)	(−2.05)	(6.28)	(−0.37)	(−1.88)	(0.55)	(−0.39)	(−0.41)	(1.50)	(0.01)	(2.48)	(0.42)	(−1.63)	(1.32)
Excess R_{t+1} Adjusted to Fama-French &																								
Cross-Sec.	0.18***	−0.19***	0.07	−0.06***	0.31***	−2.78***	−0.40*	0.08	−0.08	−3.81*	−1.14**	−0.03***	0.26***	0.12	−0.40	0.33**	0.14	0.05	0.42***	−0.68***	1.45***	1.58***	−0.48***	0.56
Mom.	(2.81)	(−2.88)	(1.65)	(−3.26)	(5.09)	(−8.59)	(−1.88)	(1.34)	(−1.39)	(−4.50)	(−2.11)	(−3.66)	(16.19)	(1.35)	(−1.63)	(2.46)	(1.69)	(0.38)	(3.28)	(−2.65)	(3.72)	(4.58)	(−5.30)	(1.14)
Time-Series	0.18***	−0.19***	0.07*	−0.06***	0.30***	−2.72***	−0.36*	0.08	−0.08	−4.19*	−1.16**	−0.03***	0.26***	0.12	−0.39	0.33**	0.15*	0.06	0.41***	−0.70***	1.51***	1.59***	−0.48***	0.64
Mom.	(2.94)	(−2.86)	(1.72)	(−3.36)	(4.76)	(−8.34)	(−1.70)	(1.41)	(−1.40)	(−4.90)	(−2.15)	(−3.69)	(16.35)	(1.46)	(−1.57)	(2.46)	(1.80)	(0.42)	(3.18)	(−2.71)	(3.86)	(4.61)	(−5.23)	(1.29)
Trend	0.17***	−0.19***	0.05	−0.08***	0.29***	−2.51***	−0.21	0.12**	−0.05	−5.81*	−1.55***	−0.03***	0.26***	0.13	−0.36	0.28**	0.17*	0.07	0.33**	−0.72***	1.65***	1.69***	−0.46***	0.66
	(2.77)	(−2.88)	(1.55)	(−4.58)	(4.68)	(−7.54)	(−1.00)	(2.00)	(−0.83)	(−6.80)	(−3.02)	(−3.62)	(16.15)	(1.43)	(−1.48)	(2.06)	(1.97)	(0.47)	(2.57)	(−2.81)	(4.17)	(5.01)	(−5.02)	(1.35)
R_{t+1}																								
Threshold	0.27***	−0.22***	0.07*	−0.10***	0.31***	−1.61***	0.49***	0.01	−0.07	−3.17***	−0.89	−0.04***	0.27***	0.15	−0.43*	0.32**	0.17**	0.12	0.35***	−0.75***	1.54***	1.53***	−0.53***	0.82
= 0.1	(4.42)	(−3.36)	(1.79)	(−3.49)	(4.22)	(−4.99)	(2.83)	(0.15)	(−1.25)	(−2.89)	(−1.55)	(−4.37)	(15.48)	(1.64)	(−1.70)	(2.15)	(1.98)	(0.80)	(2.65)	(−2.75)	(3.76)	(4.40)	(−5.39)	(1.63)
Threshold	0.36***	−0.15**	0.07*	−0.09***	0.32***	−1.81***	0.27	0.01	−0.07	−3.22***	−0.92	−0.04***	0.27***	0.15*	−0.40	0.33**	0.16*	0.12	0.34***	−0.75***	1.53***	1.55***	−0.53***	0.82
= 0.2	(5.48)	(−2.19)	(1.87)	(−3.39)	(4.36)	(−5.65)	(1.54)	(0.13)	(−1.18)	(−2.93)	(−1.57)	(−4.38)	(15.47)	(1.70)	(−1.58)	(2.19)	(1.83)	(0.80)	(2.58)	(−2.76)	(3.76)	(4.54)	(−5.38)	(1.63)
Threshold	0.37***	−0.13*	0.06	−0.09***	0.31***	−1.80***	0.37**	0.01	−0.07	−3.23***	−0.91	−0.04***	0.27***	0.16*	−0.43*	0.32**	0.15*	0.12	0.34**	−0.74***	1.54***	1.56***	−0.53***	0.80
= 0.3	(5.57)	(−1.89)	(1.54)	(−3.43)	(4.18)	(−5.65)	(2.25)	(0.18)	(−1.18)	(−2.94)	(−1.59)	(−4.37)	(15.38)	(1.74)	(−1.70)	(2.17)	(1.79)	(0.77)	(2.57)	(−2.73)	(3.78)	(4.56)	(−5.38)	(1.60)
R_{t+1}																								
High	0.20***	−0.24***	−0.00	−0.09***	0.40***	−2.68***	−0.32	0.12*	−0.03	−5.45***	−0.12	−0.03***	0.26***	0.09	−0.65**	0.11	0.16**	0.24	0.44***	−0.55*	1.29***	1.40***	−0.68***	0.36
Sentiment	(2.72)	(−3.17)	(−0.56)	(−2.57)	(4.38)	(−6.81)	(−1.22)	(1.69)	(−0.46)	(−4.10)	(−0.20)	(−3.62)	(12.83)	(0.65)	(−2.47)	(0.64)	(1.98)	(1.30)	(2.69)	(−1.71)	(3.05)	(4.33)	(−5.97)	(0.69)
Low	0.13	−0.11	0.19*	−0.10**	0.20*	−2.11***	−0.86*	−0.21*	−0.15	0.53	−2.48**	−0.06***	0.29***	0.23**	0.04	0.69**	0.14	−0.11	0.13	−1.08**	1.99**	1.87**	−0.29	1.52
Sentiment.	(1.07)	(−0.78)	(1.68)	(−2.21)	(1.69)	(−3.21)	(−1.82)	(−1.75)	(−1.56)	(0.29)	(−2.08)	(−2.69)	(8.76)	(2.36)	(0.08)	(2.56)	(0.76)	(−0.40)	(0.57)	(−2.20)	(2.40)	(2.52)	(−1.55)	(1.51)
Low	0.17*	−0.22**	0.11	−0.10***	0.53***	−2.32***	−0.84**	−0.06	0.01	−3.31**	−2.02**	−0.02	0.30***	0.14*	−0.39	0.37*	0.07	0.27	0.11	−1.15***	2.31***	1.90***	−0.56***	0.90
Volatility	(1.74)	(−2.21)	(1.38)	(−2.71)	(5.47)	(−4.65)	(−2.45)	(−0.66)	(0.17)	(−2.28)	(−2.19)	(−1.53)	(11.67)	(0.89)	(−1.00)	(1.79)	(0.58)	(1.28)	(0.66)	(−3.02)	(3.92)	(3.52)	(−3.84)	(1.40)
High	0.17**	−0.16*	0.02	−0.08**	0.14	−2.61***	−0.21	0.05	−0.16*	−3.22**	0.01	−0.07***	0.24***	0.13	−0.40	0.28	0.23**	−0.04	0.53***	−0.36	0.81	1.25***	−0.50***	0.65
Volatility	(2.08)	(−1.67)	(1.38)	(−2.11)	(1.29)	(−5.43)	(−0.62)	(0.55)	(−1.89)	(−1.98)	(0.01)	(−4.13)	(10.09)	(1.41)	(−1.23)	(1.33)	(2.00)	(−0.19)	(2.59)	(−0.94)	(1.47)	(2.99)	(−3.67)	(0.87)
High	0.26***	−0.20**	0.00	−0.07**	0.23**	−2.21***	−0.45	−0.06	−0.15**	−2.18*	−0.36	−0.05***	0.20***	0.07	−0.44	0.08	0.00	0.10	0.23	−0.01	1.02***	0.46**	−0.48***	0.68
Liquidity	(3.36)	(−2.44)	(0.07)	(−1.98)	(2.15)	(−5.39)	(−1.59)	(−0.77)	(−2.06)	(−1.76)	(−0.97)	(−3.23)	(9.10)	(0.78)	(−1.55)	(0.44)	(0.12)	(0.42)	(1.18)	(−0.03)	(2.65)	(1.88)	(−3.79)	(0.87)
Low	0.08	−0.18	0.14	−0.12***	0.43***	−2.75***	−0.59	0.06	0.01	−4.43**	−1.65	−0.03***	0.34***	0.21	−0.35	0.58**	0.31*	0.13	0.43**	−1.53***	2.10***	2.77***	−0.58***	0.88
Liquidity	(0.78)	(−1.57)	(1.64)	(−2.79)	(4.51)	(−4.84)	(−1.48)	(0.65)	(0.09)	(−2.41)	(−1.47)	(−2.97)	(12.83)	(1.29)	(−0.81)	(2.54)	(1.83)	(0.65)	(2.44)	(−4.42)	(2.89)	(4.87)	(−3.74)	(1.46)

Appendix C. Cross-sectional regressions including analysts' forecast dispersion

The table provides average slopes (multiplied by 10^4) and their t-values (in parentheses) obtained from monthly cross-sectional regressions similar to those in Table 2. The variable added to the 26 control variables in Table 2 is dispersion in forecasts across analysts, calculated as standard deviation of analysts' EPS forecasts scaled by the month-end stock price. The subsample is from August 1984 to October 2015 and restricted to stocks with at least two analysts. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	*MAD*	*MOM*	*52HIGH*	*TRND*	*Dispersion*	Average R^2
R_{t+1}	2.34***	0.57***	−1.41***	24.53***	−0.07	0.12
	(3.68)	(3.52)	(−4.30)	(4.93)	(−0.91)	
MAD Threshold = 0.1	0.17***	0.71***	−1.28***	28.09***	−0.09	0.12
	(2.72)	(4.55)	(−3.74)	(6.25)	(−1.27)	
MAD Threshold = 0.2	0.44***	0.66***	−1.39***	27.21***	−0.08	0.12
	(5.22)	(4.24)	(−4.21)	(5.64)	(−1.08)	
MAD Threshold = 0.3	0.36***	0.69***	−1.25***	28.16***	−0.09	0.12
	(3.19)	(4.51)	(−3.71)	(6.09)	(−1.24)	
$R_{t+2:t+6}$	5.75***	1.08***	−0.09	−4.54	−0.04	0.12
	(3.87)	(3.09)	(−0.13)	(−0.50)	(−0.31)	

Appendix D. *MAD* versus firm characteristics

The tables report average portfolio returns for next month, months 2 through 6, and months 7 through 12. Top and bottom portfolios correspond to 10×10 portfolios sorted independently and sequentially, first on *MAD* and then on one additional characteristic. The firm characteristics are defined in Appendix A. The first table corresponds to 2×10 portfolios in which the *MAD* signal (*MDS*) is the additional characteristic and sequential sorting is not relevant. The sample is from June 1977 to October 2015. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

Table D1.

		MAD										
	MDS	**Smallest**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Largest**	**Diff.**
R_{t+1}	*MAD* < 1	0.53	0.64	0.74	1.05	0.85	1.05	0.92	0.94	1.05	1.18	0.65**
	MAD > 1	1.20	1.19	1.15	1.15	1.31	1.21	1.42	1.44	1.81	2.05	0.85***
	Diff.	0.67**	0.55**	0.41**	0.10	0.46***	0.16***	0.50***	0.50***	0.76***	0.87***	
$R_{t+2:t+6}$	*MAD* < 1	1.29	2.89	3.74	4.14	4.61	5.43	5.57	5.56	6.00	5.94	4.65***
	MAD > 1	6.01	6.38	6.43	6.69	6.68	7.34	7.24	7.91	8.41	9.49	3.48***
	Diff.	4.72***	3.49***	2.69***	2.55***	2.07***	1.91***	1.67***	2.35***	2.41***	3.55***	
$R_{t+7:t+12}$	*MAD* < 1	5.20	5.30	6.08	6.58	6.94	7.08	6.89	7.00	7.16	7.22	2.02***
	MAD > 1	7.47	7.68	7.73	8.06	7.53	7.91	8.21	8.06	8.20	7.92	0.45
	Diff.	2.27***	2.38	1.65***	1.48***	0.59	0.83**	1.32***	1.06***	1.04**	0.70	

Table D2.

		52HIGH										
	MAD	**Smallest**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Largest**	**Diff.**
R_{t+1}	Smallest	0.68	1.45	1.34	0.85	1.07	0.88	0.80	0.97	0.86	0.16	–0.52*
	Largest	1.92	2.16	2.26	2.41	2.25	2.16	2.11	1.87	1.35	1.51	–0.41
	Diff.	1.24***	0.71*	0.92**	1.56***	1.18***	1.28***	1.31***	0.90***	0.49	1.35***	
Sorted	S.	1.04	0.76	0.39	–0.17	–0.47	–0.79	–0.99	–0.91	–0.94	–0.91	–1.95***
independently	L.	1.86	1.82	1.88	2.31	1.95	1.85	2.59	2.30	2.17	1.50	–0.36
	Diff.	0.82*	1.06**	1.49***	2.48***	2.42***	2.64***	3.58***	3.21***	3.11***	2.41***	
$R_{t+2:t+6}$	S.	0.86	2.48	2.98	2.62	2.71	3.12	4.31	4.43	4.90	5.06	4.20***
	L.	7.02	7.74	8.84	10.05	9.09	9.48	9.83	10.61	10.39	10.54	3.52***
	Diff.	6.16***	5.26***	5.86***	7.43***	6.38***	6.36***	5.52***	6.18***	5.49***	5.48***	
Sorted	S.	2.41	4.04	4.90	3.90	3.86	3.55	3.34	2.87	2.87	2.87	0.46
independently	L.	8.70	6.87	6.32	6.45	8.81	8.39	10.03	9.68	10.43	10.02	1.32
	Diff.	6.29***	2.83***	1.42	2.55***	4.95***	4.84***	6.69***	6.81***	7.56***	7.15***	
$R_{t+7:t+12}$	S.	6.61	4.84	5.78	5.97	5.73	6.12	6.15	5.97	6.19	6.13	–0.48
	L.	8.16	9.42	9.40	10.24	9.69	9.33	10.64	10.20	10.92	10.65	2.49
	Diff.	1.55	4.58***	3.62***	4.27***	3.96***	3.21***	4.49***	4.23***	4.73***	4.52***	

Table D3.

		TRND										
	MAD	**Smallest**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Largest**	**Diff.**
R_{t+1}	Smallest	–0.53	0.21	0.49	0.78	0.90	1.23	1.27	1.45	1.65	1.72	2.25***
	Largest	1.30	1.40	1.82	2.04	1.80	1.75	2.13	2.43	2.43	2.73	1.43***
	Diff.	1.83***	1.19***	1.33***	1.26***	0.90**	0.52	0.86**	0.98**	0.78	1.01**	
Sorted	S.	–0.77	0.02	0.43	1.13	0.95	0.92	1.08	1.08	1.94	1.78	2.55***
independently	L.	1.27	1.36	1.48	1.41	1.99	2.03	2.40	1.95	2.24	2.60	1.33***
	Diff.	2.04***	1.34***	1.05**	0.28	1.04**	1.11**	1.32***	0.87**	0.30	0.82*	
$R_{t+2:t+6}$	S.	1.65	2.93	3.21	2.95	3.80	3.41	3.40	4.27	3.76	4.17	2.52***
	L.	9.89	9.38	10.27	9.17	9.29	10.32	9.11	10.08	9.26	6.69	–3.20***
	Diff.	8.24***	6.45***	7.06***	6.22***	5.49***	6.91***	5.71***	5.81***	5.50***	2.52***	
Sorted	S.	3.11	3.89	3.54	3.80	3.45	3.79	4.15	3.32	4.02	4.21	1.10
independently	L.	9.42	9.32	10.06	9.18	9.97	10.20	8.50	9.21	9.22	6.80	–2.62***
	Diff.	6.31***	5.43***	6.52***	5.38***	6.52***	6.41***	4.35***	5.89***	5.20***	2.59**	
$R_{t+7:t+12}$	S.	5.95	5.22	5.73	6.93	6.12	6.56	5.76	6.29	6.20	4.73	–1.22
	L.	9.01	10.26	10.74	11.08	9.58	8.73	10.86	10.13	9.91	9.50	0.49
	Diff.	3.06**	5.04***	5.01***	4.15***	3.46***	2.17**	5.10***	3.84***	3.71***	4.77***	

Table D4.

	MAD	ME Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	0.68	0.68	0.54	0.76	1.06	1.17	1.15	1.07	1.31	0.72	0.04
	Largest	2.47	2.42	2.49	2.45	2.17	1.73	1.77	1.44	1.56	1.51	–0.96
	Diff.	1.79***	1.74***	1.95***	1.69***	1.11***	0.56	0.62*	0.37	0.25	0.79**	
Sorted	S.	0.65	0.50	0.63	0.90	0.97	1.02	1.04	1.01	0.99	0.44	–0.21
independently	L.	2.39	2.34	2.45	2.27	1.98	1.78	1.53	1.60	1.65	1.46	–0.93**
	Diff.	1.74***	1.84***	1.82***	1.37***	1.01***	0.76*	0.49	0.59	0.66	1.02**	
$R_{t+2:t+6}$	S.	2.56	2.71	2.57	2.42	2.93	4.35	4.31	4.14	4.03	3.47	0.91
	L.	11.05	11.23	10.86	9.33	8.37	8.75	9.31	8.15	8.84	7.86	–3.19***
	Diff.	8.49***	8.52***	8.29***	6.91***	5.44***	4.40***	5.00***	4.01***	4.81***	4.39***	
Sorted	S.	2.56	2.71	2.57	2.42	2.93	4.35	4.31	4.14	4.03	3.47	0.91*
independently	L.	11.05	11.23	10.86	9.33	8.37	8.75	9.31	8.15	8.84	7.86	–3.19***
	Diff.	8.49***	8.52***	8.29***	6.91***	5.44***	4.40***	5.00***	4.01***	4.81***	4.39***	
$R_{t+7:t+12}$	S.	5.69	5.76	4.77	5.84	5.65	6.19	6.42	6.61	5.96	6.62	0.93
	L.	11.03	8.86	9.67	8.94	8.88	9.55	9.31	11.29	10.94	11.06	0.03
	Diff.	5.34***	3.10***	4.90***	3.10***	3.23***	3.36***	2.89***	4.68***	4.98***	4.44***	

Table D5.

	MAD	BE/ME Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	–0.13	0.21	1.03	0.82	1.09	1.19	1.31	1.13	1.42	1.03	1.16***
	Largest	1.57	1.93	1.59	1.73	2.25	2.00	2.23	2.09	2.18	2.29	0.72**
	Diff.	1.70***	1.72***	0.56	0.91**	1.16***	0.81**	0.92**	0.96***	0.76**	1.26***	
Sorted	S.	–0.32	0.13	0.33	0.98	1.01	0.81	1.08	1.43	1.22	1.18	1.50***
independently	L.	1.57	1.56	2.33	2.22	1.84	2.26	2.11	2.02	2.02	2.34	0.77
	Diff.	1.89***	1.43***	2.00***	1.24***	0.83**	1.45***	1.03**	0.59	0.80*	1.16**	
$R_{t+2:t+6}$	S.	–0.64	2.07	3.17	3.37	3.44	4.77	4.78	4.86	3.62	4.00	4.64***
	L.	7.27	9.48	8.09	9.06	10.12	9.21	9.70	9.89	10.20	10.45	3.18***
	Diff.	7.91***	7.41***	4.92***	5.69***	6.68***	4.44***	4.92***	5.03***	6.58***	6.45***	
Sorted	S.	–1.10	0.21	2.22	2.95	3.29	3.96	4.76	4.97	4.36	4.02	5.12***
independently	L.	8.69	8.30	9.08	10.90	8.29	9.58	9.99	9.11	9.60	11.91	3.22**
	Diff.	9.79***	8.09***	6.86***	7.95***	5.00***	5.62***	5.23***	4.14***	5.24***	7.89***	
$R_{t+7:t+12}$	S.	2.57	5.03	5.80	6.24	6.49	9.02	7.48	5.55	5.40	6.04	3.47***
	L.	8.44	8.93	9.16	10.23	10.25	10.12	10.32	10.42	10.54	11.09	2.65**
	Diff.	5.87***	3.90***	3.36***	3.99	3.76***	1.10	2.84**	4.87***	5.14***	5.05***	

Table D6.

	MAD	TURN Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	0.46	0.73	1.14	0.98	1.19	0.93	1.03	1.41	0.97	0.25	–0.21
	Largest	1.71	2.15	2.34	2.21	2.21	1.98	2.12	2.23	1.75	1.22	–0.49
	Diff.	1.25***	1.42***	1.20***	1.23***	1.02**	1.05***	1.09***	0.82*	0.78*	0.97**	
Sorted	S.	0.06	0.60	0.64	0.79	1.27	1.15	0.97	0.99	1.12	0.34	0.28
independently	L.	2.06	1.92	2.34	2.32	1.83	1.98	1.94	2.33	2.06	1.64	–0.42
	Diff.	2.00***	1.32***	1.70***	1.53***	0.56	0.83**	0.97***	1.34***	0.94***	1.30***	
$R_{t+2:t+6}$	S.	3.12	3.17	4.08	3.34	3.67	3.73	4.33	3.34	3.41	1.62	–1.50**
	L.	11.38	10.76	11.04	9.96	9.78	9.49	9.56	8.48	8.15	5.03	–6.35***
	Diff.	8.26***	7.59***	6.96***	6.62***	6.11***	5.76***	5.23***	5.14***	4.74***	3.41***	
Sorted	S.	1.62	2.73	3.76	3.76	3.73	3.36	3.05	3.33	3.77	2.14	0.52
independently	L.	8.89	11.40	11.15	9.73	10.21	10.93	9.86	9.07	9.27	7.31	–1.58**
	Diff.	7.27***	8.67***	7.39***	5.97***	6.48***	7.57***	6.81***	5.74***	5.50***	5.17***	
$R_{t+7:t+12}$	S.	6.62	6.48	5.80	4.92	4.97	5.11	5.92	7.12	6.61	5.99	–0.63
	L.	10.66	11.16	10.35	11.12	9.89	9.12	9.97	10.20	8.75	7.62	–3.04*
	Diff.	4.04***	4.68***	4.55***	6.20***	4.92***	4.01***	4.05***	3.08***	2.14*	1.63	

Table D7.

		ILLIQ										
	MAD	**Smallest**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Largest**	**Diff.**
R_{t+1}	Smallest	0.98	1.02	1.22	1.12	1.16	1.08	0.76	0.89	0.60	0.30	−0.68**
	Largest	1.37	1.52	1.52	1.91	1.83	2.00	2.75	2.37	2.34	2.21	0.84**
	Diff.	0.39	0.50	0.30	0.79*	0.67*	0.92***	1.99***	1.48***	1.74***	1.91***	
Sorted	S.	0.73	0.92	1.06	1.22	1.27	0.85	0.77	0.68	0.54	0.29	−0.44
independently	L.	1.46	1.51	1.28	1.94	2.13	2.22	2.18	1.91	2.56	2.05	0.59
	Diff.	0.73*	0.59	0.22	0.72*	0.86**	1.37***	1.41***	1.23***	2.02***	1.76***	
$R_{t+2:t+6}$	S.	3.20	3.98	3.23	4.45	4.22	3.66	2.77	2.75	2.72	2.45	−0.75
	L.	7.81	8.18	7.08	8.45	8.03	8.90	10.52	11.40	10.67	11.81	4.00***
	Diff.	4.61***	4.20***	3.85***	4.00***	3.81***	5.24***	7.75***	8.65***	7.95***	9.36***	
Sorted	S.	3.19	3.27	4.67	3.45	3.85	3.76	3.37	2.71	2.92	2.17	−1.02
independently	L.	8.48	8.20	7.90	7.89	9.35	8.42	10.43	10.77	11.31	11.88	3.40***
	Diff.	5.29***	4.93***	3.23***	4.44***	5.50***	4.66***	7.06***	8.06***	8.39***	9.71***	
$R_{t+7:t+12}$	S.	6.76	6.03	7.25	6.22	5.13	5.03	5.90	4.59	5.75	6.88	0.12
	L.	10.70	9.98	10.39	9.41	8.18	8.16	10.28	9.66	10.54	11.68	0.98
	Diff.	3.94***	3.95***	3.14***	3.19***	3.05***	3.13***	4.38***	5.07***	4.79***	4.80***	

Table D8.

		VOL										
	MAD	**Smallest**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Largest**	**Diff.**
R_{t+1}	Smallest	1.49	1.64	1.64	1.59	1.25	1.15	1.03	0.55	−0.25	−0.93	−2.42***
	Largest	1.89	2.29	1.71	2.13	2.17	2.06	2.28	2.04	1.90	1.50	−0.39
	Diff.	0.40	0.65*	0.07	0.54	0.92**	0.91**	1.25***	1.49***	2.15***	2.43***	
Sorted	S.	0.93	1.22	1.65	1.42	1.46	1.64	1.60	1.36	0.68	−0.47	−1.40***
independently	L.	1.80	1.90	2.07	2.03	2.07	2.31	2.40	2.28	2.29	1.60	−0.20
	Diff.	0.87*	0.68	0.42	0.61	0.61*	0.67*	0.80*	0.92***	1.61***	2.07***	
$R_{t+2:t+6}$	S.	5.03	5.53	4.55	4.32	3.65	2.78	3.23	2.39	1.43	0.64	−4.39**
	L.	8.66	9.51	10.02	9.49	10.20	10.29	9.59	9.48	8.86	6.90	−1.76***
	Diff.	3.63***	3.98***	5.47***	5.17***	6.55***	7.51***	6.36***	7.09***	7.43***	6.26***	
Sorted	S.	3.18	4.66	4.89	4.77	5.38	5.60	3.76	3.17	2.48	1.02	−2.16***
independently	L.	6.31	8.21	8.79	10.24	10.02	10.13	10.37	10.13	9.92	8.44	2.13**
	Diff.	3.13**	3.55***	3.90***	5.47***	4.64***	4.53***	6.61***	6.96***	7.44***	7.42***	
$R_{t+7:t+12}$	S.	5.25	5.02	6.24	6.47	6.32	7.12	6.04	5.41	6.24	5.16	−0.09
	L.	9.19	10.14	10.35	10.26	10.02	10.67	11.00	10.04	9.25	7.81	−1.38
	Diff.	3.94***	5.12***	4.11***	3.79***	3.70***	3.55***	4.96***	4.63***	3.01**	2.65**	

Table D9.

		SUE										
	MAD	**Smallest**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Largest**	**Diff.**
R_{t+1}	Smallest	0.88	0.70	1.03	0.97	0.55	0.92	1.34	0.91	0.99	0.93	0.05
	Largest	1.90	1.36	1.42	1.49	2.32	1.85	2.01	2.47	2.44	2.58	0.68**
	Diff.	1.02**	0.66*	0.39	0.52	1.77***	0.93**	0.67*	1.56***	1.45***	1.65***	
Sorted	S.	0.58	1.07	0.77	0.94	1.00	1.11	0.84	0.76	1.37	1.20	0.62**
independently	L.	1.27	1.47	1.04	1.34	1.73	1.49	2.01	2.24	2.25	2.70	1.43***
	Diff.	0.69*	0.40	0.27	0.40	0.73*	0.38	1.17***	1.48***	0.88**	1.50***	
$R_{t+2:t+6}$	S.	4.19	3.65	3.34	3.92	2.80	2.65	3.93	2.44	3.21	3.56	−0.63
	L.	8.55	7.63	7.36	8.73	9.76	9.77	11.57	9.74	9.55	10.46	1.91***
	Diff.	4.36***	3.98***	4.02***	4.81***	6.96***	7.12***	7.64***	7.30***	6.34***	6.90***	
Sorted	S.	3.98	2.92	2.93	4.06	2.34	4.17	3.21	4.05	2.85	4.13	0.15
independently	L.	8.02	6.39	8.01	7.58	8.29	8.22	10.77	9.92	9.89	10.40	2.38***
	Diff.	4.04***	3.47***	5.08***	3.52***	5.95***	4.05***	7.56***	5.87***	7.04***	6.27***	
$R_{t+7:t+12}$	S.	5.98	5.56	5.23	6.20	6.63	5.95	7.26	6.27	6.43	3.70	−2.28***
	L.	9.36	11.66	10.01	11.63	9.04	8.70	10.86	10.22	9.18	8.30	−1.06
	Diff.	3.38***	6.10***	4.78***	5.43***	2.41**	2.75**	3.60***	3.95***	2.75***	4.60***	

Table D10.

	MAD	R_{t-1} Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	1.96	1.99	1.66	1.29	1.43	1.27	0.79	0.90	−0.12	−1.97	−3.93***
	Largest	2.74	2.30	2.14	2.06	1.90	1.81	1.68	1.73	1.89	1.73	−1.01***
	Diff.	0.78**	0.31	0.48	0.77**	0.47	0.54	0.89**	0.83**	2.01***	3.70***	
Sorted independently	S.	1.89	1.42	1.40	0.98	1.22	1.24	0.84	−0.08	−0.58	−2.65	−4.54**
	L.	2.62	2.57	2.39	2.00	2.20	2.29	1.79	1.71	1.70	1.83	−0.79**
	Diff.	0.73*	1.15***	0.99**	1.02**	0.98**	1.05***	0.95**	1.79***	2.28***	4.48***	
$R_{t+2:t+6}$	S.	1.68	2.83	2.59	3.71	4.32	3.69	4.05	3.98	3.99	2.71	1.03*
	L.	7.60	9.00	8.96	9.21	9.65	10.39	9.36	9.86	10.26	8.64	1.04
	Diff.	5.92***	6.17***	6.37***	5.50***	5.33***	6.70***	5.31***	5.88***	6.27***	5.93***	
Sorted independently	S.	2.28	3.55	4.07	3.93	4.86	4.02	3.46	4.26	2.45	2.52	0.24
	L.	7.66	8.06	9.06	8.76	9.26	9.44	9.87	9.91	9.67	9.62	1.96**
	Diff.	5.38***	4.51***	4.99***	4.83***	4.40***	5.42***	6.41***	5.65***	7.22***	7.10***	
$R_{t+7:t+12}$	S.	4.21	4.50	5.97	6.05	5.65	6.43	6.65	5.42	6.51	8.10	3.89***
	L.	7.00	9.11	9.54	9.53	8.87	10.97	10.21	11.18	11.65	10.87	3.87***
	Diff.	2.79**	4.61***	3.57***	3.48***	3.22***	4.54***	3.56***	5.76***	5.14***	2.77**	

Table D11.

	MAD	$R_{t-7:t-12}$ Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	0.11	0.42	0.58	0.79	1.14	0.92	1.07	1.32	1.40	1.36	1.25***
	Largest	1.99	1.97	1.99	1.85	1.72	1.85	1.95	1.97	2.20	2.29	0.30
	Diff.	1.88***	1.55***	1.41***	1.06***	0.58	0.93**	0.88**	0.65*	0.80**	0.93**	
Sorted independently	S.	0.69	1.40	1.36	0.85	1.94	0.91	1.14	1.30	1.13	1.46	0.77
	L.	2.50	1.20	2.75	1.96	3.34	2.14	2.12	1.57	1.98	2.00	−0.50
	Diff.	1.81	−0.20	1.39*	1.11	1.40	1.23	0.98	0.27	0.85	0.54	
$R_{t+2:t+6}$	S.	1.34	2.60	2.86	4.04	3.80	4.17	3.25	3.97	3.65	3.64	2.30***
	L.	7.86	9.34	8.93	8.49	9.37	9.09	10.07	10.66	10.26	9.15	1.29
	Diff.	6.52***	6.74***	6.07***	4.45***	5.57***	4.92***	6.82***	6.69***	6.61***	5.51***	
Sorted independently	S.	3.18	3.73	3.98	4.81	3.79	3.47	0.62	1.12	3.10	4.03	0.85
	L.	−3.49	1.24	3.54	2.94	6.44	9.21	6.29	8.88	8.89	9.64	13.13**
	Diff.	−6.67	−2.49	−0.44	−1.87	2.65**	5.74***	5.67***	7.76***	5.79***	5.61***	
$R_{t+7:t+12}$	S.	4.76	5.58	4.77	5.84	5.86	6.40	6.10	6.31	6.71	7.11	2.35**
	L.	9.21	10.88	10.82	9.72	10.37	10.08	11.02	9.90	9.59	7.90	−1.31
	Diff.	4.45***	5.30***	6.05***	3.88***	4.51***	3.68***	4.92***	3.59***	2.88**	0.79	

Table D12.

	MAD	$R_{t-13:t-24}$ Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	1.21	1.29	0.95	0.92	0.65	0.87	1.14	0.94	0.69	0.47	−0.74**
	Largest	2.08	2.01	2.07	2.05	2.09	1.85	2.11	1.79	2.05	1.78	−0.30
	Diff.	0.87**	0.72*	1.12***	1.13***	1.44***	0.98**	0.97***	0.85**	1.36***	1.31***	
Sorted independently	S.	1.32	1.03	1.09	1.20	1.11	0.31	0.69	1.04	0.94	0.46	−0.86***
	L.	1.95	2.15	1.96	1.83	2.05	2.20	2.04	1.95	1.80	1.81	−0.14
	Diff.	0.63	1.12***	0.87**	0.63	0.94**	1.89***	1.35***	0.91**	0.86**	1.35***	
$R_{t+2:t+6}$	S.	5.43	4.10	3.30	3.40	3.27	2.88	3.26	3.96	2.49	1.81	−3.62***
	L.	9.49	9.92	10.13	9.21	9.19	9.57	9.65	9.48	8.79	7.93	−1.56**
	Diff.	4.06***	5.82***	6.83***	5.81***	5.92***	6.69***	6.39***	5.52***	6.30***	6.12***	
Sorted independently	S.	5.35	4.20	3.48	4.41	3.13	2.41	2.91	3.76	3.55	1.98	−3.37***
	L.	9.92	9.44	10.11	10.19	9.14	9.18	8.53	9.58	8.47	8.29	−1.63**
	Diff.	4.57***	5.24***	6.63***	5.78***	6.01***	6.77***	5.62***	5.82***	4.92***	6.31***	
$R_{t+7:t+12}$	S.	6.12	6.46	6.75	5.66	6.47	5.99	5.90	6.25	5.21	5.01	−1.11
	L.	12.06	11.28	9.79	9.83	8.54	9.87	10.49	10.43	9.27	8.16	−3.90***
	Diff.	5.94***	4.82***	3.04***	4.17***	2.07**	3.88***	4.59***	4.18***	4.06***	3.15***	

Table D13.

	MAD	Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
		$R_{t-25:t-36}$										
R_{t+1}	Smallest	0.91	1.14	0.89	1.01	1.17	1.03	0.88	0.96	0.76	0.33	−0.58
	Largest	2.18	1.97	2.17	2.05	1.99	2.04	1.92	1.97	1.90	1.79	−0.39
	Diff.	1.27***	0.83**	1.28***	1.04***	0.82**	1.01**	1.04**	1.01**	1.14***	1.46***	
Sorted independently	S.	1.02	1.25	0.90	1.24	0.95	1.18	1.31	0.93	0.87	0.50	−0.52**
	L.	2.02	2.03	2.17	2.31	2.09	1.86	1.79	1.78	2.08	1.52	−0.50**
	Diff.	1.00***	0.78*	1.27***	1.07**	1.14***	0.68*	0.48	0.85**	1.21***	1.02***	
$R_{t+2:t+6}$	S.	4.55	3.89	3.35	3.45	3.55	3.11	3.55	3.46	3.30	1.52	−3.03***
	L.	8.69	7.83	9.87	8.82	10.04	9.76	9.75	9.57	9.93	9.00	0.31
	Diff.	4.14***	3.94***	6.52***	5.37***	6.49***	6.65***	6.20***	6.11***	6.63***	7.48***	
Sorted independently	S.	4.96	4.26	3.07	3.95	3.89	3.15	3.50	3.53	3.75	2.17	−2.79***
	L.	8.59	8.98	9.94	9.06	10.16	9.64	9.86	10.14	9.48	9.18	0.59
	Diff.	3.63***	4.72***	6.87***	5.11***	6.27***	6.49***	6.36***	6.61***	5.73***	7.01***	
$R_{t+7:t+12}$	S.	7.63	6.91	6.23	6.02	5.53	5.52	6.20	5.90	5.20	4.90	−2.73***
	L.	6.57	9.36	9.72	10.21	10.85	9.60	9.88	10.91	11.23	10.36	3.79***
	Diff.	−1.06	2.45**	3.49***	4.19***	5.32***	4.08***	3.68***	5.01***	6.03	5.46***	

Table D14.

	MAD	Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
		ROE										
R_{t+1}	Smallest	0.01	0.14	0.24	0.82	1.19	1.39	1.35	1.43	1.35	1.19	1.18***
	Largest	1.29	1.15	1.59	1.89	2.10	2.01	2.32	2.14	2.41	2.90	1.61***
	Diff.	1.28***	1.01**	1.35***	1.07***	0.91**	0.62*	0.97***	0.71*	1.06***	1.71***	
Sorted independently	S.	0.06	0.62	1.21	1.36	1.56	1.36	1.39	1.17	1.15	1.24	1.18***
	L.	1.08	1.00	1.50	1.86	1.91	2.00	1.81	2.22	2.18	2.71	1.63***
	Diff.	1.02***	0.38	0.29	0.50	0.35	0.64*	0.42	1.05***	1.03**	1.47***	
$R_{t+2:t+6}$	S.	0.42	1.79	3.78	3.51	4.04	4.05	3.82	3.99	4.02	3.90	3.48***
	L.	7.27	7.21	8.63	9.07	9.75	9.97	10.01	9.74	10.15	10.99	3.72***
	Diff.	6.85***	5.42***	4.85***	5.56***	5.71***	5.92***	6.19***	5.75***	6.13***	7.09***	
Sorted independently	S.	1.42	3.77	4.75	3.78	4.21	3.49	4.44	3.66	3.46	4.17	2.75***
	L.	7.01	6.59	8.07	8.73	8.98	10.55	10.30	9.41	9.86	10.64	3.63***
	Diff.	5.59***	2.82***	3.32***	4.95***	4.77***	7.06***	5.86***	5.75***	6.40***	6.47***	
$R_{t+7:t+12}$	S.	4.08	4.42	4.73	7.12	8.39	7.62	6.60	5.87	6.08	5.00	0.92
	L.	8.56	11.33	9.99	11.75	9.37	9.60	10.92	10.11	9.57	7.82	−0.74
	Diff.	4.48***	6.91***	5.26***	4.63***	0.98	1.98*	4.32***	4.24***	3.49***	2.82**	

Table D15.

	MAD	Large downgrade	Small downgrade	No change	Small upgrade	Large upgrade	Diff.
		RUD					
R_{t+1}	Smallest	1.13	1.05	0.75	1.42	1.40	0.27
	Largest	1.56	1.67	1.97	2.32	2.23	0.67
	Diff.	0.43	0.62	1.22***	0.90*	0.83	
Sorted independently	S.	1.34	1.19	0.79	0.78	1.18	−0.16
	L.	1.98	1.94	1.97	1.95	2.05	0.07
	Diff.	0.64	0.75	1.18***	1.17***	0.87**	
$R_{t+2:t+6}$	S.	4.12	5.18	2.65	3.36	4.04	−0.08
	L.	6.98	9.33	9.25	10.02	10.22	3.24**
	Diff.	2.86***	4.15***	6.60***	6.66***	6.18***	
Sorted independently	S.	5.06	5.14	2.82	4.34	3.90	−1.16
	L.	9.07	7.63	9.34	9.32	9.16	0.09
	Diff.	4.01***	2.49***	6.52***	4.98***	5.26***	
$R_{t+7:t+12}$	S.	6.74	7.82	5.41	6.32	7.96	1.22
	L.	8.16	11.83	9.60	12.38	11.83	3.67**
	Diff.	1.42	4.01**	4.19***	6.06***	3.87**	

Appendix E. Slope estimates for control variables included in the cross-sectional regressions of Table 6

	R_{t+1}											$R_{t+2:t+6}$	$R_{t+7:t+12}$	$R_{t+13:t+24}$
						Sentiment		Liquidity		Volatility				
		PDI	*PDI & MAD*	*Extended PDI*	2001-2015	Low	High	Low	High	Low	High			
ME	−0.10***	−0.10***	−0.10***	−0.10***	−0.11***	−0.11**	−0.09***	−0.11***	−0.10***	−0.09***	−0.11***	−0.34***	−0.23***	−0.18
	(−3.22)	(−3.88)	(−3.77)	(−3.89)	(−3.34)	(−2.40)	(−2.75)	(−2.89)	(−2.59)	(−2.81)	(−2.72)	(−5.23)	(−3.38)	(−1.54)
BE/ME	0.34***	0.35***	0.39***	0.36***	0.20**	0.24**	0.45***	0.53***	0.17	0.54***	0.16	1.26***	1.51***	3.74***
	(4.78)	(4.96)	(5.66)	(5.00)	(2.05)	(1.99)	(4.68)	(5.95)	(1.59)	(5.99)	(1.50)	(6.71)	(5.12)	(7.06)
R_{t-1}	−1.60***	−1.54***	−2.37***	−1.54***	−1.43***	−0.85	−1.76***	−1.85***	−1.23***	−1.25***	−1.83***	5.05***	4.93***	−0.52
	(−5.32)	(−5.09)	(−7.14)	(−5.10)	(−3.05)	(−1.53)	(−4.87)	(−4.23)	(−2.94)	(−2.97)	(−4.21)	(7.07)	(5.88)	(−0.44)
$R_{t-7:t-12}$	0.45***	0.41***	−0.47***	0.41***	0.03	0.28	0.61***	0.50***	0.32**	0.32**	0.51***	0.10	−1.72***	−1.12***
	(4.29)	(3.96)	(−2.01)	(3.90)	(0.16)	(1.41)	(5.14)	(3.24)	(2.32)	(2.05)	(3.67)	(0.38)	(−6.64)	(−2.72)
$R_{t-13:t-24}$	0.06	0.02	0.03	0.02	−0.06	−0.12	0.11	0.12	−0.07	0.04	0.01	−0.23	−0.14	−0.20
	(1.03)	(0.39)	(0.46)	(0.43)	(−0.68)	(−1.16)	(1.66)	(1.39)	(−0.96)	(0.40)	(0.13)	(−1.50)	(−0.78)	(−0.63)
$R_{t-25:t-36}$	0.03	0.02	0.02	0.02	−0.03	−0.05	0.04	0.07	−0.03	0.18**	−0.14**	0.18	0.15	−0.38
	(0.57)	(0.41)	(0.33)	(0.42)	(−0.40)	(−0.59)	(0.57)	(0.91)	(−0.45)	(2.30)	(−2.06)	(1.33)	(0.99)	(−1.56)
IVOL	−3.16***	−3.31***	−3.48***	−3.27***	−2.19*	0.46	−5.50***	−4.23**	−2.39*	−3.99**	−2.62	−4.19	−5.47*	8.32
	(−2.94)	(−3.08)	(−3.29)	(−3.04)	(−1.87)	(0.24)	(−4.07)	(−2.52)	(−1.79)	(−2.52)	(−1.81)	(−1.57)	(−1.89)	(1.49)
TURN	−0.83	−0.89	−1.03*	−0.89	−0.80***	−2.33**	−0.12	−0.73	−1.05**	−2.21***	0.44	−10.12***	−8.02***	−12.13***
	(−1.51)	(−1.63)	(−1.85)	(−1.64)	(−2.81)	(−1.97)	(−0.21)	(−0.73)	(−2.40)	(−2.58)	(0.66)	(−8.58)	(−6.23)	(−6.25)
ILLIQ	−0.04***	−0.04***	−0.04***	−0.04***	−0.03**	−0.06***	−0.04***	−0.04***	−0.05***	−0.01	−0.07***	−0.06**	0.01	−0.01
	(−4.38)	(−4.36)	(−4.17)	(−4.35)	(−1.97)	(−2.73)	(−3.69)	(−3.83)	(−2.83)	(−1.30)	(−4.45)	(−2.51)	(0.28)	(−0.16)
52HIGH	−0.44	−0.45	−0.84***	−0.43	−0.27	−1.41***	0.00	−0.75**	−0.14	−0.13	−0.76	2.45***	1.27**	−0.63
	(−1.59)	(−1.59)	(−3.01)	(−1.51)	(−0.58)	(−2.64)	(0.01)	(−2.22)	(−0.33)	(−0.44)	(−1.60)	(4.65)	(2.05)	(−0.65)
RUD	0.10	0.10	0.08	0.10	−0.06	0.26***	0.05	0.15	0.05	−0.15	0.35***	0.43***	0.00	−0.21
	(0.87)	(0.89)	(0.76)	(0.85)	(−0.49)	(2.64)	(0.32)	(0.79)	(0.41)	(−0.78)	(3.29)	(2.76)	(0.00)	(−0.46)
NS	−0.54**	−0.57**	−0.55**	−0.58**	−0.70**	−0.20	−0.77***	−0.43	−0.72**	−1.01***	−0.13	−2.62***	−3.34***	−2.98**
	(−2.28)	(−2.40)	(−2.29)	(−2.41)	(−2.10)	(−0.39)	(−2.95)	(−1.13)	(−2.45)	(−2.77)	(−0.42)	(−4.69)	(−5.05)	(−2.48)
dA/A	0.18	0.14	0.14	0.15	0.01	0.52*	−0.04	0.45**	−0.16	0.12	0.17	0.61	0.89**	2.95***
	(1.22)	(1.00)	(1.00)	(1.07)	(0.07)	(1.85)	(−0.27)	(2.08)	(−0.88)	(0.55)	(0.88)	(1.65)	(2.29)	(3.83)
Y/B	0.20**	0.19**	0.18**	0.19**	0.00	0.18	0.21***	0.32**	0.06	0.28**	0.10	0.53***	0.46**	0.42
	(2.54)	(2.39)	(2.31)	(2.40)	(0.04)	(1.00)	(2.62)	(2.15)	(1.13)	(2.22)	(1.02)	(2.98)	(2.04)	(1.46)
I/A	0.24*	0.20	0.17	0.17	0.01	0.02	0.32*	0.08	0.31	0.17	0.22	0.07	0.78*	2.35***
	(1.73)	(1.34)	(1.18)	(1.18)	(0.02)	(0.07)	(1.73)	(0.42)	(1.39)	(0.82)	(1.07)	(0.21)	(1.80)	(2.83)
GP	0.35***	0.30**	0.28**	0.30**	0.25	0.13	0.44***	0.53***	0.07	0.10	0.51***	1.65***	1.97***	2.04***
	(2.79)	(2.39)	(2.20)	(2.38)	(1.27)	(0.59)	(2.70)	(3.30)	(0.38)	(0.61)	(2.57)	(4.99)	(5.37)	(3.03)
Ac/A	−0.44	−0.48*	−0.46*	−0.49*	0.32	−0.88*	−0.44	−1.09***	0.13	−0.55	−0.40	−3.41***	−5.43***	−10.79***
	(−1.65)	(−1.82)	(−1.77)	(−1.86)	(0.74)	(−1.81)	(−1.36)	(−3.25)	(0.31)	(−1.47)	(−1.09)	(−5.09)	(−6.94)	(−7.79)
ROA	1.59***	1.35***	1.35***	1.48***	0.88**	1.75**	1.18***	1.65**	1.06***	2.45***	0.25	3.64***	1.85*	−2.33
	(3.99)	(3.47)	(3.47)	(3.80)	(2.01)	(2.09)	(2.80)	(2.46)	(2.65)	(4.14)	(0.50)	(4.20)	(1.74)	(−1.02)
NOA	−0.54***	−0.52***	−0.51***	−0.53***	−0.25**	−0.28	−0.69***	−0.53***	−0.51***	−0.41***	−0.63***	−1.61***	−1.86***	−4.19***
	(−5.61)	(−5.39)	(−5.24)	(−5.48)	(−2.16)	(−1.55)	(−5.88)	(−3.68)	(−3.98)	(−3.21)	(−4.36)	(−5.77)	(−5.88)	(−7.91)
DTRS	0.78	0.80*	0.71	0.81*	1.38	1.77*	0.28	0.79	0.81	0.94	0.65	4.06***	2.99**	3.28
	(1.60)	(1.67)	(1.50)	(1.70)	(1.39)	(1.72)	(0.55)	(1.52)	(1.01)	(1.38)	(0.98)	(4.14)	(2.48)	(1.13)

Appendix F. Sharpe ratios

This Appendix reports monthly Sharpe ratios for the zero-cost strategies (Table 5). The t-values (in parentheses) correspond to the null hypothesis that the Sharpe ratio is below or equal to that of the value-weighted CRSP index (0.139 per month). Standard errors are calculated via the delta method combined with GMM per Lo (2002). The sample is from June 1977 to October 2015. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

	Holding Period (months)					
Portfolio Strategy	**1**	**3**	**6**	**12**	**18**	**24**
MAD Signal	0.16	0.18	0.19	0.18	0.11	0.10
(long *MAD* > 1, short *MAD* ≤ 1)	(0.53)	(0.87)	(1.08)	(0.80)	(−0.51)	(−0.86)
MAD Decile	0.16	0.18	0.19	0.15	0.07	0.05*
(long Top, short Bottom)	(0.40)	(0.86)	(0.91)	(0.14)	(−1.39)	(−1.82)
MAD Threshold = 0.10	0.24**	0.27***	0.28***	0.25**	0.18	0.15
(long *MAD* ≥ 1.1, short *MAD* ≤ 0.9)	(2.02)	(2.58)	(2.57)	(2.18)	(0.76)	(0.16)
MAD Threshold = 0.20	0.25**	0.30***	0.30***	0.26**	0.17	0.14
(long *MAD* ≥ 1.20, short *MAD* ≤ 0.8)	(2.25)	(2.90)	(2.81)	(2.26)	(0.58)	(−0.05)
MAD Threshold = 0.30	0.22*	0.27**	0.28***	0.23*	0.14	0.10
(long *MAD* ≥ 1.30, short *MAD* ≤ 0.7)	(1.66)	(2.48)	(2.67)	(1.71)	(−0.03)	(−0.75)
PDI Decile	0.61***	0.50***	0.32***	0.26**	0.21	0.21
(long Top, short Bottom)	(7.46)	(6.18)	(3.37)	(2.07)	(1.12)	(1.28)

Appendix G. Descriptive statistics on international data

This Appendix displays descriptive statistics for international data. The sample includes 38 markets, and spans January 2001 to November 2015, with shorter periods for a few markets.

	Number of Months	Monthly Average Return	Standard Deviation of Monthly Returns	Average *MAD*
Australia	179	0.71	3.79	1.030
Austria	179	0.79	5.69	1.030
Belgium	179	0.85	4.96	1.030
Brazil	179	1.03	6.14	1.041
Chile	155	1.05	3.91	1.046
China	179	0.85	8.12	1.031
Columbia	115	0.34	5.12	1.018
Denmark	179	1.02	5.10	1.039
Egypt	179	1.38	6.98	1.070
Finland	179	0.30	7.85	1.002
France	179	0.41	4.87	1.013
Germany	179	0.54	5.44	1.015
Hong Kong	179	0.80	6.09	1.029
Hungary	179	0.73	6.69	1.022
India	179	1.56	7.65	1.059
Indonesia	179	1.70	5.67	1.067
Ireland	179	0.53	5.35	1.019
Italy	179	0.22	5.08	1.004
Japan	179	0.42	4.99	1.012
Malaysia	179	0.89	4.13	1.033
Mexico	179	1.37	4.82	1.053
Nederland	179	0.44	5.26	1.013
New Zealand	179	0.78	3.29	1.030
Norway	179	0.91	5.71	1.034
Philippines	179	1.24	5.51	1.053
Poland	179	0.58	6.16	1.022
Portugal	179	0.14	5.18	1.001
Singapore	179	0.63	5.50	1.023
South Africa	152	1.56	4.33	1.062
South Korea	179	1.04	6.30	1.035
Spain	179	0.59	5.33	1.019
Sweden	179	0.71	5.71	1.022
Switzerland	179	0.34	4.16	1.013
Taiwan	179	0.73	6.57	1.018
Thailand	179	1.23	6.37	1.047
Turkey	108	1.17	7.51	1.043
United Kingdom	179	0.44	4.06	1.017
United States (2001-2015)	179	0.55	4.49	1.019

Appendix H. Anchoring and underreaction

In this appendix, we motivate the analysis in Section 4.1 by showing that anchoring can lead to underreaction to new information, and that the strength of this underreaction is related to whether the sign and magnitude of succesive signals match those of the deviation of recent prices from the anchor. Consider a security that has a random payoff of θ. At date 1, a risk-neutral representative agent receives a noisy signal $\theta + \varepsilon_1$. Another signal $\theta + \varepsilon_2$ is received at date 2. At date 3 the security pays off its liquidation value, θ. All random variables are mutually independent and normally distributed with zero mean. The quantity v_X denotes the variance of the random variable X, with $v_{\varepsilon_1} = v_{\varepsilon_2} = v_\varepsilon$.

Since the agent is risk neutral, rational prices at each date t are set to equal conditional expected values. That is $P_t = E(\theta \mid \phi_t)$ where ϕ_t is the information set of the representative agent at date t. That is, the rational prices P_i at dates i are:

$$P_1 = \frac{v_\theta}{v_\theta + v_\varepsilon}(\theta + \varepsilon_1),$$

$$P_2 = \frac{v_\theta}{2v_\theta + v_\varepsilon}(2\theta + \varepsilon_1 + \varepsilon_2),$$

$$P_3 = \theta .$$

It is easy to verify that in the above setting $\rho \equiv \text{corr}(P_3 - P_2, P_2 - P_1) = 0$, since prices are martingales. Further, $\text{corr}(P_3 - P_2, \theta + \varepsilon_2) = \text{corr}(P_2 - P_1, \theta + \varepsilon_1) = 0$, i.e., price changes are not predictable from public signals.

Now consider the anchoring bias. Let A be any arbitrary (random) anchor. Then, we propose that

$$P_1 = g_1(\theta + \varepsilon_1),$$

and

$$P_2 = g_2(2v_\theta + \varepsilon_1 + \varepsilon_2)$$

where

$$g_1 = \frac{v_\theta}{v_\theta + v_\varepsilon} - h_1 \,|\, \theta + \varepsilon_1 - A \,|$$

and

$$g_2 = \frac{v_\theta}{2v_\theta + v_\varepsilon} - h_2 \,|\, \theta + \varepsilon_2 - A \,|.$$

where h_1 and h_2 are constants. In the above setting, the weights on the signals deviate from rationality based on how far the signal is from the anchor. Let $M \equiv P_1 - A$. The parameter M represents the deviation of the date 1 price from the anchor and thus is analogous to *MAD*. In the above scenario, returns tend to be positively predictable from M, as we find in our empirical work. Specifically, the correlation $\rho_M \equiv \text{corr}(P_2 - P_1, M)$, tends to be positive. Further, there is generic underreaction, i.e., ρ also is generally positive. For example, suppose that $v_\theta = 2$, $v_\varepsilon = 1$, $h_1 = 0.1$, $h_2 = 0.05$, and A is drawn from a uniform [1,2] distribution. [The general patterns are not sensitive to the particular parameters.] Then, Monte Carlo simulations based on one million draws show that $\rho = 0.312$ and $\rho_M = 0.365$. We now examine underreaction to the second signal when M and the date 2 signal $\theta + \varepsilon_2$ both are either high or versus when one is high and the other low. To model this, let δ_1 and δ_2 be threshold parameters, that we set to 0.2 and 0.1, respectively. Then, we have that

$$\text{corr}(P_3 - P_2, \theta + \varepsilon_2 \,|\, M > \delta_1, \theta + \varepsilon_2 > \delta_2) = 0.523$$

but

$$\text{corr}(P_3 - P_2, \theta + \varepsilon_2 \mid M > \delta_1, \theta + \varepsilon_2 < \delta_2) = 0.073$$

and

$$\text{corr}(P_3 - P_2, \theta + \varepsilon_2 \mid M < -\delta_1, \theta + \varepsilon_2 < -\delta_2) = 0.538$$

but

$$\text{corr}(P_3 - P_2, \theta + \varepsilon_2 \mid M < -\delta_1, \theta + \varepsilon_2 > -\delta_2) = 0.136.$$

The basic idea is that underreaction to the second signal tends to be greater when both signals are high (i.e., higher than the thresholds) or both are low, than otherwise. The reason is that a large first signal is followed by an insufficient move of the price and a large second signal of the same sign causes a further underreaction. The latter happens because the second signal represents a further move away from the anchor and is therefore under-weighted. On the other hand when the first signal is large but the second signal is of modest magnitude, the underreaction is muted because the second signal represents a smaller move from the anchor and is therefore relatively overweighted, which tends to dampen the initial underreaction. We interpret M as *MAD* (as mentioned earlier), and the second signal $\theta + \varepsilon_2$ as subsequent earnings surprises. The analysis then indicates that large positive *MAD* followed by a large positive earnings surprise will cause a bigger underreaction and drift than a large positive *MAD* followed by a muted or negative surprise. An analogous argument holds for negative *MAD*. Overall, these results justify our exploration in Section 4.1.