The Predictability of Equity Returns from Past Returns: A New Moving Average-Based Perspective

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Keywords: market efficiency, technical analysis, moving averages

JEL classification codes: G12, G14

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We thank Yakov Amihud, Chen Yao, Si Cheng, Bill Sherman, Guofu Zhou, and seminar participants of National University of Taiwan (NUT), National University of Singapore, Nanyang Technological University, Korean University, and Korea Advanced Institute of Science and Technology (KAIST) for valuable comments and suggestions.

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Abstract

The distance between the short- and long-run moving averages of prices is a potent predictor of stock returns in the cross-section and its predictive power goes well beyond momentum and a comprehensive set of other characteristics. The greater the positive (negative) distance between the short-run average and the long-run one, the greater (lower) is the expected return. The corresponding strategy yields reliable profits that do not decay even after several months and that survive modern factor models and reasonable transaction costs. The distance also reliably predicts returns at the market and industry levels, as well as in international settings. We propose and provide supporting evidence for the notion that large deviations of prices from their long-run moving averages represent surprises relative to prevailing anchors to which investors react insufficiently.

1. Introduction

In a capital market that is weak-form efficient, prices aggregate all available information contained in the history of stock prices. It is generally assumed that this form of efficiency is easy to enforce via simple forms of arbitrage and as such, should hold in capital markets. At odds with the notion of weak-form efficiency, however, practitioners use a large number of technical trading rules, analyzed in Brock, LeBaron, and Lakonishok (1992), Lo, Mamaysky, and Wang (2000), and Han, Zhou, and Zhu (2016). These applications are also used in portfolio management (e.g., Chincarini and Kim, 2006; Lo and Hasanhodzic, 2009). It is intriguing that while weak-form market efficiency indicates that technical trading rules may not be consistently reliable, these techniques are heavily used by practitioners. In this paper, we show that a hitherto-unconsidered technical indicator, the distance between short- and long-run moving averages of past price, has surprisingly strong predictive power for returns, and that this power goes beyond that of other oft-used rules as well as a comprehensive set of other return predictors, including the momentum effect of Jegadeesh and Titman (1993).

Moving averages have been analyzed in previous literature. Thus, Brock, LeBaron, and Lakonishok (1992) and Han, Yang, and Zhou (2013) present evidence that moving averages are predictive of equity returns to economically significant degrees. Crossing rules refine the use of moving averages. They signal a buy when a short-run (faster) moving average crosses a long-run (slower) moving average from below and a sell when the short-run moving average crosses the long-run one from above. Similarly, Appel (2005) proposes the moving average convergence/divergence (MACD) measure. This signal involves first computing the signed distance between short- and long-run moving averages and then again using a binary signal based on the signed difference between the distance and its moving average.[1] We note, however, that conditioning a rule on the binary event of one moving average crossing another, a common practice, is rather specific, and a stock's future expected performance is likely to reflect a continuous function of the distance between moving averages. The focus of our paper is on the signed value of this distance.

In particular, we show that the greater the positive (negative) distance between a short-run (21-day) and long-run (200-day) average, the higher (lower) is the average return. This strategy (that we term moving average distance, or *MAD*) yields reliable profits that do not decay even after several months. Indeed, the alphas from the hedge portfolios remain significant even after two years. The *MAD* also survives a long list of other anomalies, including standard momentum, the moving average binary crossing rule, the recently proposed "trend" factor of Han, Zhou, and Zhu (2016), short- and long-run reversals, the 52-week high, post announcement earnings drift, analysts' revisions, and forecast dispersions. The profitability demonstrated through the application of the rule remains significant in the 2001-2016 period, even when a number of other anomalies have been shown to decay considerably (Chordia, Subrahmanyam, and Tong, 2014). Moreover, while several prominent anomalies extract their profitability from the short-leg of a trade, our proposed strategy yields significant returns on both the long- and short-legs.

In terms of magnitude, we find that the usual extreme decile hedge portfolios formed on *MAD* stocks generate average returns of more than 13% per year. After adjusting for standard systematic factors, the performance of our application still exceeds 12% on an annualized basis. This is about the same order of magnitude as the profitability of the momentum strategy of Jegadeesh and Titman (1993). Even in large cap stocks, the magnitude of the hedge portfolio

[1] See, for example, http://www.investopedia.com/articles/forex/05/macddiverge.asp.

returns exceeds 10% on an annualized basis.

We document that the *MAD* rule remains viable after a host of robustness checks. First, the breakeven levels of transaction costs for the rule are well above reasonable trading cost levels. Second, the rule remains viable not only in traditional factor models such as Fama and French (1993), but also in more recently developed settings such as the five-factor model of Fama and French (2015) and the q-factor model considered in Hou, Xue, and Zhang (2015) (HXZ). The rule also survives value-weighted portfolios, as considered in HXZ, and is predictive of returns at the market and industry levels. Further, the *MAD* effect obtains within *all ten* momentum deciles (i.e., deciles sorted by past 6-12 month performance alone). Finally, cross-country Fama-MacBeth-type regressions and portfolio analyses across and within countries provide reliable evidence that the *MAD* rule yields material profits in international settings as well.

Why should such a rule yield positive abnormal profits? Since the profits survive traditional as well as novel factor models, and top *MAD* stocks do not display materially higher risk measures relative to other stocks, a risk-based explanation does not seem plausible. This leaves us with the possibility that the results are attributable to investor misreaction. Because *MAD* stock 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 market frictions- based underreaction proposed by Hou and Moskowitz (2005) do not seem to explain the *MAD* effect we observe. In particular, the 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) information in forming assessments (Tversky and Kahneman, 1974).[2] 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) and Kaustia, Alho, and Puttonen (2008), who indicate that agents' estimates of future market performance are anchored to past performance. The anchoring bias then implies that agents deviate insufficiently from the anchor in forming estimates of future stock prices. Specifically, suppose some material news is released about a stock. If such news causes the price to deviate considerably from its long-term average, the news causes a marked departure from investors' prevailing anchor, the moving average. Agents thus underreact to the news. This means that the price drifts upward (downward) if the distance is large and positive (negative).[3]

One potential implication of the anchoring hypothesis is that when *MAD* is large and positive, the market should continue to underreact to future good news, and vice versa. Conversely, for a large positive *MAD*, since investors already are anchored on the lower long-term moving average, the underreaction to subsequent negative news should be less extreme (a reverse argument holds for large negative *MAD*). Supporting this conjecture, we show that when the short-long distance is large and positive, the drift following positive earnings surprises, new buy recommendations (over the next six months), and dividend initiations is considerably higher than the same drift for firms with a large negative distance. Similarly, when the short-long

[2] 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 two numbers.

[3] See Cen, Hilary, and Wei (2013) for an application of the anchoring bias to the security analysis industry.

distance is large negative, the drift following negative earnings surprises, new sell recommendations, and seasoned equity issues is considerably lower (more negative) than for firms with a large positive distance. This shows that investors underreact to both positive and negative news that leans in the same direction as the long-short distance, supporting the anchoring rationale. We also show that the effect of the negative distance is stronger in stocks with greater arbitrage constraints (as measured by institutional holdings), indicating that limits to arbitrage play a role in preventing the short leg of the trade from being arbitraged away completely.

Our work relates to the extensive literature on behavioral biases applied to explain return anomalies. For example, Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998) respectively use the representativeness bias and overconfidence to explain value and momentum effects. Barberis and Huang (2001) show that mental accounting can explain value effects. Barberis, Mukherjee, and Wang (2016) support empirically the notion that a stock whose past return distribution has a higher prospect theory value earns, on average, a lower subsequent return. Our work fits into this literature by proposing that the anchoring phenomenon of Tversky and Kahneman (1974) accords with a remarkably robust technical trading strategy based on crossing rules.

2. The Data

We consider all U.S. firms listed on the NYSE, AMEX, and NASDAQ with share codes 10 and 11 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 firm characteristics known to predict the cross-section of average returns.

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 for every year, we update the previous fiscal year's accounting data to make sure that information for predicting future stock returns is available to economic agents 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 a variant on the MACD rule proposed by Appel (2005), which involves measuring the distance between the short-term and long-term moving averages. We term our variable the moving average distance (*MAD*). The *MAD* 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).[4] We focus both on the quantitative value of *MAD*, and consider an *MAD* signal that records the value of unity if *MAD* exceeds a threshold, and zero if it falls below a threshold. In computing moving averages, stock prices are adjusted for splits and dividend

[4] Our results are robust to considering MA(250), the approximated annual moving average in terms of trading days.

distributions.

To ensure that *MAD* does not merely capture well-established phenomena or technical rules, we control for various firm-level variables which are formally defined in Appendix A. In particular, we control for 18 firm characteristics detailed below. We also control for the 200-day moving average signal denoted *MAS* (records the value one if the current price exceeds the 200-day moving average and zero otherwise), the *MAD* signal (*MDS*) noted above, and five past return variables reflecting short- and long-term price reversals, as well as intermediate-term momentum per DeBondt and Thaler (1985), Jegadeesh (1990), and Jegadeesh and Titman (1993).

The 18 firm control characteristics are as follows. 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*) accounts for 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 squared residuals from daily Fama-French time series regressions per Ang et al. (2006).

Turnover (*TURN*) is constructed as the ratio between the trading volume and the outstanding shares (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 absolute return per dollar of daily trading volume. The 52-week high (*52HIGH*) price denotes the reference point known to affect the tendency of investors to underreact to news (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). Recommendation upgrade-downgrade (*RUD*) is calculated as the number of recommendation upgrades minus downgrades divided by the total number of outstanding recommendations. This variable 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*) 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).

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*) is associated with higher future returns, Sloan (1996) finds a negative relation between accruals (*Ac/A*) and return, Chen, Novy-Marx, and Zhang (2010) 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*) is 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 the descriptive statistics for the variables. There is large variability in profitability (*Y/B*) and illiquidity (*ILLIQ*) relative to their means; however, these variables are not crucial to our analysis.

[Please insert Table 1 here]

3. The *MAD*-Return Relation

In this section, we explore the ability of the *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 the *MAD*. The evidence indicates that average returns increase almost monotonically with *MAD* from 0.84% (bottom portfolio) to 1.92% (top portfolio). The null hypothesis of equal means across the extreme *MAD* deciles is strongly rejected (*t*-value = 3.62). Figure 1 displays the average returns per *MAD* deciles for various investment horizons that vary from one month to two years. Panel A depicts the next month's average returns, as in Panel B of Table 1. Panel B in Figure 1 displays the average cumulative returns for months 2 through 6. This five-month horizon delivers a return spread between the top and bottom *MAD* portfolios that is economically large (about 7%). There is a weaker *MAD*-return relation for months 7-12 (Panel C), while average returns for months 13-24 (Panel D) no longer increase with *MAD*.

We next examine whether the *MAD*-return relation is a significant and robust phenomenon that is unexplained by previously explored lagged return effects, including short-term reversals, intermediate-term momentum, or technical indicators. We show that the MAD-return relation exists at both the cross-section and aggregate and it 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 through various market states including high versus low investor sentiment, high versus low market volatility, as well as high versus low market illiquidity.

[Please insert Figure 1 here]

3.1 Cross-Sectional Regressions

First, we employ the Fama and MacBeth (1973) cross-sectional regression setup. For each month, we regress monthly stock returns on *MAD*, the above-described 18 firm characteristics, the *MAS* and *MDS* binary signals, and past return instruments. Table 2 reports the regression 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 focus on their interaction with the *MAD*. Estimated slope coefficients for all other control variables are reported in Appendix B.

[Please insert Table 2 here]

The dependent variable in the first test is the one-month return. In Table 2, the *MAD* coefficient is economically large at 2.83% and highly significant (*t*-value = 5.99). The *MOM* and *TRND* coefficients are also positive and highly significant. Interestingly, the *52HIGH* displays negative coefficients even as we confirm that it is positively associated with future one-month return on a stand-alone basis.

For an investment horizon of 2-6 months, the *MAD* coefficient is especially large (9.47%)

and highly significant (*t*-value = 7.82). While on a stand-alone basis, *MOM*, *52HIGH*, and *TRND* produce positive and significant slope coefficients over the 2-6-month horizon, they all turn insignificant in an all-inclusive specification. For this investment horizon, the coefficients for the binary *MAS* and *MDS* are also indistinguishable from zero (reported in Appendix B). 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 is also strong significance for returns for the 7-12 month investment horizon (5.93%, *t*-value = 5.00). The *MAD* effect turns insignificant for the 13-24-month horizon.

We next examine the *MAD* effect for the 2001-2015 period. This period is important, as Schwert (2003), Chordia, Subrahmanyam, and Tong (2014), and McLean and Pontiff (2016) show that anomalies tend to attenuate and even disappear in more recent years. Indeed, consistent with these studies, we show that over the 2001-2015 period, the momentum, 52-week high price, and trend effects all disappear (*t*-value=0.72, -1.25, and 0.41, respectively). In contrast, investment rules based on the *MAD* still produce a positive and significant coefficient (*t*-value = 2.82).

We next examine 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 is still at work even for factor-adjusted returns.

Thus far we have focused on the quantitative value of *MAD*. We next consider three time-invariant thresholds, equal to 0.1, 0.2, and 0.3. To illustrate, consider the 0.2 threshold. The *MAD Threshold* variable takes on the value one if the *MAD* is greater than 1.2, a negative one if the *MAD* is smaller than 0.8, and zero otherwise. Considering fixed thresholds neutralizes the common variation of stock-level *MAD* with the market. *MAD Threshold* with fixed thresholds produces highly significant coefficients (*t*-value = 4.37, 6.19, and 5.20, for the 0.1, 0.2, and 0.3

thresholds, respectively). Moreover, the slope coefficient increases with the threshold, with values of 0.23 (for 0.1), 0.45 (for 0.2), and 0.51 (for 0.3). Thus, higher thresholds are associated with higher investment return in ways unrelated to momentum, 52-week high, various trend variables, or other technical rules.

We next examine the predictive power of *MAD* over different market 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 emerges during high sentiment or high market states. Moreover, Avramov, Cheng, and Hameed (2016) show that momentum is robust only when markets are highly liquid. To examine the potential effects of market conditions, we run cross-sectional regressions for high-versus-low sentiment, volatility, and illiquidity states. The sentiment index follows Baker and Wurgler (2006), market illiquidity as 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 illiquidity 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 affect is also robust to forecast dispersion across analysts.

In sum, the evidence indicates that *MAD* is a strong and significant predictor of future returns up to one year. Unlike prominent anomalies that have attenuated during the most recent years, the *MAD* effect still stands out. The effect is not captured by simple moving average rules or the *MAD* signal. It is also left unexplained by well-known predictive characteristics that use past returns, prices, and trends. The robustness of our proposed *MAD* during the sample period, in recent years, as well as throughout market states related to volatility, illiquidity, 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 month average returns for the top 30%, mid 40%, and bottom 30% portfolios sorted on *MAD* and, independently, on *MOM*, *52HIGH*, and *TRND*. In all cases, the top *MAD* portfolios yield average returns that are significantly higher than the bottom *MAD* portfolios. 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 predictability of next month returns.

[Please insert Table 3 here]

In Appendix D, we report the results of the double-sort analyses. Table C1 reports the results of ten *MAD* portfolios and two portfolios based on the *MAD* signal (above and below one). Tables C2-C15 report payoffs of 10 × 10 portfolios constructed by double sorts on *MAD* and, in turn, each of the 14 characteristics: (i) momentum (*MOM*), (ii) 52-week high price (*52HIGH*), (iii) trend (*TRND*), (iv) size (*ME*), (v) book-to-market (*BE/ME*), (vi) turnover (*TURN*), (vii) illiquidity (*ILLIQ*), (viii) volatility (*VOL*), (ix) previous month's return ($R_{t\text{-}1}$), (x) past returns for months 7-12 ($R_{t\text{-}7:t\text{-}12}$), (xi, xii) returns for months 13-24 ($R_{t\text{-}13:t\text{-}24}$) and for months 25-36 ($R_{t\text{-}25:t\text{-}36}$), (xiii) standardized unexpected earnings (*SUE*), and (xiv) recommendation upgrade-downgrade (*RUD*). We implement both independent and sequential sorts and examine various investment horizons.

Table C1 also 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 positive and mostly significant across the board. The results are even sharper for the intermediate investment horizons (months 2-6). Investment payoffs for months 7-12 reveal a weaker *MAD* effect, while reversal is at work for longer horizons (months 13-24). Notably, for the 2-6 investment horizon, neither momentum nor trend exhibit significant patterns across *MAD* deciles. Altogether, none of the predictive characteristics we evaluate captures the MAD effect.

We next assess the annual alpha 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 are bought and all stocks with *MAD* smaller than one are sold. Note that the *MAD signal* is not our major focus in the cross-section, as we focus more on the distance. Accordingly, in the second strategy, stocks in the top *MAD* decile are bought and stocks in the bottom decile are 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. Notice that a zero threshold boils down 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 end 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.

[Please insert Figure 2 here]

In Table 4, we summarize the abnormal investment payoffs and their significance for multiple holding periods ranging from one to 24 months. In Panel A, we summarize the annual alpha estimates obtained from regressing top-minus-bottom portfolio payoffs on the Fama-French and cross-sectional and time-series momentum factors. The alphas of the *MAD signal* strategy are positive and significant for investment horizons of up to 12 months. The *MAD* decile strategy yields substantially larger alphas for investment horizons of up to six months. For the 0.1 threshold, alpha ranges between 2.46% (*t*-value = 2.89) for the 24-month horizon and 6.35% (*t*-value = 5.16) for the three-month horizon. The corresponding figures for the 0.2 and 0.3 thresholds are 2.60% (*t*-value = 2.16), 10.68% (*t*-value = 6.52), 1.66% (*t*-value = 0.95), and 14.31% (*t*-value = 4.58). Remarkably, considering fixed thresholds, the *MAD* effect is robust even after 18 months and often also after two years.

[Please insert Table 4 here]

We also examine the long-leg of *MAD* rules. Notably, Stambaugh, Yu, and Yuan (2012) and Avramov et al. (2013) show that market anomalies extract their profitability primarily from the short-leg of the trading strategy, as investors tend to overprice subsets of stocks with extreme equity characteristics. Figure 2 shows that top *MAD* stocks outperform the market. To complete the long-only analysis, Panel B of Table 4 reports long-leg annual alpha estimates. The results show 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 make *MAD* rules unique relative to competing investment strategies that employ past returns and prices.

Do investment strategies that employ the *MAD* 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 break-even transaction costs 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 the 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 5 reports the two break-even transaction 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 transaction 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 the 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.

[Please insert Table 5 here]

As also shown in Table 5, the break-even transaction costs increase with the threshold. Focusing on the one-month holding period, the cutoff costs are 103, 147, and 172 bps for the 0.1, 0.2, and 0.3 thresholds, respectively, compared to 29 bps for the *MAD signal* strategy and 30 bps for the *MAD* decile strategy. Recall, the *MAD signal* strategy is tantamount to a zero threshold. The corresponding figures for the 12-month holding period are 486, 587, and 616, 205, and 102.

Moving to our second scheme of transaction costs 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 investment payoffs that largely exceed reasonable transaction costs.

Indeed, for the most part, the reported break-even transaction costs are substantially 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 earning announcing drift for 1963-2013 ranges from 10 to 40 bps.

For the sake of completeness, we also assess whether our *MAD* strategy delivers Sharpe ratios that are significantly higher than the market Sharpe ratio, as in MacKinlay (1995). The results are reported in Appendix E. In brief, portfolios that employ the *MAD signal* or extreme *MAD*-based deciles produce Sharpe ratios that are not significantly greater than that of a market proxy. In contrast, considering all fixed thresholds noted earlier yields Sharpe ratios that are significantly greater than the market index for investment horizons of up to one year.

Recent years have given rise to new generation of competing asset pricing models. Fama and French (2015, 2016) propose a five-factor model comprised of market, size, and book-to-market spread (items in the three factor model), as well as investment and profitability factors. Hou, Xue, and Zhang (2015) propose a four-factor model comprised of market, size, investment, and profitability (return on equity). Both studies provide theoretical motivation for why these factors contain information about expected returns. Fama and French (2015) invoke comparative statics of a present-value relation, while Hou, Xue, and Zhang (2015) rely on an investment-based pricing model. These authors show that this new generation of asset pricing models captures the vast majority of anomaly payoffs. Fama and French (2015) suggest that their five-factor model captures size, value, profitability, and investment patterns better than their three-factor model. Fama and French (2016) show that their five-factor model eliminates several persistent anomalies including market beta, net share issues, and volatility. Hou, Xue, and Zhang (2015) show that under their model, only five out of 35 persistent anomalies yield significant alphas.

It is instructive to examine the alpha produced by our *MAD* strategies, relative to the newly proposed factors by Fama and French (2015) and Hou, Xue, and Zhang (2015). Accordingly, we regress excess returns generated by our five buy-minus-sell portfolios described above on the Fama and French (2015) five-factor model and the Hou, Xue, and Zhang (2015) q-factor model. Table 6 reports the alphas for investment horizons of one, three, six, and 12 months. In Panel A, stocks are equally-weighted to form top and bottom *MAD* portfolios. Remarkably, the alpha of the top-minus-bottom portfolio is economically large and mostly significant for both models, as well as for all investment horizons. Moreover, for all trading strategies that employ *MAD* time-invariant thresholds, the *t*-values are greater than three.

[Please insert Table 6 here]

In a recent paper, Hou, Xue, and Zhang (2017) argue that abnormal profits from investing in 64% of previously documented anomalies are not identifiable when the impact of microcap stocks is mitigated by value weighting returns. Investing in 71% of the remaining anomalies fail to produce significantly positive alphas when excess returns are regressed using the Hou, Xue, and Zhang (2014) q-factor risk model. In this context, Fama and French (2015) note that the most serious problems of asset pricing models are concentrated in small cap stocks.

As noted in the data section, 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 experiment on value-weighted portfolios.

Panel B of Table 6 reports the alphas for the value-weighted portfolios. While these are smaller than those reported in Panel A, they are still economically large and mostly significant for the *MAD threshold* strategies. To illustrate, for the Fama-French five-factor model, all strategies that employ the *MAD* decile or fixed thresholds produce statistically significant alphas for all investment horizons. In addition, such strategies also produce positive alphas relative to the q-factor model while significance is recorded for fixed thresholds equal to 0.2 and 0.3 for all investment horizons. Note that the differences between equally-weighted and value-weighted portfolios decrease in the case of the 0.3 threshold as those portfolios are characterized by relatively smaller firms.

Higher *MAD* stocks could be potentially riskier than lower *MAD* stocks, thereby commanding higher required returns. While we do control for prominent common factors, nevertheless, in Panel A of Table 7 we compare the risk profile of top versus bottom *MAD* decile portfolios. Results are reported for equally-weighted portfolios as their value-weighted counterparts are qualitatively similar. The second column in Panel A reports the past 200-day mean standard deviation of daily stock returns. The mean standard deviation for the top *MAD* portfolio is slightly higher than that for the bottom portfolio, 17.03% versus 16.03% in monthly terms. This relation is reversed in the third column, as the top decile's average volatility is smaller than that of the bottom portfolio. We also report the loadings on the five Fama and French (2015) factors. We find that the market and value factor loading estimates are smaller for the top versus the bottom deciles. A *t*-test confirms that such differences are significant. The factor loadings on operating profitability are indistinguishable. The size and investment factor loading estimates are larger for the top versus bottom portfolios and the differences are significant. Overall, the results do not support the notion that top *MAD* stocks are distinctly riskier and merit a considerable premium.

[Please insert Table 7 here]

Could gradual information diffusion cause the *MAD* effect? 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 recognized, smaller cap, more volatile, and more illiquid stocks.

We examine whether such channels of gradual information diffusion could provide explanatory power for the MAD effect. Tables D5, D7, and D8 in Appendix D show that the *MAD* effect is robust among all size, turnover, and illiquidity groups. Further, we report in Panel B of Table 7 the average firm characteristics for ten *MAD* groups and for the various *MAD* thresholds. The average 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. In addition, the average number of analysts covering the top *MAD* stocks is 5.82 and the average share of institutional holdings is 0.37. 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 relative to that for other *MAD* deciles suggesting that the *MAD* effect is not driven by credit risk.

In sum, the top *MAD* stocks are not considerably riskier or the most prone to gradual information diffusion or market friction. Altogether, the modern factor models do not capture the *MAD* effect, although they do provide explanatory power for various predictable cross-sectional patterns in average stock returns. The *MAD* effect is also inconsistent with gradual information diffusion models. The notions that (i) risk factors are unable to capture the *MAD* effect, (ii) outperforming *MAD* portfolios are not riskier, and (iii) gradual information diffusion due to market frictions does not accord with the *MAD* effect, leaves us with the possibility that the *MAD* effect is a behaviorally-induced phenomenon that is unrelated to risk or market frictions.

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 the *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 long-run reversals for returns up to 36 months after portfolio formation based on *MAD*. In addition, the results in Table 4 show that portfolio payoffs do not reverse even after two years. Thus, the evidence accords with investor underreaction, rather than overreaction.

There are possible behavioral rationales for agent underreaction; for example, those based on limited attention, which causes agents to ignore news (Hirshleifer and Teoh, 2003), or conservatism (Barberis, Shleifer, and Vishny, 1998). However, these do not readily apply to the *MAD* indicator. Since the indicator is simply the difference between two moving averages, it does not inherently represent an information signal. In other words, while a price move (return) contains information, there is no fundamental information contained in the *deviation* of a moving average from an arbitrary baseline (the long-run moving average). Thus, limited attention only applies when agents ignore valid information signals (e.g., earnings announcements) owing to limited processing capacity, not signals that contain no inherent information. And again, agent conservatism relative to a Bayesian updater (Edwards, 1968) implies underreaction to tangible news. The preceding arguments indicate that any explanation for the *MAD* has to involve a special role for the seemingly irrelevant baseline (the long-run moving average).

We propose an underreaction-based explanation for the predictive power of the *MAD* that relies on the anchoring bias (Tversky and Kahneman, 1974). The notion is that agents rely on readily available but often irrelevant information to form estimates and then shift insufficiently from these estimates. What is a reasonable anchor? We propose that it is 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 performance of stock markets 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, either good or bad, 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 low *MAD* stocks are overpriced while high *MAD* stocks are underpriced. The proposed rationale suggests that markets would continue to underreact to future good (bad) news when *MAD* is large positive (large negative). Note, however, that since investors are already anchored to the lower long-run moving average for a large positive *MAD* and vice versa, the underreaction should be weaker for subsequent negative announcements when *MAD* is large positive, and for positive announcements following a large negative *MAD*. The above arguments are formalized within a simple setting in Appendix G. Below, we provide empirical evidence supporting the above 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 the drift 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. Note that we do not include dividend cancellations as a complement to positive dividend initiations because in our sample there are no top *MAD* stocks that record cancelled 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 plots display payoffs following positive earnings surprises, the mid plots exhibit payoffs following buy investment recommendations, while the right plots display payoffs following dividend initiations. In Panel A, we focus on equally-weighted returns in excess of the CRSP equally-weighted composite index, while in Panel B we focus on value-weighted returns in excess of the value-weighted counterpart. 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 accumulate returns for six months (126 trading days) using the closing price one day after the event announcement. We consider stocks belonging to the top (bold line) versus the bottom (dashed line) *MAD* deciles. As the statistical evidence is qualitatively similar using *t*-ratios versus Patell (1976) *z*-scores (the latter accounts for return compounding), we report only *t*-ratios.

[Please insert Figure 3 here]

We first discuss the equally-weighted portfolios. The top *MAD* stocks exhibit a large drift during the 126-day window following positive earnings surprises. For such stocks, the zero-drift hypothesis is rejected (*t*-value = 4.61). For the bottom *MAD* stocks, the drift following positive earnings surprises is indistinguishable from zero. The hypothesis of equal drifts across top and bottom *MAD* stocks is clearly rejected (*t*-value = 2.37). Likewise, following buy recommendations, the top *MAD* stocks exhibit a large positive drift (*t*-value = 3.63), while the bottom *MAD* stocks display a negative drift. The hypothesis of equal drifts among top and bottom *MAD* stocks is again rejected (*t*-value = 7.67). A similar pattern emerges following dividend initiations, where the difference in returns across deciles after six months tops 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*).

Moving to the value-weighted portfolios, the top *MAD* stocks exhibit significant positive drifts, whereas the bottom *MAD* stocks exhibit insignificant drifts following both 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 large negative drifts that are statistically and economically significant. The drifts of the top and bottom *MAD* stocks of value-weighted portfolios in Panel B are indeed 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 that for positive MAD stocks, investors anchor to the lower long-run moving average, thus underreacting to positive news, and vice versa.

[Please insert Figure 4 here]

Focusing on the short leg of the *MAD* effect, limits to arbitrage (short-selling constraints, viz D'Avolio, 2002) could possibly explain why over-valuation cannot be easily arbitraged away. To explore the potential effects of limits to arbitrage, 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 are expected to 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 reports equally-weighted returns in excess of the CRSP equal-weighted composite index, while Panel B reports value-weighted returns in excess of the CRSP value-weighted composite index.

[Please insert Figure 5 here]

In both panels, the more difficult-to-arbitrage stocks exhibit more negative drifts. The six-month returns on low institutional holdings stocks are uniformly smaller vis-à-vis their counterparts and the differences are significant (*t*-values = 7.67 and 2.25, respectively).

5. *MAD* and the Aggregate Equity Premium

Thus far, we have examined the predictive ability of *MAD* for the cross-section of average stock returns. Our major theme is behavioral: investors underweight information releases that are at odds with their anchoring reference, which in turn is based on the 200-day moving average. 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 effect applies at the aggregate. Accordingly, we examine whether *MAD* constructed using the market index and industry portfolios can properly time the market.[5]

We consider market-timing strategies that are similar to Moskowitz, Ooi, and Pedersen (2012). In the *MAD signal* strategy, investors buy 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. Notice that the volatility of *MAD* at the aggregate level is considerably lower than that of the cross-section of single stocks. Put another way, high enough thresholds induce a position that for the most part invests in Treasury bills. Thus, 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 starts at the start of the sample, using as many months as are available up to 60 months for the window, and thereafter stays fixed 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 all employed strategies.

Table 8 reports the annualized market alphas for the value-weighted composite index

[5] The analysis at the aggregate level is essentially an analysis of the *MAD* 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,[6] 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.

Starting with the market index, the alpha of the *MAD signal* strategy is positive and significant for the entire sample period, as well as for the 2001-2015 period. Moreover, both the alpha and the *t*-ratio increase with the threshold. The same pattern emerges in all individual industry portfolios, as well as in the all-industry portfolio. In unreported tests, we uncover similar patterns using value weighted industry portfolios. In sum, the *MAD* effects work at the cross-section and at the market and industry levels for U.S. equities.

We have thus far exclusively focused on U.S. equity markets. In what follows, we study the predictive power of *MAD* for international markets in an attempt to provide further out-of-sample evidence for our results.

[Please insert Table 8 here]

6. International Analysis

In this section, we evaluate 37 international equity markets. Descriptive statistics for these markets are reported in Appendix F. Due to data availability, the international analysis focuses on the more recent years starting from 2001. 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.

[6] The industries are defined as in Ken French's website at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research.

We start with Fama-MacBeth cross-country regressions. Each month, we regress country returns (raw and risk adjusted) on previous month *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 9 reports the coefficient estimates of the MAD effects and momentum factors and their significance. For 1-24-month investment horizons and raw returns, the slope coefficients for *MAD* are uniformly positive and mostly significant. Similar patterns emerge when returns are risk-adjusted using the international CAPM and the global Fama-French and momentum factors. Altogether, the cross-country regression results support the hypothesis that the *MAD* effect extends beyond U.S. markets.

[Please insert Table 9 here]

We next employ double-sort portfolio analysis to understand the interaction between the *MAD* effect and prominently studied international momentum strategies. The international market indices (37), along with the U.S. index are sorted by month into 3 × 3 portfolios, first on the *MAD* and then on past 12-month returns. Table 10 reports the results. All rows in Panel A report average returns for the next month, months 2-6, months 7-12, and months 13-24 for top versus bottom *MAD* portfolios. For all investment horizons considered, the return spreads between top and bottom *MAD* portfolios are large and statistically significant. The results also show that in an international asset pricing context, the *MAD* interacts well with momentum. The most significant and largest payoffs are for economies with the highest *MAD* and largest momentum.

[Please insert Table 10 here]

Panel B of Table 10 reports alpha estimates obtained from regressing monthly returns on zero-cost top-minus-bottom *MAD* portfolios, as well as winner and loser countries (from Table

10), on the market (international CAPM) and the Fama-French and momentum global factors. The CAPM alpha is always positive. It is significant for all investment horizons for all indices, as well as for winner countries, but often insignificant for loser countries. The four-factor alpha exhibits similar patterns. Overall, the evidence in Tables 9 and 10 indicates that the *MAD* effect and momentum factors are strong predictors of the cross-section of average country returns.

We next examine whether *MAD* can be employed to time international markets. We again implement market-timing strategies that buy the market index if *MAD* is above one plus a threshold and holds Treasury bills otherwise, where the *MAD* signal amounts to a zero threshold. Table 11 reports the alpha estimates obtained from regressing next month excess returns on the corresponding market factor. The results provide 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 examined, and it is significant for 32 economies, at least at the 10% level. 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 11. 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 any of the equity markets. While the value-weighted strategy is clearly tilted towards the more developed economies, the equal-weighted one gives the same prominence for all economies, even emerging markets. We assess the investment payoff of that all-inclusive strategy using alpha (with respect to the global market portfolio).

The results are reported at the bottom of Table 11. The market alphas are large (8.11% -

12.28% equal-weighted and 6.42% - 9.81% value-weighted) and highly significant (*t*-value = 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.

[Please insert Table 11 here]

In sum, the international evidence reinforces the predictive power of the *MAD*. From a cross-sectional perspective (cross-sectional regressions along with portfolio sorts), *MAD* is statistically and economically significant. High *MAD* countries considerably outperform low *MAD* countries, and *MAD* is a phenomenon distinct from 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.

7. Conclusion

While moving average-based crossing rules have been extensively analyzed in earlier literature, the distance between short- and long-run averages has not yet received extensive attention. This signed distance (that we term *MAD*) is a surprisingly strong predictor of equity returns and survives a host of controls based on accounting statements as well as past returns. Versions of this rule also yield supernormal profits at the market and industry levels and in cross-country contexts. The remarkable robustness of our results sheds important light on market efficiency.

Since profits from the rule do not reverse in the long-run, they indicate investor underreaction, as opposed to continuing overreaction and correction. We propose that such underreaction occurs because investors are overly anchored to the long-run average and update beliefs insufficiently in the light of new information. This implies greater underreaction to positive information subsequent to a large positive *MAD* and vice versa. Further, because investors already are anchored to a low (high) moving average when *MAD* is large positive (negative), we expect muted underreaction to negative announcements following large positive *MAD* and vice versa. 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*.

Our work suggests implications for future research. First, it is worth considering whether the moving average trading rule documented here applies to accounting data. That is, for example, a large deviation from long-run average values for widely followed numbers such as sales and profit margins could cause large underreactions due to the anchoring bias. Second, it is worth considering whether the profitability of the *MAD* rule depends on the extent to which there is material public information available on companies, which, in turn, depends on disclosure requirements across countries. These and other topics are left for future research

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Table 1. Descriptive statistics

Panel A displays descriptive statistics for the economic variables. The variables are defined in Appendix A. Panel B reports the next month average returns for ten portfolios sorted on *MAD*. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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
Net Operating Assets (*NOA*)	0.680	0.441
Distress O-Score (*DTRS*)	-0.013	0.091
Moving Average Distance *(MAD)*	1.050	0.210

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 provides average slopes (multiplied by 10^4) and their t-values (in parentheses) obtained from monthly cross-sectional regressions. The dependent variable is stock return for the next month, months 2-6, 7-12, and 13-24. We also run the analysis for the most recent period of 2001-2015. Risk-adjusted excess returns are based on the Fama-French factors, along with one of three momentum factors: cross-section momentum, time series momentum, and the trend factor per Han, Zhou, and Zhu (2016). *MAD* and the control variables are defined in Appendix A. *MAD Threshold* = *p* is a variable that takes the value one if *MAD* is greater than 1 plus *p*, negative 1 if *MAD* is smaller than 1-*p*, and zero otherwise. Cross-sectional regression coefficients are reported for the entire sample as well as for various market states. We consider positive versus negative sentiment per Baker and Wurgler (2006), below versus above median previous month market volatility, and below versus above median previous month market illiquidity measure per Amihud (2002). The sample is from June 1977 to October 2015. One, two, and three asterisks indicate 10%, 5%, and 1% significance, respectively.

Dependent variable	*MAD*	*MOM*	*52HIGH*	*TRND*	Averaged R^2
R_{t+1}	2.83***	0.43***	-1.03***	28.06***	0.09
	(5.99)	(4.02)	(-3.43)	(7.71)	
$R_{t+2:t+6}$	9.47***	-0.14	0.94	-1.37	0.10
	(7.82)	(-0.55)	(1.48)	(-0.19)	
$R_{t+7:t+12}$	5.93***	-2.15***	-0.51	-10.06	0.09
	(5.00)	(-7.49)	(-0.75)	(-1.05)	
$R_{t+13:t+24}$	-0.22	-1.09**	-2.15**	-1.79	0.09
	(-0.12)	(-2.44)	(-2.05)	(-0.12)	
R_{t+1} for 2001-2015	2.00***	0.13	-0.67	3.03	0.09
	(2.82)	(0.72)	(-1.25)	(0.41)	
Excess R_{t+1} adjusted to FF &					
Cross-Section Momentum	2.49***	0.39***	-0.76***	26.96***	0.07
	(5.99)	(3.97)	(-3.30)	(7.71)	
Time-Series Momentum	2.83***	0.43***	-1.03***	28.06***	0.09
	(5.99)	(4.02)	(-3.43)	(7.71)	
Trend	2.14***	0.45***	-0.69***	27.60***	0.07
	(4.96)	(4.53)	(-3.00)	(7.74)	
R_{t+1}					
MAD Threshold = 0.1	0.23***	0.59***	-0.87***	30.93***	0.09
	(4.37)	(5.57)	(-2.77)	(9.08)	
MAD Threshold = 0.2	0.45***	0.56***	-0.92***	30.57***	0.09
	(6.19)	(5.24)	(-3.01)	(8.89)	
MAD Threshold = 0.3	0.51***	0.57***	-0.77**	30.77***	0.09
	(5.20)	(5.35)	(-2.54)	(9.08)	
R_{t+1}					
High Sentiment	2.93***	0.60***	-0.62*	28.19***	0.09
	(5.24)	(4.83)	(-1.79)	(5.80)	
Low Sentiment	2.66***	0.15	-1.73	27.83***	0.10
	(3.11)	(0.76)	(-3.14)	(5.27)	
Low Volatility	3.37***	0.35	-0.51	33.36***	0.09
	(5.18)	(2.39)	(-1.47)	(8.00)	
High Volatility	2.31***	0.51***	-1.52***	23.02***	0.10
	(3.40)	(3.26)	(-3.16)	(3.92)	
Low Illiquidity	2.68***	0.31**	-0.94**	13.54**	0.09
	(4.22)	(2.31)	(-2.04)	(2.36)	
High Illiquidity	3.00***	0.57***	-1.12***	43.76***	0.10
	(4.26)	(3.32)	(-2.99)	(10.72)	

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

The table reports next month average returns (*R*) on the 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 10%, 5% and 1% significance degrees, 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. Annual alpha 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 Fama-French and cross-sectional and time-series momentum factors. Panel A reports long positions in the top *MAD* stocks, along with short positions in the bottom *MAD* stocks. Panel B focuses on the long leg of the trade only. Annual alphas are obtained by multiplying monthly alpha by 12 without 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. The time-series factor is based on the CS_{TVM} strategy of Goyal and Jegadeesh (2018) which is constructed as the sum of all-stock cross-sectional strategy plus time-varying investment in the market equally-weighted index. Portfolios are constructed by from equally-weighted stocks. Portfolios with different time horizons are equally-weighted. Holding periods are identical for *MAD* and CS_{TVM} strategies. The sample is from June 1977 to October 2015. One, two, and three asterisks indicate 10%, 5%, and 1% significance, respectively.

	Holding Period (months)					
Portfolio Strategy	**1**	**3**	**6**	**12**	**18**	**24**
			A. Long-Short Equities			
MAD Signal	1.21	1.14	1.30**	1.45***	0.63	0.60
(long *MAD* > 1, short *MAD* ≤ 1)	(1.27)	(1.46)	(2.04)	(2.60)	(1.12)	(1.09)
MAD Decile	2.43	2.86*	2.69**	1.39	-0.88	-0.90
(long Top, short Bottom)	(1.11)	(1.73)	(1.98)	(1.18)	(-0.74)	(-0.80)
MAD Threshold = 0.10	6.22***	6.35***	5.94***	4.91***	3.08***	2.46**
(long *MAD* ≥ 1.1, short *MAD* ≤ 0.9)	(4.11)	(5.16)	(5.67)	(5.31)	(3.46)	(2.89)
MAD Threshold = 0.20	10.12***	10.68***	9.22***	6.76***	3.46***	2.60**
(long *MAD* ≥ 1.20, short *MAD* ≤ 0.8)	(4.41)	(5.62)	(5.68)	(4.87)	(2.69)	(2.16)
MAD Threshold = 0.30	13.03***	14.31***	12.49***	7.79***	3.16	1.66
(long *MAD* ≥ 1.30, short *MAD* ≤ 0.7)	(3.50)	(4.58)	(4.87)	(3.58)	(1.63)	(0.95)
			B. Long Equities, Short T-bills			
MAD Signal	1.31**	1.53***	1.91**	2.36***	2.20***	2.51***
(long *MAD* > 1, short T-bills)	(2.01)	(2.59)	(3.41)	(4.24)	(3.90)	(4.38)
MAD Decile	4.38***	3.68***	3.23***	2.31**	1.36	1.75
(long Top, short T-bills)	(3.07)	(3.19)	(3.13)	(2.37)	(1.43)	(1.90)
MAD Threshold = 0.10	2.52***	2.45***	2.56***	2.72***	2.40***	2.55**
(long *MAD* ≥ 1.1, short T-bills)	(2.82)	(3.13)	(3.62)	(4.03)	(3.57)	(3.80)
MAD Threshold = 0.20	5.04***	3.63***	3.10***	2.77***	2.00**	2.10**
(long MAD ≥ 1.20, short T-bills)	(4.15)	(3.32)	(3.16)	(3.14)	(2.36)	(2.56)
MAD Threshold = 0.30	6.31***	3.77***	3.22**	2.51**	1.22	1.24
(long *MAD* ≥ 1.30, short T-bills)	(3.72)	(2.40)	(2.34)	(2.13)	(1.13)	(1.22)

Table 5. Break-even transaction costs

The table reports two break-even transaction costs: (i) transaction costs that would zero out average abnormal returns (alpha) on the 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). 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 positive certainty equivalent return.

		Holding Period (months)					
Portfolio Strategy		**1**	**3**	**6**	**12**	**18**	**24**
MAD Signal	(i)	29	40	91	205	132	168
(long *MAD* > 1, short *MAD* ≤ 1)	(ii)	na	na	na	na	na	na
MAD Decile	(i)	30	52	98	102	na	na
(long Top, short Bottom)	(ii)	27	68	129	10	na	na
MAD Threshold = 0.10	(i)	103	157	293	486	457	487
(long *MAD* ≥ 1.1, short *MAD* ≤ 0.9)	(ii)	78	136	246	222	na	na
MAD Threshold = 0.20	(i)	147	232	401	587	451	452
(long *MAD* ≥ 1.20, short *MAD* ≤ 0.8)	(ii)	118	212	376	409	28	na
MAD Threshold = 0.30	(i)	172	283	493	616	374	263
(long *MAD* ≥ 1.30, short *MAD* ≤ 0.7)	(ii)	114	233	443	437	na	na

Table 6. Does the *MAD* effect survive modern asset pricing models?

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 and the Hou, Xue, and Zhang (2015) q-factor model. The results for the zero-cost strategies are given in Tables 4 and 5. The sample is from June 1977 to October 2015. One, two, and three asterisks indicate 10%, 5%, and 1% significance, respectively.

	Five-Factor Model					**Q-Model**				
			Threshold					**Threshold**		
Horizon	**Signal**	**Decile**	**0.10**	**0.20**	**0.30**	**Signal**	**Decile**	**0.10**	**0.20**	**0.30**
				A. Equally Weighted Portfolios						
1-Month	5.47***	12.51***	12.15***	17.78***	22.24***	2.34	5.68	7.65***	12.52***	14.84***
	(3.43)	(3.46)	(5.21)	(5.60)	(4.79)	(1.51)	(1.60)	(3.37)	(3.98)	(3.23)
3-Months	5.41***	12.64***	12.38***	18.53***	23.63***	2.22	5.50*	7.77***	12.69***	16.35***
	(3.68)	(3.87)	(5.82)	(6.41)	(5.78)	(1.57)	(1.77)	(3.81)	(4.52)	(4.08)
6-Months	5.27***	11.60***	11.75***	16.66***	21.03***	1.97	4.17	6.82***	10.04***	13.00***
	(3.93)	(3.88)	(5.99)	(6.30)	(5.90)	(1.58)	(1.49)	(3.73)	(4.05)	(3.82)
12-Months	4.48***	7.82***	9.19***	12.23***	13.84***	1.50	1.59	4.98***	6.42***	6.69**
	(4.20)	(3.40)	(5.97)	(5.75)	(4.76)	(1.58)	(0.74)	(3.48)	(3.25)	(2.44)
				B. Value Weighted Portfolios						
1-Month	0.39	9.97**	7.43**	15.85***	22.45***	-3.16	2.03	2.43	10.09**	13.83**
	(0.20)	(2.15)	(2.39)	(3.83)	(3.74)	(-1.65)	(0.45)	(0.80)	(2.47)	(2.32)
3-Months	0.81	9.50**	7.41***	17.18***	26.45***	2.68	1.21	2.32	10.59***	17.79***
	(0.44)	(2.31)	(2.62)	(4.54)	(5.27)	(-1.49)	(0.31)	(0.84)	(2.85)	(3.58)
6-Months	1.81	9.95***	8.54***	16.30***	23.45***	-1.55	1.41	2.93	8.83***	14.45***
	(1.10)	(2.72)	(3.33)	(4.82)	(5.50)	(-0.99)	(0.40)	(1.19)	(2.67)	(3.43)
12-Months	2.69**	8.05***	8.45***	12.90***	16.41***	-0.40	0.05	3.23	5.78**	7.97**
	(2.05)	(2.72)	(4.07)	(4.56)	(4.72)	(-0.31)	(0.02)	(1.61)	(2.08)	(2.34)

Table 7. Risk and characteristic profiles of *MAD* portfolios

Panel A reports various risk measures for top *MAD* decile, bottom *MAD* decile, and top-minus-bottom equally-weighted portfolios. Panel B reports average firm characteristics for *MAD* 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 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* decile or *MAD threshold* portfolios. The firm variables are defined in Appendix A. The sample is from June 1977 to October 2015. One, two, and three asterisks indicate 10%, 5%, and 1% significance, respectively.

A. Risk of *MAD* 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	0.85***	0.98***	1.09***	-0.43***	-0.28***	0.26***
			(5.86)	(28.19)	(21.09)	(-6.34)	(-4.30)	(2.60)
Bottom *MAD* Decile	16.03	7.87	-0.20	1.24***	0.70***	0.34***	-0.38***	-0.54***
			(-1.01)	(26.65)	(10.07)	(3.77)	(-4.40)	(-4.03)
(Equal Slopes *t*-test)			(4.32)***	(-4.45)***	(4.57)***	(-6.82)***	(0.92)	(4.78)***
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)

B. Characteristics of *MAD* Portfolios

***MAD* Decile**	**Market Cap ($ million)**	***BE/ME***	***TURN***	***ILLIQ***	***IVOL***	***O-Score***	**Share of Institutional Holdings**	**Number of Analysts**
Bottom	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	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

Table 8. 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* 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* signal strategy buys the industry index each month if *MAD* > 1 and holds Treasury bills otherwise. The *MAD* threshold strategy buys (1/*e* ×(industry index) - (1-1/*e*) × Treasury bills) if *MAD* > 1 + threshold, and holds Treasury bills otherwise. The equity exposure scale factor *e* = (number of months *MAD* > 1 + threshold) / (number of months *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 market portfolio is the all-stock value-weighted composite index. In the last row, we test joint significance by equally weighting industry *MAD* timing portfolios. One, two, and three asterisks indicate 10%, 5%, and 1% significance degrees, respectively.

Industry Portfolio	1927-2015 Signal	1927-2015 Threshold 0.025	1927-2015 Threshold 0.05	2001-2015 Signal	2001-2015 Threshold 0.025	2001-2015 Threshold 0.05
Market	2.88***	4.54***	5.67***	4.90**	5.88***	7.00***
	(2.85)	(3.97)	(4.08)	(2.52)	(2.64)	(2.74)
NoDur	2.89***	4.91***	7.64***	6.39***	6.74**8	6.40*
	(2.87)	(4.24)	(4.88)	(3.22)	(2.77)	(1.96)
Durbl	2.99*	4.72***	7.27***	4.15	6.38	8.23*
	(1.90)	(2.79)	(3.78)	(1.18)	(1.59)	(1.75)
Manuf	3.09**	3.63***	4.25***	4.78*	4.87	9.85***
	(2.47)	(2.63)	(2.67)	(1.76)	(1.63)	(2.68)
Enrgy	4.54***	5.40***	4.72**	6.29	8.51**	4.67
	(3.14)	(3.39)	(2.39)	(1.63)	(2.07)	(1.02)
Chems	3.17***	4.14***	5.18***	5.13**	5.18**	5.77**
	(2.61)	(3.05)	(3.34)	(2.30)	(2.05)	(1.98)
BusEq	2.29	4.29**	5.62***	2.62	4.39	4.65
	(1.49)	(2.52)	(2.98)	(0.93)	(1.53)	(1.39)
Telcm	4.01***	6.66***	9.20***	6.18***	7.52***	9.32***
	(3.72)	(5.38)	(5.69)	(2.57)	(2.81)	(3.18)
Utils	3.90***	5.73***	5.92***	7.12***	5.92*	3.79
	(3.08)	(4.09)	(3.80)	(2.66)	(1.90)	(1.04)
Shops	1.80	3.64**	6.46***	0.70	4.57*	7.53**
	(1.43)	(2.53)	(3.74)	(0.30)	(1.74)	(2.28)
Hlth	4.68***	5.31***	7.31***	2.91	3.93	6.47*
	(3.66)	(3.67)	(4.19)	(1.23)	(1.45)	(1.95)
Money	2.50*	5.06***	7.47***	3.48	3.24	3.17
	(1.96)	(3.49)	(4.48)	(1.43)	(1.17)	(0.95)
Other	2.04	3.48**	4.61***	5.32**	6.39**	6.43**
	(1.58)	(2.44)	(2.66)	(2.27)	(2.56)	(2.08)
All-Industry	3.13***	4.71***	6.27***	5.03***	6.08***	6.78***
	(3.81)	(5.15)	(5.83)	(3.14)	(3.29)	(3.13)

Table 9. International perspective: 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 to global market, and returns adjusted to the Fama-French and momentum global factors. The control variables are past 12-month returns ($R_{t-1:t-12}$); the *MAD* signal (*MDS*), which is equal 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 it includes data on 38 markets. One, two, and three asterisks indicate 10%, 5%, and 1% significance degrees, respectively.

Dependent Variable	Investment Horizon	*MAD*	*MDS*	*MAS*	*Int. Momentum* ($R_{t-1:t-12}$)	Averaged R^2
Raw Returns	R_{t+1}	4.84**	-035	-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 10. International perspective: MAD and momentum

The table reports average returns (in %) for next month, months 2-6, 7-12, and 13-24, on top versus bottom portfolios corresponding to 3 × 3 sorts first on *MAD* and then on previous 12-month returns ($R_{t-1:t-12}$). Panel B reports annual alphas (in %) obtained from regressing monthly excess returns on zero-cost top-minus-bottom *MAD* portfolios on the market (international CAPM) excess returns and on the Fama-French and momentum global factors, respectively. Annual alpha obtains by multiplying monthly alpha by 12. The sample period is from January 2001 to November 2015 consisting of 38 markets. One, two, and three asterisks indicate 10%, 5%, and 1% significance degrees, respectively.

Int. Momentum		**Investment Horizon**			
($R_{t-1:t-12}$)	***MAD***	R_{t+1}	$R_{t+2:t+6}$	$R_{t+7:t+12}$	$R_{t+13:t+24}$
		A. Average Return (%)			
All	Bottom	0.64	3.55	4.37	10.77
	Top	1.11	5.28	7.16	15.59
	Diff.	0.48**	1.73**	2.79***	4.82***
Bottom	Bottom	0.59	3.04	3.04	10.37
	Top	0.74	4.70	5.86	13.16
	Diff.	0.15	1.66	2.82**	2.79
Mid	Bottom	0.80	4.49	5.34	10.93
	Top	1.38	5.31	7.60	14.99
	Diff.	0.58**	0.82	2.26**	4.06***
Top	Bottom	0.84	4.19	5.54	12.07
	Top	1.50	7.01	9.09	18.91
	Diff.	0.22**	2.82**	3.56***	6.84***
		B. Annual Alpha for Top-minus-Bottom *MAD* Portfolio			
Model					
International CAPM	All	6.28***	4.46**	5.67***	4.74***
	Bottom	2.69	4.53	5.73**	2.27
	Top	8.46**	6.74**	7.21***	7.33***
Global FF & Momentum	All	2.82	1.24	4.15**	5.01***
	Bottom	-0.13	1.54	4.07*	2.75
	Top	5.52*	3.74	5.50**	7.91***

Table 11. Market timing strategies for various economies

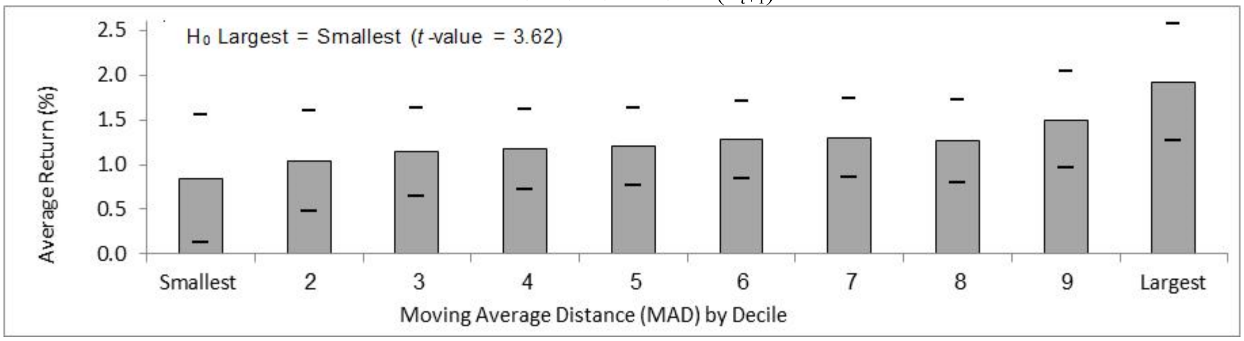
The table reports the annual alphas (in %) and their *t*-values (in parentheses) obtained from regressing *MAD* portfolio monthly excess returns on the corresponding market factor. Annual alpha obtains by multiplying monthly alpha by 12. There are two portfolio strategies. The signal strategy buys the mark31et 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 *MAD* > 1 + threshold) / (number of months *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 all markets *MAD* timing portfolios at either equal or value weights, where "value" corresponds to annual market capitalization of listed domestic companies as per the World Bank. The sample period is from January 2001 to November 2015. One, two, and three asterisks indicate 10%, 5%, and 1% significance degrees, 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***	N. 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**	S. 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***	S. 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)

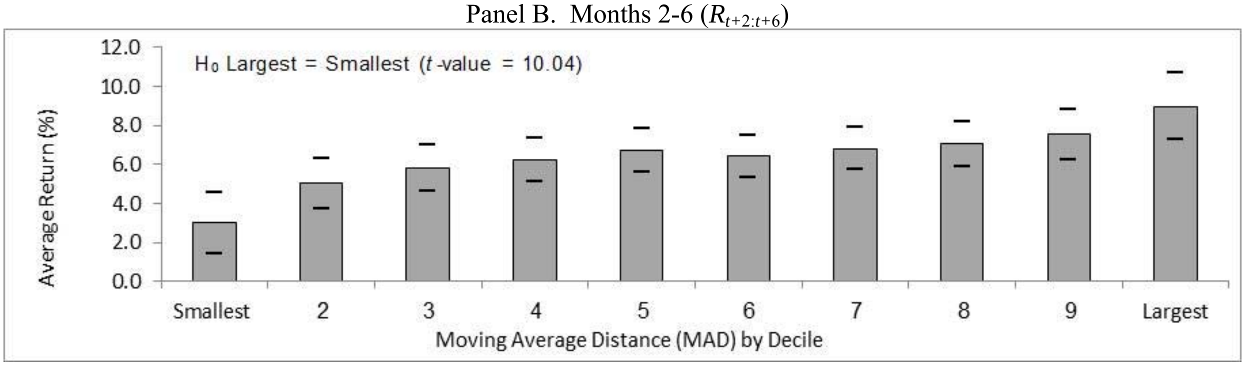
Figure 1. Average returns and the moving average distance (*MAD*)

The Figures 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.

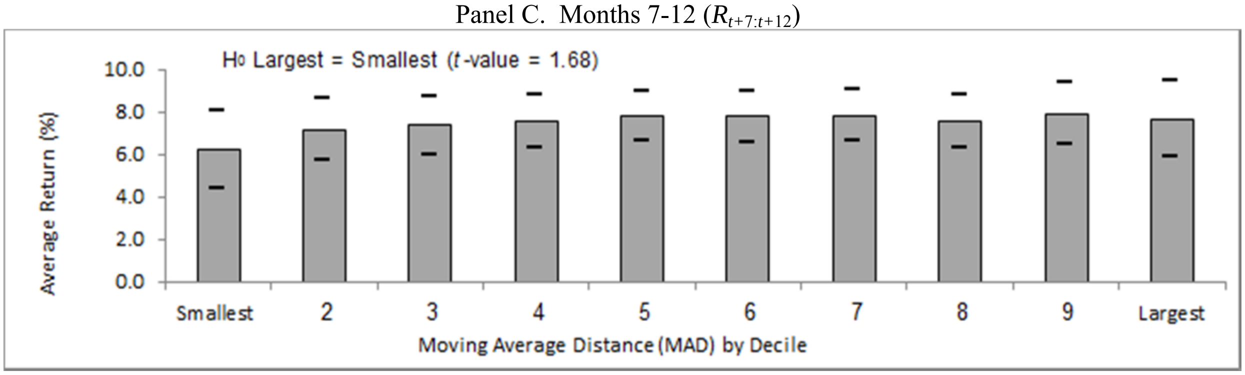
Panel A. Next Month (R_{t+1})



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



Panel C. Months 7-12 ($R_{t+7:t+12}$)



Panel D. Months 13-24 ($R_{t+13:t+24}$)

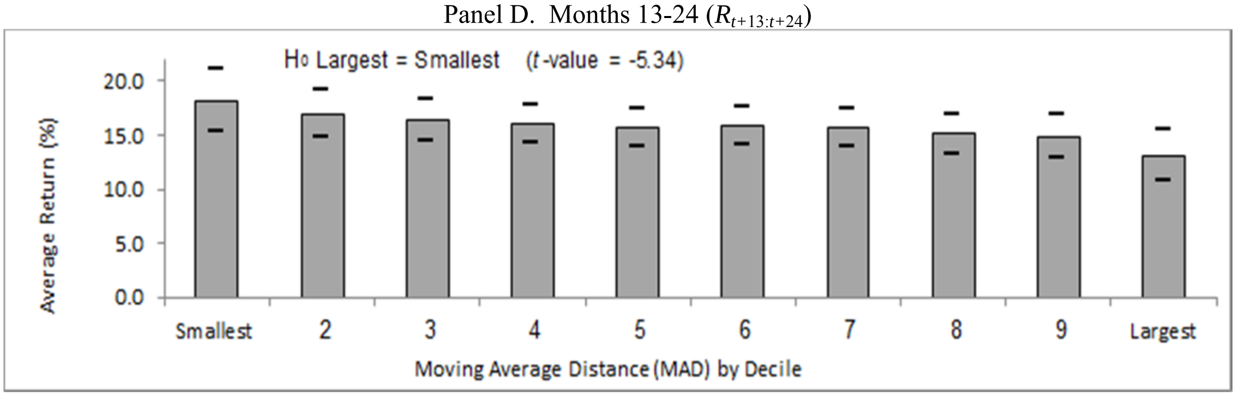


Figure 2. *MAD* investing

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) 10% top (10% bottom) *MAD* stocks. 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. All-market total return reflects the CRSP value-weighted composite index. Gray bars represent NBER-defined recessions.

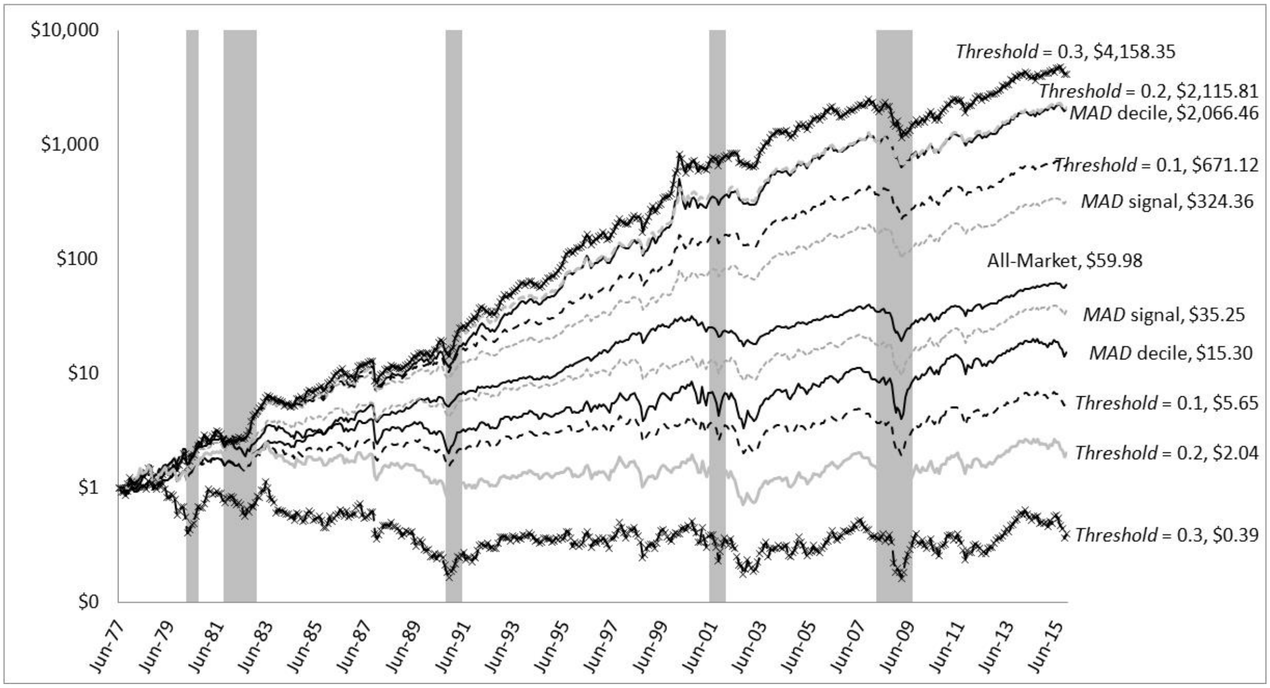
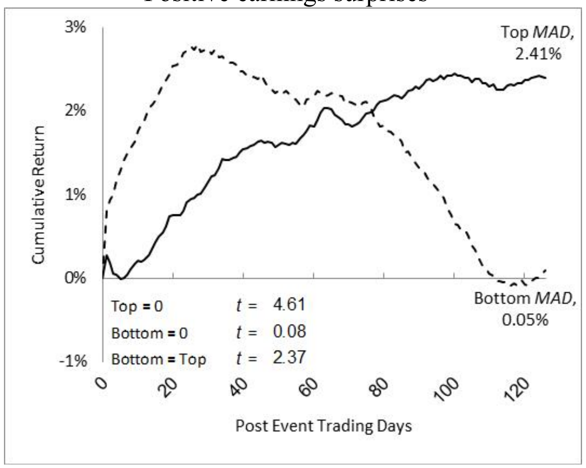


Figure 3. Positive news: Cumulative excess returns and *MAD*

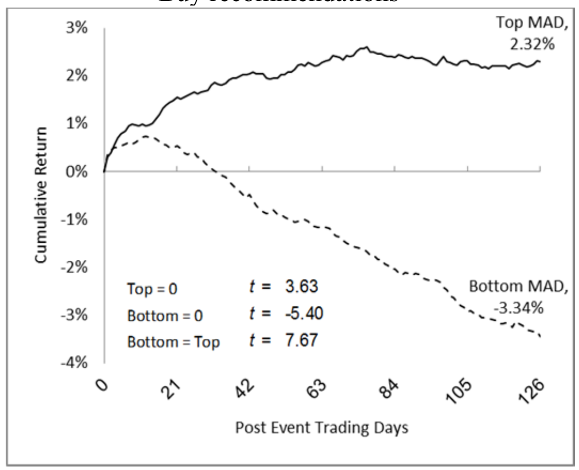
The figure depicts the cumulative excess returns post positive earnings surprises, first-time buy recommendation announcements, and dividend intimations. Portfolios consist of top and bottom *MAD* stocks at the end of the month prior to earnings, recommendations, or dividend initiation announcements. 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

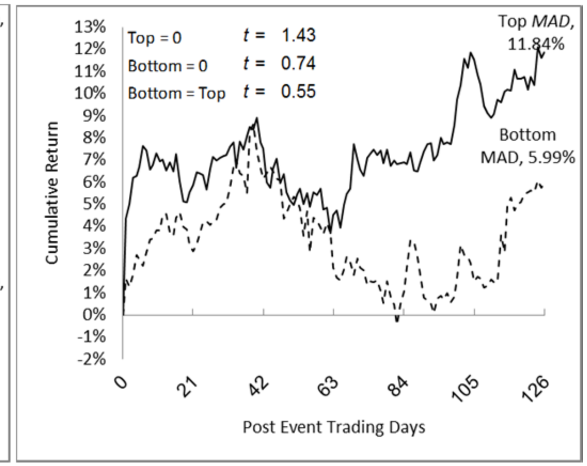
Positive earnings surprises



Buy recommendations

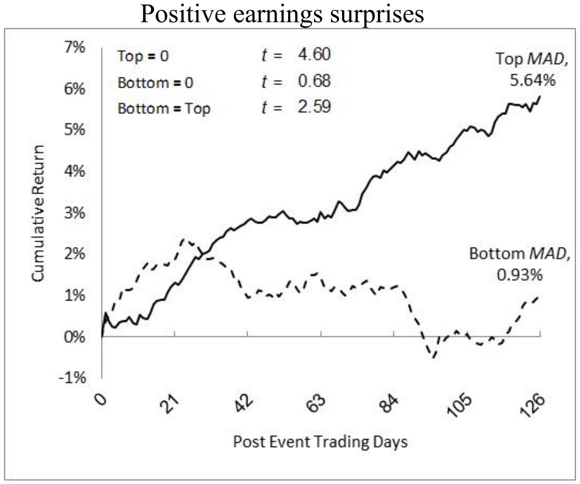


Dividend initiations

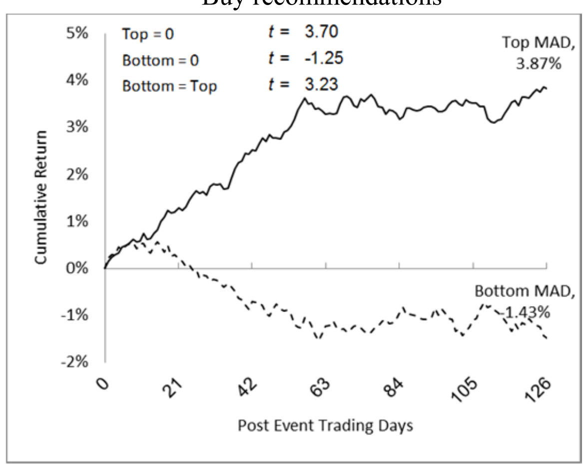


Panel B. Value-Weighted Portfolios

Positive earnings surprises



Buy recommendations



Dividend initiations

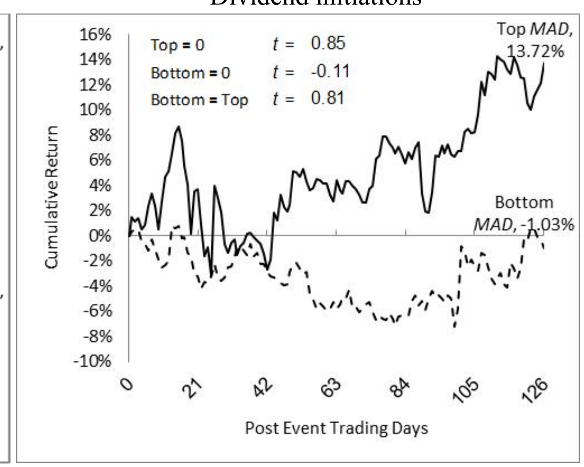
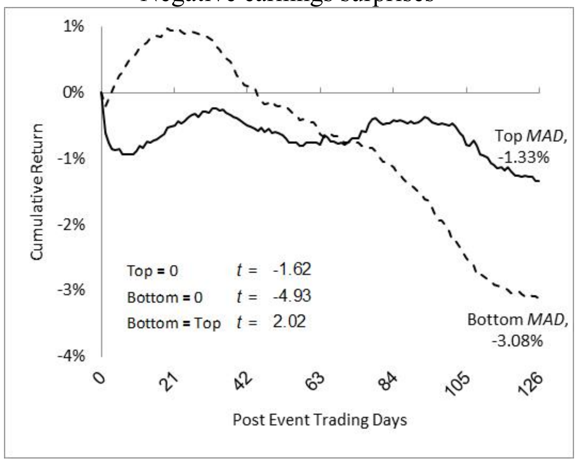


Figure 4. Negative news: Cumulative excess returns and *MAD*

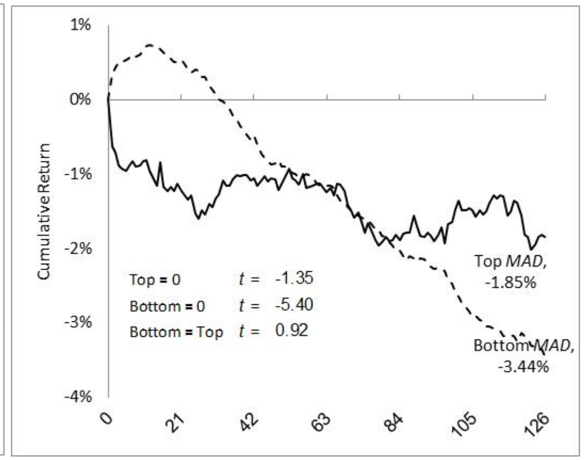
The figure depicts the cumulative excess returns post negative earnings surprises, first-time sell recommendation announcements, and seasoned equity issues (SEOs). Portfolios consist of top and bottom *MAD* stocks at the end of the month prior to earnings, recommendation, or SEO announcements. Equal 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

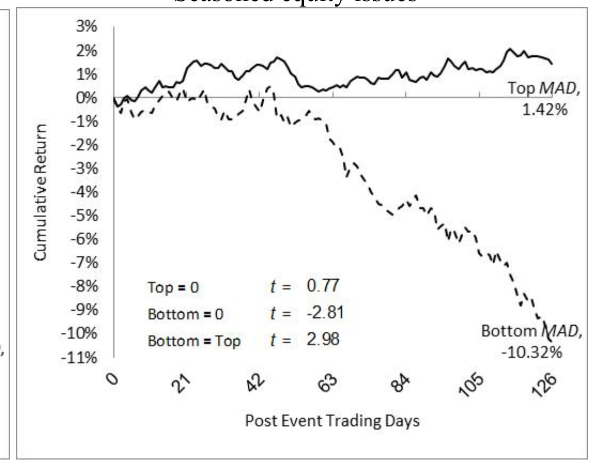
Negative earnings surprises



Sell recommendations

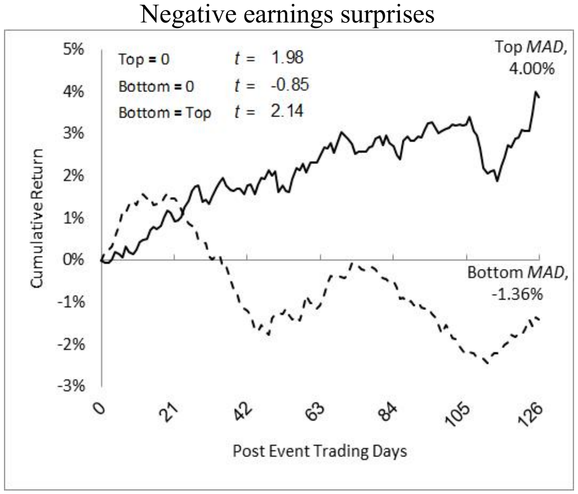


Seasoned equity issues

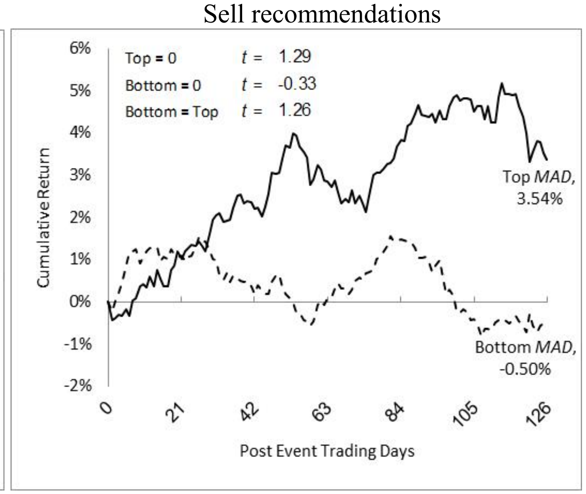


Panel B. Value-Weighted Portfolios

Negative earnings surprises



Sell recommendations



Seasoned equity issues

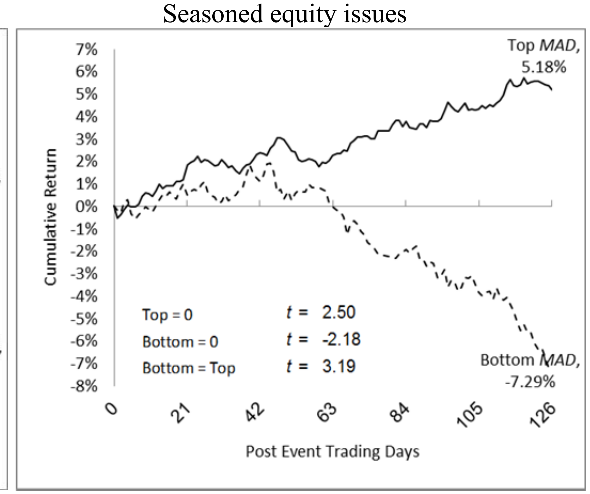
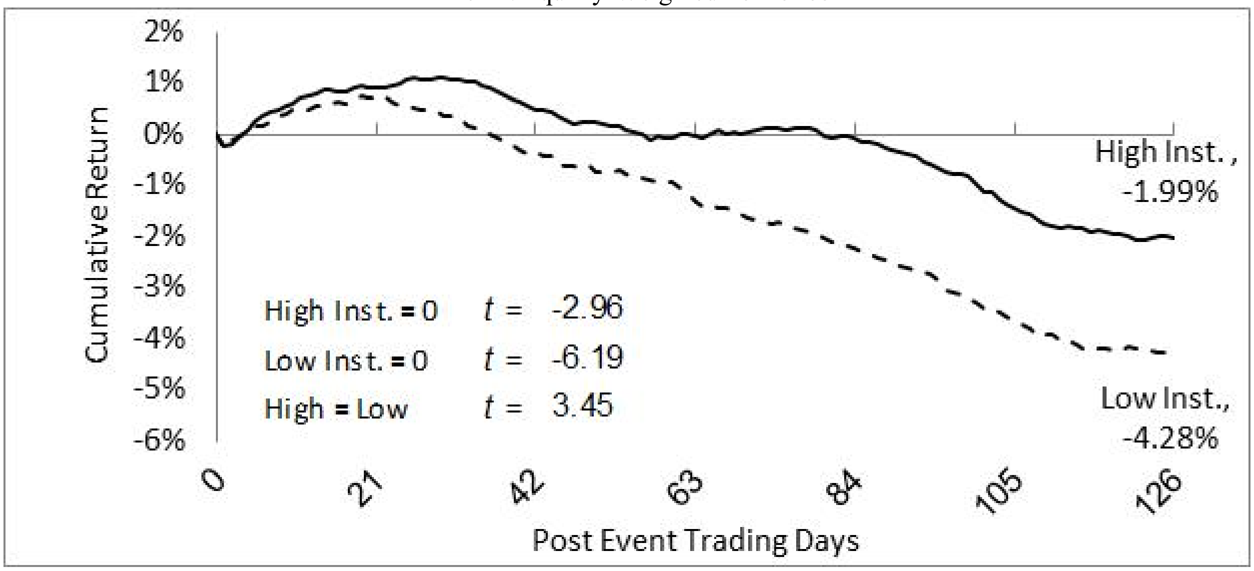


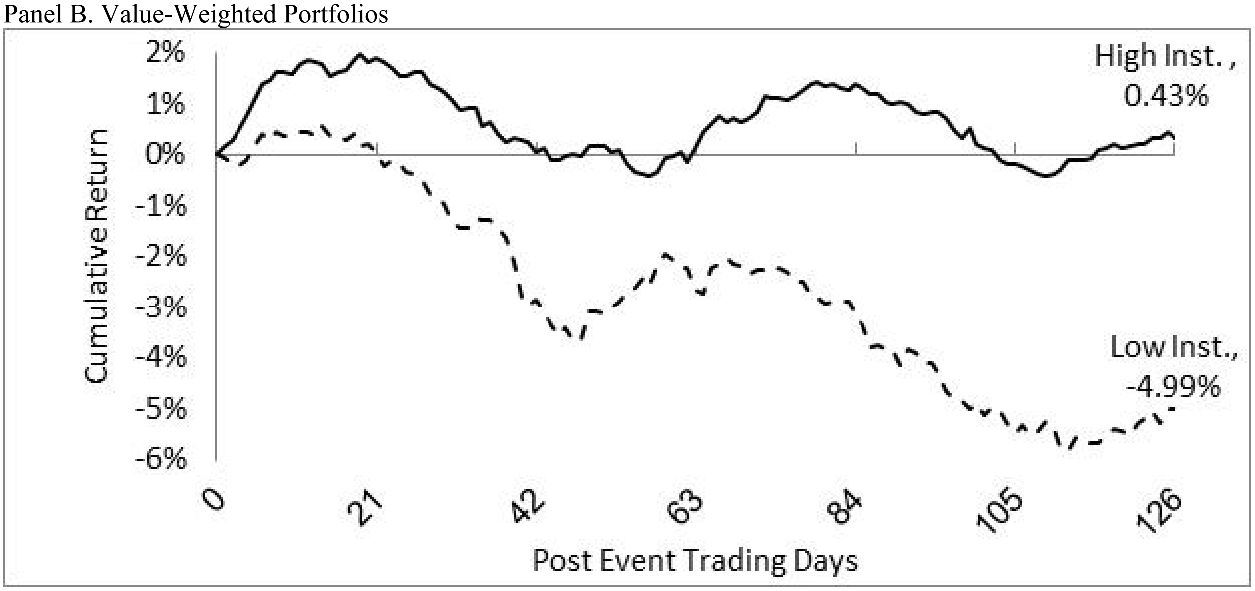
Figure 5. Cumulative excess returns, *MAD*, and short-sale constraints

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 equally- 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. Variables Definition

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

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.

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

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

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

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 (in the following order: Compustat items Data56 or Data10 or Data130).

Trend (*TRND*) = expected return calculated as the product between 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 and the most recent realized values of these moving average, as in Han, Yang and Zhou (2016).

Idiosyncratic Volatility (*IVOL*) = volatility 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, as in Sloan (1996).

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

Net Stock Issues (*NS*) = annual change in the log 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 Premium (*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 (2010).

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

Appendix B. Slope estimates from cross-section regression results described in Table 2

Dependent variable	*MDS*	*MAS*	*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*	*RCR*	*NS*	*dA/A*	*Y/B*	*I/A*	*GP*	*Ac/A*	*ROA*	*NOA*	*DTRS*
R_{t+1}	0.17***	-0.19***	-0.09***	0.31***	-2.38***	-0.49**	0.01	-0.07	-3.50***	-0.99*	-0.04***	0.28***	0.14	-0.38	0.31**	0.20**	0.12	0.35***	-0.75***	1.80***	-0.53***	0.80
	(2.70)	(-2.81)	(-3.43)	(4.34)	(-6.99)	(-2.07)	(0.19)	(-1.20)	(-3.19)	(-1.69)	(-4.22)	(15.51)	(1.54)	(-1.49)	(2.12)	(2.36)	(0.81)	(2.63)	(-2.77)	(4.46)	(-5.29)	(1.63)
$R_{t+2:t+6}$	-0.04	0.21	-0.31***	1.37***	1.28*	-0.87	-0.02	0.33**	-4.11	-11.62***	-0.06**	0.45***	0.23	-2.47***	0.86**	0.58***	0.23	1.79***	-4.01***	3.71***	-1.57***	4.10***
	(-0.28)	(1.27)	(-4.62)	(7.05)	(1.69)	(-1.40)	(-0.13)	(2.22)	(-1.52)	(-9.03)	(-2.36)	(10.03)	(1.56)	(-4.13)	(2.21)	(3.10)	(0.64)	(5.21)	(-5.73)	(4.12)	(-5.51)	(3.99)
$R_{t+7:t+12}$	0.45***	0.63***	-0.22***	1.59***	1.83**	-2.01***	-0.37*	0.20	-5.31	-9.05***	0.01	-0.02	0.07	-3.51***	0.81**	0.53**	0.72	2.14***	-5.74***	2.06*	-1.76***	2.82**
	(2.83)	(3.79)	(-3.07)	(5.14)	(1.99)	(-3.16)	(-1.88)	(1.24)	(-1.82)	(-6.65)	(0.29)	(-0.47)	(0.31)	(-5.18)	(2.05)	(2.27)	(1.62)	(5.54)	(-7.14)	(1.84)	(-5.36)	(2.19)
$R_{t+13:t+24}$	0.62	0.49	-0.13	3.72***	-0.78	-2.17*	-0.25	-0.38	9.37	-12.19***	-0.00	0.69***	-0.11	-2.51	3.21***	0.56**	3.56***	2.31***	-11.19***	-2.48	-4.12***	2.63
	(2.03)	(1.91)	(-1.13)	(6.86)	(-0.52)	(-1.96)	(-0.69)	(-1.41)	(1.65)	(-5.96)	(-0.08)	(10.54)	(-0.22)	(-1.91)	(4.02)	(1.97)	(4.27)	(3.29)	(-7.61)	(-1.08)	(-7.55)	(0.91)
R_{t+1} for	0.02**	-0.21**	-0.10***	0.16	-1.84***	-0.40	-0.05	-0.10	-2.04*	-0.83***	-0.04**	0.16***	-0.04	-0.65*	0.12	0.01	-0.12	0.34	0.00	1.16**	-0.20	1.42
2001-2015	(2.34)	(-2.34)	(-2.80)	(1.35)	(-3.67)	(-1.15)	(-0.48)	(-1.20)	(-1.66)	(-2.60)	(-2.02)	(6.07)	(-0.39)	(-1.80)	(0.58)	(0.23)	(-0.44)	(1.56)	(-0.00)	(2.43)	(-1.71)	(1.30)
Excess R_{t+1} Adjusted to Fama-French &																						
Cross-Sec. Mom.	0.18***	-0.20***	-0.06***	0.30***	-2.70***	-0.38*	0.09	-0.07	-4.04***	-1.15**	-0.03***	0.27***	0.12	-0.37	0.32**	0.19**	0.07	0.44***	-0.69***	1.71***	-0.49***	0.62
	(2.83)	(-2.98)	(-3.31)	(4.87)	(-8.54)	(-1.81)	(1.58)	(-1.29)	(-4.74)	(-2.08)	(-3.52)	(16.35)	(1.36)	(-1.55)	(2.39)	(2.30)	(0.47)	(3.44)	(-2.69)	(4.39)	(-5.29)	(1.27)
Time-Series Mom.	0.17***	-0.19***	-0.09***	0.31***	-2.38***	-0.49**	0.01	-0.07	-3.50***	-0.99*	-0.04***	0.28***	0.14	-0.38	0.31**	0.20**	0.12	0.35***	-0.75***	1.80***	-0.53***	0.80
	(2.70)	(-2.81)	(-3.43)	(4.34)	(-6.99)	(-2.07)	(0.19)	(-1.20)	(-3.19)	(-1.69)	(-4.22)	(15.51)	(1.54)	(-1.49)	(2.12)	(2.36)	(0.81)	(2.63)	(-2.77)	(4.46)	(-5.29)	(1.63)
Trend	0.17***	-0.19***	-0.09***	0.28***	-2.43***	-0.19	0.13**	-0.04	-6.07***	-1.56	-0.03***	0.28***	0.13	-0.34	0.27**	0.22***	0.08	0.35***	-0.73***	1.91***	-0.47***	0.70
	(2.81)	(-2.98)	(-4.61)	(4.46)	(-7.42)	(-0.88)	(2.25)	(-0.71)	(-7.05)	(-2.97)	(-3.49)	(16.35)	(1.46)	(-1.42)	(2.00)	(2.61)	(0.56)	(2.73)	(-2.86)	(4.86)	(-5.01)	(1.45)
R_{t+1}																						
Threshold = 0.1	0.28***	-0.23***	-0.10***	0.30***	-1.49***	0.54***	0.02	-0.07	-3.41***	-0.90	-0.04***	0.29***	0.15*	-0.41	0.31**	0.21**	0.14	0.37	-0.76***	1.79***	-0.53***	0.85*
	(4.49)	(-3.42)	(-3.53)	(4.03)	(-4.73)	(3.12)	(0.38)	(-1.16)	(-3.08)	(-1.54)	(-4.29)	(15.64)	(1.69)	(-1.62)	(2.07)	(2.53)	(0.89)	(2.80)	(-2.79)	(4.39)	(-5.36)	(1.70)
Threshold = 0.2	0.36***	-0.16**	-0.09***	0.31***	-1.70***	0.31*	0.02	-0.06	-3.47***	-0.93	-0.04***	0.29***	0.15*	-0.38	0.32**	0.20**	0.14	0.36	-0.76***	1.78***	-0.53***	0.85*
	(5.55)	(-2.25)	(-3.44)	(4.18)	(-5.43)	(1.78)	(0.36)	(-1.08)	(-3.14)	(-1.57)	(-4.30)	(15.61)	(1.75)	(-1.50)	(2.12)	(2.39)	(0.89)	(2.74)	(-2.81)	(4.39)	(-5.37)	(1.72)
Threshold = 0.3	0.37***	-0.13*	-0.09***	0.29***	-1.71***	0.41**	0.03	-0.06	-3.48***	-0.90	-0.04***	0.29***	0.16*	-0.41	0.31**	0.20**	0.13	0.36***	-0.75***	1.79***	-0.53***	0.84*
	(5.65)	(-1.94)	(-3.47)	(3.99)	(-5.45)	(2.50)	(0.41)	(-1.08)	(-3.15)	(-1.55)	(-4.28)	(15.55)	(1.77)	(-1.61)	(2.12)	(2.36)	(0.86)	(2.72)	(-2.78)	(4.42)	(-5.37)	(1.69)
R_{t+1}																						
High Sentiment	0.19***	-0.24***	-0.09***	0.39***	-2.68***	-0.28	0.13	-0.03	-5.73***	-0.14	-0.03***	0.28***	0.09	-0.66**	0.09	0.20**	0.25	0.46***	-0.54*	1.52***	-0.68***	0.36
	(2.69)	(-3.22)	(-2.62)	(4.26)	(-6.83)	(-1.08)	(1.91)	(-0.39)	(-4.28)	(-0.24)	(-3.63)	(13.16)	(0.66)	(-2.49)	(0.53)	(2.45)	(1.39)	(2.79)	(-1.68)	(3.66)	(-5.97)	(0.70)
Low Sentiment.	0.14	-0.11	-0.10**	0.18	-1.87***	-0.86*	-0.19	-0.14	0.36	-2.46**	-0.06***	0.30***	0.23	0.11	0.70**	0.20	-0.10	0.15	-1.12**	2.29***	-0.26	1.57
	(1.13)	(-0.83)	(-2.22)	(1.54)	(-2.94)	(-1.85)	(-1.64)	(-1.48)	(0.19)	(-2.00)	(-2.57)	(8.68)	(2.35)	(0.22)	(2.55)	(1.10)	(-0.38)	(0.69)	(-2.29)	(2.74)	(-1.39)	(1.56)
Low Volatility	0.17*	-0.23**	-0.10***	0.52***	-2.19***	-0.80	-0.04	0.02	-3.57**	-2.01**	-0.01	0.32***	0.14	-0.37	0.34	0.14	0.29	0.13	-1.14***	2.63***	-0.55***	0.97
	(1.77)	(-2.27)	(-2.72)	(5.35)	(-4.53)	(-2.36)	(-0.44)	(0.26)	(-2.44)	(-2.12)	(-1.41)	(11.89)	(0.94)	(-0.96)	(1.65)	(1.12)	(1.37)	(0.80)	(-3.02)	(4.41)	(-3.79)	(1.50)
High Volatility	0.17**	-0.16**	-0.08**	0.12	-2.57***	-0.21	0.06	-0.16*	-3.44**	-0.02	-0.07***	0.25***	0.13	-0.38	0.28	0.25**	-0.03	0.55***	-0.38	1.01*	-0.50***	0.65
	(2.08)	(-1.72)	(-2.15)	(1.16)	(-5.35)	(-0.61)	(0.65)	(-1.85)	(-2.11)	(-0.02)	(-4.09)	(10.10)	(1.38)	(-1.15)	(1.36)	(2.28)	(-0.16)	(2.69)	(-0.99)	(1.86)	(-3.69)	(0.87)
Low Illiquidity	0.26***	-0.20**	-0.07**	0.23**	-2.24***	-0.46	-0.06	-0.15**	-2.25*	-0.36	-0.05	0.21***	0.07	-0.45	0.08	0.03	0.09	0.25	-0.01	1.09***	-0.49***	0.68
	(3.35)	(-2.45)	(-2.01)	(2.11)	(-5.43)	(-1.64)	(-0.80)	(-2.06)	(-1.80)	(-0.98)	(-3.22)	(9.03)	(0.76)	(-1.57)	(0.44)	(0.72)	(0.40)	(1.26)	(-0.02)	(2.84)	(-3.81)	(0.88)
High Illiquidity	3.00***	0.09	-0.12***	0.41***	-2.54***	-0.53	0.09	0.02	-4.87***	-1.67	-0.03***	0.36***	0.21	-0.29	0.56**	0.38**	0.16	0.45***	-1.55***	2.57***	-0.57***	0.93
	(4.26)	(0.82)	(-2.81)	(4.28)	(-4.61)	(-1.35)	(0.96)	(0.22)	(-2.64)	(-1.45)	(-2.81)	(13.16)	(1.34)	(-0.69)	(2.43)	(2.27)	(0.82)	(2.58)	(-4.54)	(3.53)	(-3.70)	(1.59)

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 additional variable to the 25 control variables in Table 2 is dispersion in forecasts across analysts, calculated as standard deviation of analysts' EPS forecast scaled by 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 10%, 5%, and 1% significance, respectively.

Dependent variable	***MAD***	***MOM***	***52HIGH***	***TRND***	***Dispersion***	**Averaged 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 the average portfolio returns for next month, months 2 through 6, months 7 through 12, and months 13 through 24. 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 *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 10%, 5% and 1% significance degrees, 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 > 0	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	
$R_{t+13:t+24}$	*MAD* < 1	18.16	16.50	16.87	16.23	16.24	15.99	16.07	14.95	15.64	15.19	-2.97***
	MAD > 1	15.63	15.19	15.26	15.31	15.77	15.16	14.92	15.43	14.45	12.41	-3.22***
	Diff.	-2.53*	-1.31	-1.61*	-0.92	-0.47	-0.83	-1.15	0.48	-1.19*	-2.78***	

Table D2.

		MOM **($R_{t-2:t-6}$)**										
	MAD	**Smallest**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Largest**	**Diff.**
R_{t+1}	Smallest	0.27	0.73	0.61	0.67	0.91	1.18	0.98	0.96	1.19	0.95	0.68*
	Largest	1.37	1.60	1.94	2.03	1.83	1.93	2.03	2.05	2.12	2.28	0.91***
	Diff.	1.10**	0.87**	1.33***	1.36***	0.92**	0.75*	1.05***	1.09***	0.93***	1.33***	
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.	2.18	2.63	3.29	3.16	3.81	3.51	2.92	3.14	2.89	2.53	0.35
	L.	7.91	9.33	9.04	9.71	9.68	9.39	9.78	8.83	8.15	7.74	-0.17
	Diff.	5.73***	6.70***	5.75***	6.55***	5.87***	5.88***	6.86***	5.69***	5.26***	5.21***	
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.	8.62	6.77	7.26	6.70	6.96	6.30	5.47	5.14	5.05	3.95	-4.67***
	L.	9.58	8.68	8.42	8.41	7.61	7.92	7.39	7.05	6.80	5.72	-3.86***
	Diff.	0.96	1.91	1.16*	1.71	0.65*	1.62*	1.92**	1.91**	1.75**	1.77**	
$R_{t+13:t+24}$	S.	18.61	17.76	19.15	19.95	18.39	18.47	17.90	17.84	17.45	15.51	-3.10**
	L.	13.54	13.70	13.69	14.94	15.28	12.33	13.93	14.19	11.93	8.92	-4.62***
	Diff.	-5.07***	-4.06***	-5.46***	-5.01	-3.11**	-6.14**	-3.97***	-3.65**	-5.52***	-6.59***	

Table D3.

	MAD	***52HIGH*** Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	0.57	1.30	1.22	0.83	0.97	0.84	0.75	0.92	0.80	0.12	-0.45
	Largest	1.76	2.02	2.25	2.30	2.16	2.12	2.09	1.82	1.34	1.46	-0.30
	Diff.	1.19***	0.72*	1.03***	1.47***	1.19***	1.28***	1.34***	0.90**	0.54*	1.34***	
Sorted	S.	0.95	0.71	0.28	-0.20	-0.49	-0.79	-0.98	-0.91	-0.94	-0.91	-1.86***
independently	L.	1.63	1.68	1.77	2.10	1.86	1.76	2.56	2.22	2.12	1.47	-0.14
	Diff.	0.68	0.97**	1.49***	2.30***	2.35***	2.55***	3.54***	3.13***	3.06***	2.38***	
$R_{t+2:t+6}$	S.	0.35	1.99	2.53	2.32	2.31	2.78	3.99	4.17	4.49	4.77	4.42***
	L.	6.54	7.44	8.49	9.64	8.66	9.22	9.56	10.35	10.09	10.15	3.61***
	Diff.	6.19***	5.45***	5.96***	7.32***	6.35***	6.44***	5.57***	6.18***	5.60***	5.38***	
Sorted	S.	2.00	3.75	4.56	3.56	3.48	3.17	2.97	2.52	2.52	2.52	0.52
independently	L.	8.32	6.24	5.95	5.94	8.60	7.96	9.59	9.36	10.15	9.70	1.38*
	Diff.	6.32***	2.49***	1.39	2.38**	5.12***	4.79***	6.62***	6.84***	7.63***	7.18***	
$R_{t+7:t+12}$	S.	5.88	5.27	6.26	6.43	6.05	6.50	6.48	6.25	6.16	6.63	0.75
	L.	6.43	7.34	7.26	7.81	7.63	7.34	8.48	7.86	7.96	7.90	1.47**
	Diff.	0.55	2.07*	1.00	1.38	1.58*	0.84	2.00**	1.61**	1.80**	1.27	
$R_{t+13:t+24}$	S.	18.01	17.83	18.36	18.30	18.22	19.21	18.05	19.66	17.09	16.76	-1.25***
	L.	11.31	12.14	12.99	13.73	13.33	13.48	14.42	14.44	13.07	12.33	1.02***
	Diff.	-6.70***	-5.69	-5.37***	-4.57***	-4.89***	-5.73***	-3.63***	-5.22***	-4.02***	-4.43***	

Table D4.

	MAD	***TRND*** Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	-0.59	0.16	0.43	0.71	0.84	1.22	1.21	1.35	1.61	1.49	2.08***
	Largest	1.21	1.40	1.76	2.01	1.73	1.71	2.08	2.35	2.33	2.64	1.43***
	Diff.	1.80***	1.24**	1.33***	1.30***	0.89***	0.49	0.87**	1.00***	0.72*	1.15**	
Sorted	S.	-0.80	0.03	0.40	1.07	0.85	0.82	0.99	1.03	1.94	1.68	2.48***
independently	L.	1.28	1.26	1.47	1.32	1.95	1.98	2.33	1.92	2.13	2.41	1.13***
	Diff.	2.08***	1.29***	1.07***	0.25	1.10***	1.16**	1.34***	0.89**	0.19	0.73*	
$R_{t+2:t+6}$	S.	1.27	2.57	2.92	2.56	3.57	3.09	3.11	3.89	3.30	3.53	2.26***
	L.	9.47	9.12	9.92	8.99	8.98	9.92	8.77	9.79	8.96	6.02	-3.45***
	Diff.	8.20***	6.55***	7.01***	6.43***	5.41***	6.83***	5.66***	5.90***	5.66***	2.49**	
Sorted	S.	2.71	3.48	3.30	3.51	3.17	3.63	3.85	3.10	3.71	3.72	1.01
independently	L.	9.07	9.05	9.68	8.97	9.66	9.83	8.27	8.83	8.65	6.25	-2.82***
	Diff.	6.36***	5.57***	6.38***	5.46***	6.49***	6.20***	4.42***	5.73***	4.94***	2.53***	
$R_{t+7:t+12}$	S.	5.16	4.89	5.39	6.23	6.27	6.86	6.66	6.05	7.66	6.84	1.68*
	L.	6.90	7.41	8.07	8.31	7.89	6.84	8.13	8.23	7.45	7.68	0.78
	Diff.	1.74*	2.52***	2.68***	2.08**	1.62*	-0.02	1.47	2.18**	-0.21	0.84	
$R_{t+13:t+24}$	S.	16.84	17.95	16.22	16.61	18.63	17.78	18.64	18.59	18.97	21.49	4.65***
	L.	9.71	11.54	13.10	13.98	13.19	13.20	13.57	15.52	13.74	12.72	3.01***
	Diff.	-7.13***	-6.41***	-3.12**	-2.63*	-5.44***	-4.58***	-5.07***	-3.07**	-5.23***	-8.77***	

Table D5.

	MAD	ME: Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	0.57	0.62	0.48	0.67	1.01	1.12	1.07	0.99	1.19	0.65	0.08
	Largest	2.43	2.25	2.39	2.29	2.12	1.67	1.73	1.42	1.53	1.56	-0.87***
	Diff.	1.86***	1.63***	1.91***	1.62***	1.11***	0.55	0.66*	0.43	0.34	0.91**	
Sorted independently	S.	0.55	0.43	0.61	0.82	0.88	0.94	0.92	0.91	0.95	0.41	-0.13
	L.	2.33	2.19	2.31	2.20	1.92	1.74	1.51	1.54	1.64	1.48	-0.90**
	Diff.	1.78***	1.76***	1.70***	1.38***	1.04***	0.80**	0.59	0.63	0.69*	1.07**	
$R_{t+2:t+6}$	S.	2.41	2.29	2.12	2.02	2.63	4.03	3.85	3.65	3.56	3.20	0.79
	L.	10.57	10.77	10.30	9.03	7.97	8.41	9.23	7.81	8.62	7.62	-2.95***
	Diff.	8.16***	8.48***	8.18***	7.01***	5.34***	4.38***	5.38***	4.16***	5.06***	4.42***	
Sorted independently	S.	2.05	2.17	2.43	2.62	3.53	3.51	3.91	4.28	3.36	3.13	1.08
	L.	9.98	10.81	9.64	8.99	8.29	9.14	8.39	8.62	8.08	8.02	-1.96**
	Diff.	7.93***	8.64***	7.21***	6.37***	4.76***	5.85***	4.48***	4.34***	4.72***	4.89***	
$R_{t+7:t+12}$	S.	6.16	5.87	5.23	6.22	6.66	6.43	6.89	6.36	6.80	5.57	-0.59
	L.	8.56	7.02	7.66	7.20	7.28	7.50	7.10	8.45	8.27	7.61	-0.95
	Diff.	2.40***	1.15	2.43**	0.98	0.62	1.07	0.21	2.09**	1.47**	2.04**	
$R_{t+13:t+24}$	S.	19.92	18.97	17.25	16.24	19.16	17.85	18.38	16.73	18.00	18.53	-1.39
	L.	14.48	13.81	12.89	12.10	10.96	13.76	14.30	13.82	11.77	12.71	-1.77
	Diff.	-5.44***	-5.16***	-4.36***	-4.14***	-8.20***	-4.09**	-4.08***	-2.91**	-6.23***	-5.82***	

Table D6.

	MAD	BE/ME: Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	-0.14	0.15	1.06	0.77	1.04	1.14	1.24	1.04	1.27	0.79	0.93***
	Largest	1.57	1.79	1.50	1.67	2.20	1.95	2.15	2.01	2.10	2.24	0.67*
	Diff.	1.71***	1.64***	0.44	0.90**	1.16***	0.81**	0.91***	0.97***	0.83**	1.45***	
Sorted independently	S.	-0.36	0.07	0.37	0.95	0.91	0.79	1.04	1.36	1.20	1.01	1.37***
	L.	1.53	1.46	2.27	2.13	1.80	2.19	1.99	2.00	2.01	2.32	0.79
	Diff.	1.89***	1.39***	1.90***	1.18***	0.89**	1.40***	0.95**	0.64	0.81*	1.31**	
$R_{t+2:t+6}$	S.	-0.69	1.79	2.89	3.12	3.08	4.35	4.54	4.40	3.04	3.19	3.88***
	L.	7.19	9.16	7.72	8.75	9.76	8.91	9.33	9.44	9.73	10.10	2.91***
	Diff.	7.88***	7.37***	4.83***	5.63***	6.68***	4.56***	4.79***	5.04***	6.69***	6.91***	
Sorted independently	S.	-1.18	0.11	2.01	2.57	3.03	3.75	4.40	4.75	3.94	3.37	4.55***
	L.	8.47	7.94	8.76	10.43	8.01	9.25	9.50	8.74	9.20	11.23	2.76**
	Diff.	9.65***	7.83***	6.75***	7.86***	4.98***	5.50***	5.10***	3.99***	5.26***	7.86***	
$R_{t+7:t+12}$	S.	2.83	4.37	5.32	5.90	6.28	8.96	7.79	6.34	6.74	7.64	4.81***
	L.	5.32	6.90	6.55	8.06	7.85	7.55	7.96	8.38	8.68	9.20	3.88***
	Diff.	2.49***	2.53***	1.23	2.16**	1.57*	-1.41	0.17	2.04**	1.94**	1.56	
$R_{t+13:t+24}$	S.	13.83	15.34	16.81	17.77	19.06	21.06	17.12	20.06	18.32	21.84	8.01***
	L.	6.39	7.81	11.70	12.27	11.30	13.98	15.69	15.64	16.74	18.81	12.42***
	Diff.	-7.44***	-7.53***	-5.11***	-5.50***	-7.76***	-7.08***	-1.43	-4.42***	-1.58	-3.03*	

Table D7.

	MAD	*TURN* Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	0.44	0.66	1.08	0.99	1.13	0.87	0.94	1.28	0.85	0.12	-0.32
	Largest	1.72	2.07	2.30	2.16	2.13	1.89	2.02	2.17	1.65	1.18	-0.54
	Diff.	1.28***	1.41***	1.22***	1.17***	1.00**	1.02***	1.08***	0.89**	0.80*	1.06**	
Sorted	S.	0.07	0.55	0.61	0.73	1.16	1.16	0.98	0.90	1.02	0.24	0.15
independently	L.	2.04	1.93	2.23	2.26	1.78	1.94	1.91	2.23	1.98	1.54	-0.50
	Diff.	1.97***	1.38***	1.62***	1.53***	0.62*	0.78**	0.93***	1.33***	0.96***	1.30***	
$R_{t+2:t+6}$	S.	2.98	2.83	3.87	2.94	3.26	3.32	3.99	2.98	2.95	0.95	-2.03**
	L.	11.04	10.49	10.61	9.64	9.44	9.24	9.13	8.15	7.76	4.83	-6.21***
	Diff.	8.06***	7.66***	6.74***	6.70***	6.18***	5.92***	5.14***	5.17***	4.81***	3.88***	
Sorted	S.	1.50	2.49	3.40	3.57	3.54	2.94	2.66	2.92	3.42	1.68	0.18
independently	L.	8.58	11.16	10.88	9.40	9.90	10.55	9.50	8.77	8.85	6.93	-1.65**
	Diff.	7.08***	8.67***	7.48***	5.83***	6.36***	7.61***	6.84***	5.85***	5.43***	5.25***	
$R_{t+7:t+12}$	S.	6.78	7.54	6.45	6.03	5.75	5.89	5.98	6.85	6.27	4.45	-2.33***
	L.	8.24	9.41	8.12	8.47	7.46	7.90	7.87	7.65	6.05	5.14	-3.10***
	Diff.	1.46*	1.87**	1.67*	2.44***	1.71	2.01*	1.89*	0.80	-0.22	0.69	
$R_{t+13:t+24}$	S.	18.18	19.35	18.53	17.64	18.23	18.67	18.34	18.86	17.04	16.62	-1.56
	L.	15.03	15.76	15.41	13.17	13.30	12.18	13.02	12.11	12.43	9.15	-5.88***
	Diff.	-3.15**	-3.59***	-3.12**	-4.47***	-4.93***	-6.49***	-5.32***	-6.75***	-4.61***	-7.47***	

Table D8.

	MAD	*ILLIQ* Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	0.88	0.90	1.15	1.03	1.10	1.07	0.66	0.83	0.52	0.24	-0.64*
	Largest	1.37	1.49	1.48	1.85	1.81	1.95	2.59	2.20	2.27	2.11	0.74**
	Diff.	0.49	0.59	0.33	0.82**	0.71*	0.88**	1.93***	1.37***	1.75***	1.87***	
Sorted	S.	0.71	0.83	0.89	1.14	1.19	0.81	0.71	0.62	0.46	0.21	-0.50
independently	L.	1.42	1.53	1.27	1.86	2.08	2.17	2.04	1.75	2.48	2.01	0.59
	Diff.	0.71**	0.70*	0.38	0.72*	0.89**	1.36***	1.33***	1.13***	2.02***	1.80***	
$R_{t+2:t+6}$	S.	2.85	3.53	2.80	3.98	3.89	3.30	2.40	2.20	2.40	2.35	-0.50
	L.	7.53	7.86	6.86	8.19	7.78	8.61	10.09	10.82	10.28	11.13	3.60
	Diff.	4.68***	4.33***	4.06***	4.21***	3.89***	5.31***	7.69***	8.62***	7.88***	8.78***	
Sorted	S.	3.22	2.81	4.02	3.05	3.50	3.29	3.12	2.27	2.40	2.07	-1.15
independently	L.	8.13	8.08	7.56	7.62	9.06	8.11	10.12	10.28	10.81	11.44	3.31***
	Diff.	4.91***	5.27***	3.54***	4.57***	5.56***	4.82***	7.00***	8.01***	8.41***	9.37***	
$R_{t+7:t+12}$	S.	5.29	6.46	6.72	6.23	6.64	5.77	6.03	5.40	6.72	6.81	1.52**
	L.	7.11	7.48	7.92	7.18	6.63	6.63	7.45	7.95	8.71	9.05	1.94*
	Diff.	1.82**	1.02	1.20	0.95	-0.01	0.86	1.42	2.55	1.99***	2.24**	
$R_{t+13:t+24}$	S.	17.89	18.09	16.44	17.30	18.53	17.95	18.67	18.98	17.32	20.24	2.35**
	L.	12.78	11.70	13.58	11.53	12.51	11.39	12.74	14.46	13.89	16.27	3.49**
	Diff.	-5.11***	-6.39***	-2.86**	-5.77***	-6.02***	-6.56***	-5.93***	-4.52***	-3.43***	-3.97***	

Table D9.

	MAD	*VOL* Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	1.48	1.55	1.60	1.47	1.21	1.09	0.94	0.43	-0.36	-0.97	-2.45***
	Largest	1.83	2.24	1.73	2.06	2.08	2.06	2.21	1.93	1.75	1.41	-0.42
	Diff.	0.35	0.69**	0.13	0.59	0.87**	0.97***	1.27***	1.50***	2.11***	2.38***	
Sorted	S.	0.92	1.23	1.60	1.41	1.38	1.56	1.58	1.29	0.61	-0.54	-1.46***
independently	L.	1.72	1.87	2.04	1.96	2.06	2.30	2.34	2.25	2.18	1.49	-0.25
	Diff.	0.80*	0.64	0.44	0.55	0.68*	0.74**	0.76**	0.96***	1.59***	2.03***	
$R_{t+2:t+6}$	S.	4.81	5.17	4.24	3.94	3.28	2.28	2.73	2.07	1.06	0.27	-4.54***
	L.	8.41	9.20	9.67	9.30	9.83	9.93	9.33	9.08	8.23	6.81	-1.60*
	Diff.	3.60***	4.03***	5.43***	5.36***	6.55***	7.65***	6.60***	7.01***	7.17***	6.54***	
Sorted	S.	3.14	4.43	4.82	4.42	5.15	5.24	3.44	2.84	2.10	0.61	-2.53**
independently	L.	6.13	8.02	8.54	9.94	9.64	9.88	10.05	9.87	9.55	7.93	1.80*
	Diff.	2.99***	3.59***	3.72***	5.52***	4.49***	4.64***	6.61***	7.03***	7.45***	7.32***	
$R_{t+7:t+12}$	S.	6.44	5.32	6.96	6.36	6.36	7.32	5.96	5.95	6.06	5.14	-1.30*
	L.	7.21	7.82	8.13	7.94	7.74	8.32	8.21	7.56	7.26	5.79	-1.42
	Diff.	0.77	2.50***	1.17	1.58*	1.38	1.00	2.25**	1.61	1.20	0.65	
$R_{t+13:t+24}$	S.	15.83	18.14	18.45	18.48	18.86	18.00	19.46	18.87	17.20	18.01	2.18*
	L.	14.06	14.94	14.65	14.57	15.25	12.64	13.04	11.88	11.70	8.60	-5.46***
	Diff.	-1.77*	-3.20**	-3.80***	-3.91***	-3.61***	-5.36***	-6.42***	-6.99***	-5.50***	-9.41***	

Table D10.

	MAD	*SUE* Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	0.83	0.66	0.96	0.92	0.51	0.86	1.24	0.78	0.85	0.85	0.02
	Largest	1.84	1.32	1.38	1.48	2.27	1.82	1.93	2.39	2.36	2.47	0.63**
	Diff.	1.01***	0.66*	0.42	0.56	1.76***	0.96**	0.69*	1.61***	1.51***	1.62***	
Sorted	S.	0.51	1.00	0.65	0.84	0.96	0.99	0.75	0.74	1.25	1.13	0.62**
independently	L.	1.18	1.41	0.99	1.28	1.68	1.48	1.92	2.19	2.22	2.59	1.41***
	Diff.	0.67*	0.41	0.34	0.44	0.72*	0.49	1.17***	1.45***	0.97**	1.46***	
$R_{t+2:t+6}$	S.	3.71	3.31	3.08	3.40	2.35	2.33	3.61	1.95	2.86	3.29	-0.42
	L.	8.09	7.33	7.15	8.42	9.50	9.33	11.31	9.28	9.33	10.03	1.94***
	Diff.	4.38***	4.02***	4.07***	5.02***	7.15***	7.00***	7.70***	7.33***	6.47***	6.74***	
Sorted	S.	3.68	2.53	2.61	3.52	2.03	3.64	2.90	3.56	2.54	3.79	0.11
independently	L.	7.77	5.94	7.55	7.55	7.99	7.86	10.26	9.67	9.65	9.91	2.14***
	Diff.	4.09***	3.41***	4.94***	4.03***	5.96***	4.22***	7.36***	6.11***	7.11***	6.12***	
$R_{t+7:t+12}$	S.	6.38	4.52	5.24	6.04	5.69	5.02	6.20	6.29	6.34	5.35	-1.03*
	L.	6.86	8.12	6.62	7.35	6.39	6.57	6.68	6.69	5.59	5.90	-0.96
	Diff.	0.48	3.60***	1.38	1.31	0.70	1.55*	0.48	0.40	-0.75	0.55	
$R_{t+13:t+24}$	S.	18.47	18.27	16.67	18.60	17.69	18.69	17.46	18.29	17.97	18.72	0.25
	L.	11.21	14.40	12.01	11.54	11.24	13.65	14.12	14.57	14.65	12.60	1.39
	Diff.	-7.26***	-3.87**	-4.66***	-7.06***	-6.45***	-5.04***	-3.34**	-3.72**	-3.32**	-6.12**	

Table D11.

	MAD	***R_{t-1}*** Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	1.83	1.91	1.55	1.20	1.36	1.16	0.71	0.86	-0.20	-1.95	-3.78***
	Largest	2.56	2.25	2.09	2.01	1.83	1.77	1.66	1.67	1.83	1.58	-0.98***
	Diff.	0.73**	0.34	0.54	0.81**	0.47	0.61	0.95**	0.81**	2.03***	3.53***	
Sorted independently	S.	1.78	1.36	1.34	0.93	1.12	1.19	0.73	-0.18	-0.63	-2.66	-4.44***
	L.	2.40	2.51	2.38	1.90	2.23	2.19	1.71	1.69	1.65	1.77	-0.63*
	Diff.	0.62*	1.15***	1.04***	0.97***	1.11***	1.00***	0.98***	1.87***	2.28***	4.43***	
$R_{t+2:t+6}$	S.	1.43	2.48	2.24	3.24	4.01	3.35	3.65	3.53	3.60	2.31	0.88
	L.	7.27	8.68	8.71	8.81	9.21	10.08	9.12	9.60	9.86	8.30	1.03
	Diff.	5.84***	6.20***	6.47***	5.57***	5.20***	6.73***	5.47***	6.07***	6.26***	5.99***	
Sorted independently	S.	1.96	3.19	3.70	3.70	4.41	3.72	3.15	3.76	2.36	2.02	0.06
	L.	7.26	7.78	8.73	8.55	9.02	9.03	9.37	9.63	9.34	9.23	1.97**
	Diff.	5.30***	4.59***	5.06***	4.85***	4.61***	5.31***	6.22***	5.87***	6.98***	7.21***	
$R_{t+7:t+12}$	S.	4.46	4.68	5.14	5.77	5.86	6.25	5.89	5.54	6.41	7.34	2.88***
	L.	4.74	6.14	5.95	6.54	6.53	7.65	6.77	7.80	7.79	7.21	2.47***
	Diff.	0.28	1.46*	0.81	0.77	0.67	1.40	0.88	2.26**	1.38	-0.13	
$R_{t+13:t+24}$	S.	18.50	19.47	16.65	18.50	17.85	18.72	17.54	17.32	18.64	17.98	-0.52
	L.	12.35	11.62	14.48	14.32	12.84	14.35	13.78	14.21	12.75	10.35	-2.00
	Diff.	-6.15***	-7.85***	-2.17	-4.18***	-5.01***	-4.37***	-3.76***	-3.11**	-5.89***	-7.63***	

Table D12.

	MAD	***$R_{t-7:t-12}$*** Smallest	2	3	4	5	6	7	8	9	Largest	Diff.
R_{t+1}	Smallest	0.05	0.37	0.52	0.72	1.07	0.89	0.97	1.24	1.33	1.20	1.15***
	Largest	1.90	1.91	1.94	1.77	1.68	1.79	1.93	1.95	2.07	2.20	0.30
	Diff.	1.85***	1.54***	1.42***	1.05***	0.61*	0.90**	0.96***	0.71*	0.74**	1.00**	
Sorted independently	S.	0.63	1.30	1.22	0.68	1.83	0.73	0.92	1.09	0.95	1.15	0.52
	L.	2.56	0.74	2.65	2.81	2.97	2.13	2.10	1.49	1.91	1.93	-0.63
	Diff.	1.93	-0.56	1.43*	1.13	1.14	1.40*	1.18	1.40	0.96	0.78	
$R_{t+2:t+6}$	S.	0.70	2.14	2.57	3.68	3.36	3.86	3.06	3.65	3.30	3.25	2.55***
	L.	7.40	9.00	8.60	8.27	9.10	8.77	9.75	10.33	9.86	8.91	1.51*
	Diff.	6.70***	6.86***	6.03***	4.59***	5.74***	4.91***	6.69***	6.68***	6.56***	5.66***	
Sorted independently	S.	2.79	3.41	3.67	4.40	3.48	3.09	0.25	0.80	2.74	3.27	0.48
	L.	-4.31	0.75	2.98	2.67	6.23	8.52	5.70	8.59	8.56	9.30	13.61***
	Diff.	-7.10	-2.66	-0.69	-1.73	2.75**	5.43***	5.45***	7.79***	5.82***	6.03***	
$R_{t+7:t+12}$	S.	5.17	6.83	6.25	6.69	6.44	6.81	6.46	6.55	7.17	6.86	1.69**
	L.	7.79	8.67	9.02	8.05	8.03	8.09	8.58	7.75	7.25	6.01	-1.78*
	Diff.	2.62***	1.84*	2.77***	1.36	1.59*	1.28	2.12**	1.20	0.08	-0.85	
$R_{t+13:t+24}$	S.	18.25	18.55	18.17	17.55	18.16	17.39	18.49	17.85	18.54	17.76	-0.49
	L.	12.29	13.37	13.85	14.02	13.61	14.69	13.92	13.14	13.01	10.41	-1.88
	Diff.	-5.96***	-5.18***	-4.32***	-3.53**	-4.55***	-2.70*	-4.57***	-4.71***	-5.53***	-7.35***	

Table D13.

	MAD	$R_{t-13:t-24}$										
		Smallest	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Largest**	**Diff.**
R_{t+1}	Smallest	1.00	1.25	0.89	0.88	0.62	0.79	1.04	0.84	0.63	0.44	-0.56*
	Largest	1.94	1.97	1.97	1.96	2.04	1.82	2.07	1.78	1.97	1.66	-0.28
	Diff.	0.94**	0.72**	1.08***	1.08***	1.42***	1.03***	1.03***	0.94***	1.34***	1.22***	
Sorted	S.	1.18	0.97	1.00	1.17	1.03	0.22	0.64	0.96	0.84	0.44	-0.74***
independently	L.	1.85	2.03	1.94	1.77	2.05	2.13	1.97	1.94	1.77	1.72	-0.13
	Diff.	0.67*	1.06***	0.94**	0.60	1.02**	1.91***	1.33***	0.98***	0.93***	1.28***	
$R_{t+2:t+6}$	S.	4.85	3.69	2.96	3.10	2.82	2.56	2.78	3.53	2.20	1.65	-3.20***
	L.	8.95	9.49	9.66	8.84	8.84	9.37	9.27	9.29	8.52	7.73	-1.22*
	Diff.	4.10***	5.80***	6.70***	5.74***	6.02***	6.81***	6.49***	5.76***	6.32***	6.08***	
Sorted	S.	4.81	3.79	3.10	4.08	2.79	2.00	2.54	3.25	3.20	1.78	-3.03***
independently	L.	9.39	9.04	9.72	9.89	8.69	8.89	8.33	9.30	8.23	8.02	-1.37**
	Diff.	4.58***	5.25***	6.62***	5.81***	5.90***	6.89***	5.79***	6.05***	5.03***	6.24***	
$R_{t+7:t+12}$	S.	7.94	7.89	7.62	6.80	7.03	7.04	5.82	5.82	5.10	4.56	-3.38***
	L.	9.93	9.05	7.83	7.97	6.97	7.75	8.03	8.39	7.34	5.92	-4.01***
	Diff.	1.99*	1.16	0.21	1.17	-0.06	0.71	2.21**	2.57***	2.24**	1.36	
$R_{t+13:t+24}$	S.	18.57	18.83	19.47	19.23	17.97	17.14	19.20	18.40	17.46	15.24	-3.33**
	L.	13.76	12.37	13.54	14.88	13.30	14.04	14.27	13.60	12.07	9.96	-3.80***
	Diff.	-4.81***	-6.46***	-5.93***	-4.35**	-4.67***	-3.10***	-4.93***	-4.80***	-5.39***	-5.28***	

Table D14.

	MAD	$R_{t-25:t-36}$										
		Smallest	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Largest**	**Diff.**
R_{t+1}	Smallest	0.71	1.06	0.75	0.92	1.11	0.98	0.85	0.94	0.74	0.27	-0.44
	Largest	2.08	1.87	2.12	1.99	1.95	2.01	1.85	1.91	1.82	1.71	-0.37
	Diff.	1.37***	0.81**	1.37***	1.07***	0.84**	1.03***	1.00**	0.97**	1.08***	1.44***	
Sorted	S.	0.85	11	0.81	1.19	0.88	1.16	1.20	0.90	0.81	0.46	-0.39
independently	L.	1.92	1.96	2.09	2.30	2.04	1.82	1.73	1.73	2.01	1.46	-0.46*
	Diff.	1.07***	0.85***	1.28***	1.11***	1.16***	0.66*	0.53	0.83**	1.20***	1.00***	
$R_{t+2:t+6}$	S.	4.10	3.33	2.86	3.09	3.22	2.88	3.26	3.20	2.96	1.10	-3.00***
	L.	8.16	7.28	9.61	8.41	9.66	9.46	9.39	9.28	9.66	8.92	0.76
	Diff.	4.06***	3.95***	6.75***	5.32***	6.44***	6.58***	6.13***	6.08***	6.70***	7.82***	
Sorted	S.	4.43	3.70	2.70	3.61	3.59	2.89	3.27	3.19	3.44	1.83	-2.60***
independently	L.	8.01	8.77	9.57	8.67	9.87	9.26	9.57	9.74	9.33	9.01	1.00
	Diff.	3.58***	5.07***	6.87***	5.06***	6.28***	6.37***	6.30***	6.55***	5.89***	7.18***	
$R_{t+7:t+12}$	S.	8.43	7.03	6.79	6.67	6.57	6.22	6.57	6.06	5.88	5.47	-2.96***
	L.	5.75	7.18	7.36	7.61	8.25	7.99	8.35	9.26	8.65	7.99	2.24**
	Diff.	-2.68	0.15	0.57	0.94	1.68**	1.77**	1.78*	3.20***	2.77***	2.52***	
$R_{t+13:t+24}$	S.	19.87**	19.14	17.31	17.95	17.50	17.95	18.76	18.54	18.49	16.40	-3.47**
	L.	8.68	11.94	13.30	13.66	15.00	13.94	15.13	13.75	13.92	11.46	2.78*
	Diff.	-11.19***	-7.20***	-4.01***	-4.29***	-2.50**	-4.01***	-3.63**	-4.79***	-4.57***	-4.94***	

Table D15.

	MAD	Large downgrade	Small Downgrade	No change	Small upgrade	Large upgrade	Diff.
		RUD					
R_{t+1}	Smallest	1.03	0.92	0.69	1.15	1.27	0.24
	Largest	1.50	1.58	1.91	2.24	1.97	0.47
	Diff.	0.47	0.66	1.22***	1.09*	0.70	
Sorted independently	S.	1.13	1.01	0.72	0.36	1.12	-0.01
	L.	1.89	1.72	1.92	1.52	1.58	-0.31
	Diff.	0.76	0.71	1.20***	1.16*	0.46	
$R_{t+2:t+6}$	S.	3.54	4.42	2.43	2.74	3.75	0.21
	L.	6.48	8.82	8.93	8.78	9.21	2.73***
	Diff.	2.94**	4.40***	6.50***	6.04***	5.46***	
Sorted independently	S.	4.02	3.98	2.60	4.90	4.21	0.19
	L.	8.20	6.80	9.02	6.69	7.15	-1.05
	Diff.	4.18***	2.82**	6.42***	1.79	2.94	
$R_{t+7:t+12}$	S.	7.18	8.04	5.90	6.45	8.86	1.68*
	L.	6.40	9.03	7.51	9.15	8.65	2.25**
	Diff.	-0.78	0.99	1.61**	2.70**	-0.21	
$R_{t+13:t+24}$	S.	20.00	21.55	17.64	18.87	23.80	3.80
	L.	9.56	12.39	13.02	14.22	16.72	7.16**
	Diff.	-10.44***	-9.16***	-4.62***	-4.65	-7.08	

Appendix E. Sharpe ratios

This Appendix reports monthly Sharpe ratios for the zero-cost strategies (Table 4). The *t*-values (in parentheses) correspond to the null hypothesis that the Sharpe ratio is below or equal to that of the market (0.139 per month). Standard errors are calculated through the delta method combined with the GMM per Lo (2002). The sample is from June 1977 to October 2015. One, two, and three asterisks indicate 10%, 5%, and 1% significance, 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)

Appendix F. 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
Malesia	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
Nonwage	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 G. Anchoring and Underreaction

In this appendix, we show that anchoring can lead to underreaction. Thus, consider a security that has a random payoff of θ, which is normally distributed with zero mean. 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:

$$P_1 = \frac{v_\theta}{v_\theta + v_\varepsilon}(\theta + \varepsilon_1), \tag{G1}$$

$$P_2 = \frac{v_\theta}{2v_\theta + v_\varepsilon}(2\theta + \varepsilon_1 + \varepsilon_2), \tag{G2}$$

$$P_3 = \theta. \tag{G3}$$

It is easy to verify that $corr(P_3 - P_2, P_2 - P_1) \equiv \rho = 0$ in the above setting, since prices are martingales.

Now consider the anchoring bias. Let $k \equiv \frac{v_\theta}{v_\theta + v_\varepsilon}$, and $k_1 \equiv \frac{v_\theta}{2v_\theta + v_\varepsilon}$. Let A be any arbitrary anchor. Then, we propose that

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

and

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

where

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

and

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

where h_1 and h_2 are arbitrary constants. In the above setting, the weights on the signals deviate from rationality based on how far the signal is from the anchor. In the above scenario, there tends to be underreaction to the signals because of the anchoring bias. For example, suppose $v_\theta = v_\varepsilon = 1$, and $A = 2$. Then, Monte Carlo simulations based on one million draws show that $\rho = +0.144$ indicating generic underreaction.

More interestingly, $corr(P_3 - P_2, P_2 - P_1 \,|\, \theta + \varepsilon_1 > A, \theta + \varepsilon_2 > A) = +0.186$, but

$corr(P_3 - P_2, P_2 - P_1 \,|\, \theta + \varepsilon_1 > A, \theta + \varepsilon_2 < A) = -0.049$, and

$corr(P_3 - P_2, P_2 - P_1 \,|\, \theta + \varepsilon_1 < A, \theta + \varepsilon_2 < A) = +0.154$, but

$corr(P_3 - P_2, P_2 - P_1 \,|\, \theta + \varepsilon_1 < A, \theta + \varepsilon_2 > A) = +0.064$.

It can also be shown that $corr(P_3 - P_2, \theta + \varepsilon_2 \,|\, \theta + \varepsilon_1 < A, \theta + \varepsilon_2 < A) = +0.205$, but

$corr(P_3 - P_2, \theta + \varepsilon_2 \,|\, \theta + \varepsilon_1 < A, \theta + \varepsilon_2 > A) = -0.042$, and

$corr(P_3 - P_2, \theta + \varepsilon_2 \,|\, \theta + \varepsilon_1 < A, \theta + \varepsilon_2 < A) = +0.229$, but

$corr(P_3 - P_2, \theta + \varepsilon_2 \,|\, \theta + \varepsilon_1 < A, \theta + \varepsilon_2 > A) = +0.105$.

The basic idea is that underreaction (and the drift in the direction of the second signal) is greater when both signals are higher than the anchor or both are lower than the anchor than otherwise. The reason is that a big deviation of the first signal from the anchor causes an insufficient move of the price and another big deviation of the second signal from the price causes a further underreaction. When the sign of the difference between the second signal and the anchor is opposite to that between the first signal and the anchor, the underreaction is muted because the second signal is overweighted relative to the first, which tends to cause an overreaction that mutes the initial underreaction. These results motivate our analysis in Section 4.