January 8, 2020

# Anchoring on Past Fundamentals

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We thank Yakov Amihud, Chen Yao, Buly Cardak, Mohammad Al Mamun, Jan Libich, Si Cheng, Sudha Krishnaswami, Matthew Lutey, Tarun Mukherjee, Luca Pezzo, Guofu Zhou, Jing Zhao, Xue Wang, and seminar participants at Chinese University of Hong Kong (Shenzhen), Korean Advanced Institute of Science and Technology, Korean University, La Trobe University, National University of Singapore, National University of Taiwan, University of New Orleans, Nanyang Technological University, Tsinghua University (SEM), Xiamen University, and the 2018 CICF conference, for valuable comments and suggestions.

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## Abstract

Deviations of accounting fundamentals from their preceding means strongly predict future equity returns in the cross-section. Comprehensive measures based on such deviations yield annualized alphas that generally exceed 15% (6%) for equal- (value-) weighted portfolios. The return predictability goes beyond momentum, 52-week highs, profitability, and other prominent anomalies. The deviation-based investment profitability applies strongly to the long-leg and survives value weighting and excluding microcaps, unlike for other well-known return predictors. We provide evidence that the predictability arises because investors underreact to deviations from prevailing fundamental anchors.

# Introduction

We show that deviations of accounting items from their preceding means predict returns incremental to other established predictors. The predictive power of these variables goes well beyond momentum (Jegadeesh and Titman, 1993), 52-week highs (George and Hwang, 2004), earnings momentum (Ball and Brown, 1968), recent evidence of predictability based on levels of fundamentals (Bartram and Grinblatt, 2018), and a comprehensive list of other anomalies. The predictability obtains for both long- and short-legs and remains viable in recent years, unlike for many other cross-sectional predictors.[1] We propose and provide evidence that such predictability obtains because investors are anchored to long-term averages of fundamentals, so that they underreact to deviations from such averages.

In our empirical analysis, defining a measure based on deviations of accounting variables related to operating performance (termed performance deviation index, or $PDI$), we show that this fundamentals-based measure strongly predicts cross sectional stock returns. In particular, the $PDI$ rule generates economically large and statistically significant alphas (with respect to Fama-French, 1993, plus standard momentum, $UMD$) during the entire sample period, in the most recent years, and across various states of the economy. In addition, the rule easily survives value weighting, the exclusion of microcap stocks, and reasonable transaction costs.[2]

In an extension of the $PDI$ strategy, we suggest a comprehensive fundamental-based measure that considers deviations of all Compustat items and a select list of financial ratios from their recent means. To avoid the usual data-dredging criticism, we allow for a flexible machine learning approach to pick an optimal combination of deviation-based predictors.

[1] Hong, Lim, and Stein (2000), Stambaugh, Yu, and Yuan (2012), and Avramov, Chordia, Jostova, and Philipov (2013) show that anomalies extract profitability especially from the short leg, while McLean and Pontiff (2016) and Chordia, Roll, and Subrahmanyam (2014) document that anomalies decay considerably in the most recent years.

[2] Hou, Xue, and Zhang (2018) show that 65% (82%) of the 452 anomalies turn insignificant upon excluding microcap stocks and employing value-weighted returns, using a $t$-statistic cutoff of 1.96 (2.78).

We find that the resulting index, termed $FDI$, is equally significant in predicting returns. In a standard Fama-MacBeth (FM) regression, $FDI$ generates an FM coefficient of close to thirteen for our full sample.

Why should investment rules based on $PDI$ or $FDI$ yield positive abnormal profits? Since returns from the $PDI/FDI$ strategies easily survive an array of factor models, a risk-based explanation is challenging. This leaves us with the possibility that the results are attributable to investors' biases. Because $PDI/FDI$ 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, evidence indicates that the $PDI/FDI$ effects are distinct from the gradual information diffusion-based underreaction advocated by Hong and Stein (1999) and Hong, Lim, and Stein (2000), or the frictions-based underreaction proposed by Hou and Moskowitz (2005). Specifically, top $PDI/FDI$ stocks are not markedly different from other stocks in terms of size, institutional holdings, or forecast dispersion. Further, the liquidity of top $PDI/FDI$ stocks is not markedly different from that of the rest of the sample.

We provide an explanation for our result based on the psychological bias of anchoring, wherein individuals rely too heavily on readily obtainable (but often irrelevant) signals in forming assessments (Tversky and Kahneman, 1974). As an example of this bias, in Ariely, Loewenstein, and Prelec (2003), participants are asked to write the last two digits of their social security number and then asked to assess how much they would pay for items of unknown value. Participants having higher numbers bid up to more than double relative to those with higher numbers, indicating that they anchor on these digits. Furnham and Boo (2011) provide a comprehensive review of the various studies that have shown the anchoring bias to prevail in a number of experimental settings. Beggs and Graddy (2009) show that experts' pre-sale valuations of art are biased towards previously-established prices of the art pieces. In finance, Campbell and Sharpe (2009) show that experts' forecasts of macroeconomic quantities are systematically biased towards their past values.

We posit that the $PDI/FDI$ effects occur because investors get anchored to long-run moving averages of fundamentals. Specifically, consider that investors are anchored on the average sales of a company over the past few quarters.[3] The bias implies that investors deviate insufficiently from this anchor in forming estimates of future sales. Thus, suppose some material news causes a large move in sales and results in a large departure of the current sales from the investors prevailing anchor, the long-term moving average. Investors underreact to the news, which implies that the price drifts upward (downward) if the distance is large positive (negative).[4] As an example, suppose the anchor (the long-run moving average) is 40. Now suppose that recent sales are announced to be 60. The number 60 is so far away from 40 that the investor underreacts. This implies that the price also underreacts to the information conveyed by current sales. Now suppose the anchor is 40 and sales are announced to be 41. This is not far from the anchor, so the misreaction is minimal, and the price quickly adjusts to the new sales number. This argument demonstrates how $PDI/FDI$ reflect underreaction.

The anchoring hypothesis predicts that $PDI/FDI$ should be stronger for sudden (versus gradual) changes in the current values of accounting fundamentals relative to their long-term averages, which is when the degree of underreaction should be greater. We find support for this hypothesis. We then investigate the notion that if anchoring is pervasive, then evidence of this should also be discernible in a primary source of information to retail investors, namely, analysts' advice. The results indicate that investors do anchor on analysts' forecasts (based

[3]Welch (2000), Kaustia, Alho, and Puttonen (2008), and Kaplanski et al. (2016) indicate that investors' forecasts of future market performance are anchored to past performance.

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

on short and longer-term earnings, price targets, and investment recommendations), and thus underreact to deviations from the forecasts. In turn, portfolios with extreme deviations from analyst-based anchors earn abnormal returns incremental to $PDI/FDI$.

We also propose an asset pricing factor that reflects deviations of fundamentals from their preceding means. The factor, termed $FDF$, is formed on $FDI$-sorted portfolios in a manner analogous to standard momentum, $UMD$. We find that $FDF$ complements a large set of existing factors in that it earns materially significant alphas after accounting for the five Fama and French (2016) factors, $UMD$, the mispricing factors of Daniel, Hirshleifer, and Sun (2019), the quality minus junk factor of Asness, Frazzini, and Pedersen (2014), the betting against beta factor of Frazzini and Pedersen (2014), the mispricing factors proposed by Stambaugh and Yuan (2016), and the investment and profitability factors of Hou, Xue, and Zhang (2015). Experimenting on an alternative factor based on $PDI$ yields equally strong performance. To illustrate, the Sharpe ratio based on $PDI$ is as high as 1.48 throughout the entire sample, and it remains large in recent years. For perspective, standard momentum achieves a Sharpe ratio of 0.48, whereas the corresponding figure for the Novy-Marx (2013) gross-profitability factor is about 0.41.

Our work relates to the extensive literature on behavioral biases applied to explain return anomalies. Barberis, Shleifer, and Vishny (1998) use the representativeness bias to explain value and momentum effects. Daniel, Hirshleifer, and Subrahmanyam (1998) and Luo, Subrahmanyam, and Titman (2019) apply overconfidence to explain momentum and reversals in financial markets. Barberis and Huang (2001) argue that mental accounting can explain value effects. Shefrin and Statman (2000) derive optimal portfolio choice in a model that combines traditional preferences with mental accounting and prospect theory. Barberis, Huang, and Santos (2001) apply prospect theory to explain stock return patterns. Supporting an implication of this theory, Barberis, Mukherjee, and Wang (2016) show that stocks whose past return distributions have higher prospect theory values earn, on average, lower subsequent returns. Our paper fits into this literature by proposing that the anchoring bias of Tversky and Kahneman (1974) accords with robust trading strategies based on firm fundamentals. Specifically, $PDI$ yields significant returns in periods of high and low sentiment, market volatility, and aggregate liquidity.

Moving-average-based rules, of course, have been extensively considered in earlier literature. Indeed, our paper complements important work on technical indicators by Brock, LeBaron, and Lakonishok (1992), Han, Yang, and Zhou (2013), Han, Zhou, and Zhu (2016), and Zhu and Zhou (2009).[5] These papers consider technical strategies that are mostly based on binary rules which apply when short- and long-term moving averages of prices intersect. To the best of our knowledge, we are the first to show that analogs of moving-average-based rules are also profitable when applied to a wide array of firm fundamentals.

We also contribute to the fast-growing literature on machine learning (ML) as applied to asset pricing. Existing work on this topic, such as Gu, Kelly, and Xu (2018), Avramov, Cheng, and Metzker (2019), Chen, Pelger, and Zhu (2019), and Feng, Polson, and Xu (2019), generally applies ML to existing anomaly variables. Chinco, Clark-Joseph, and Ye (2019) use ML to predict stock returns from past returns at intradaily horizons. Jia, Wu, and Yan (2019) adapt ML to predict currency returns. In our application, we show that ML is powerful when applied to deviations of fundamentals from their preceding means. At the one-month horizon, our technique produces alphas that generally exceed 15% per year for equal-weighted portfolios and 6% per year for value-weighted counterparts, with or without microcap stocks.

Our paper is related to the notion developed in recent years that investors' expectations are slow-moving relative to a Bayesian. In economics, Coibion and Gorodnichenko (2015) employ surveys of consumers, firms, central bankers, and professional forecasters to document that mean forecasts fail to completely adjust on impact to shocks, leading to statistically and

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

economically significant deviations from the null of full information. Bouchaud et al. (2019) employ the sticky expectations paradigm to show that analysts systematically underestimate future profits when current profits are high. Sticky beliefs can in fact be rationalized via the anchoring heuristic, which is the explanation we pursue in our paper.

Beyond expectations-based data, empirical evidence has largely supported the notion of underreaction to a wide variety of information signals. For instance, investors underreact to earnings news, information about a firm's customers and R&D quality, changes in a firm's 10-K statement, news about demographic shifts, foreign market news, news that is harder to process, or news that is released on a gradual basis (e.g., Cohen and Frazzini, 2006; DellaVigna and Pollet, 2007; Hirshleifer, Lim, and Teoh, 2009; Cohen and Lou, 2012; Cohen, Diether, and Malloy, 2013; Da, Gurun, and Warachka, 2014; Giglio and Shue, 2014; Cohen, Malloy, and Nguyen, 2018; Jiang, Li, and Wang, 2019). We add to the preceding literature by constructing a comprehensive measure, $FDI$, which is based on a complete list of firm fundamentals. Further, we show that deviations of fundamentals from their recent means predict returns incremental to the levels of the measures. We attribute the predictive ability of the deviation-based measure to the anchoring bias, wherein investors are anchored to past means of fundamentals and thus underreact to large deviations from the anchor.

Our work also relates to the several papers which show that accounting fundamentals predict earnings and stock returns. Sloan (1996) shows that stock returns are positively related to earnings quality. Abarbanell and Bushee (1998) provide evidence that returns are predictable from a set of accounting fundamentals related to managerial efficiency and earnings quality. Piotroski (2000) indicate that the returns to value stocks (those with high book/market ratios) are predictable via nine binary signals related to fundamentals. Mohanram (2005) demonstrates a similar finding for stocks with low book/market ratios. Huang et al. (2019) show that a combination of fundamentals related to firm profitability and net payouts predicts returns. Ou and Penman (1989), Lev and Thiagarajan (1993), Yan and Zheng

(2017), and Bartram and Grinblatt (2018) also demonstrate that fundamentals-based predictability applies to a range of accounting variables. We contribute to this literature in two ways. First, we document that deviations of accounting fundamentals from their averages over past quarters, beyond the actual fundamentals used in earlier work, are reliable predictors of stock returns. We attribute this predictability to investors' underreaction relative to prevailing anchors (i.e., the past means of fundamentals). Second, in our extended $FDI$ approach, we use a comprehensive predictor obtained from applying ML to the complete set of deviations from fundamentals.

Of course, the literature on the vast set of equity return predictors is by now quite mature and the question naturally arises as to the contribution of our paper to this body of research. To reiterate, there are at four noteworthy aspects to our work. First, the documented predictability is stronger on the long side relative to the short side, and robustly prevails in states of high and low sentiment, liquidity, and volatility, which contrasts with the features of several other anomalies. Second, the $PDI/FDI$ predictability survives in recent decades when most anomalies have attenuated. Third, $PDI/FDI$ largely survive a comprehensive set of established factors and anomalies, with $t$-ratios that readily clear the hurdle proposed by Harvey, Liu, and Zhu (2016). Fourth, Sharpe ratios associated with the anchoring-based investing are markedly higher than those generated by well-known anomalies.

This paper proceeds as follows. In Section 1, we describe the data and the methods used in our analysis. Section 2 discusses the role of $PDI$ using regressions as well as a portfolio approach. Section 3 extends our analysis to consider $FDI$. Section 4 considers an anchoring-based rationale for our results. In Section 5, we propose an anchoring factor ($FDF$) based on deviations of fundamentals from their preceding means. Section 6 concludes.

# 1 Data and Methodology

We consider all U.S. firms listed on the NYSE, AMEX, and NASDAQ with share codes 10 and 11 and with positive equity book values in Compustat for the previous year. We exclude stocks with an end-of-month price below \$5, stocks that are not traded during the month, stocks that do not have return observations for the previous 12 months, and stocks for which there are no records to construct plausible controls for cross-sectional return predictors, as detailed below.

To mitigate backfilling biases, we require that a firm be listed on Compustat for at least two years before it is included in the sample (Fama and French, 1993). At the end of June of every year, we update the previous fiscal year's accounting data to make sure that information for predicting future stock returns is available in real time. We start in 1976 to ensure availability of reliable Compustat data (see, e.g., Bennin, 1980). The testing sample starts in June 1977, when accounting reports for 1976 are publicly available, and ends in October 2017. Altogether, we capture 849,794 firm-month observations per 9,331 firms. We also assess return predictability after excluding microcap stocks (below the NYSE benchmark for bottom 20%). Following Shumway (1997), we incorporate delisting returns based on the CRSP daily delisting file.

To explore stock market reactions to major fundamental variables, we first construct a Performance Deviation Index ($PDI$) from seven items related to firms' operating performance: (i) Cash and short-term investments, (ii) retained earnings, (iii) operating income, (iv) sales, (v) capital expenditures, (vi) invested capital, and (vii) inventories. In brief, these variables capture managerial efficiency by considering measures of generated and accumulated income, financial health, capital investment, and inventory build up. [We also use a more general version of $PDI$, as described later.] Appendix A provides detailed definitions of $PDI$ as well as other variables used in our analyses. If the exact release date of the accounting reports within the month is unavailable, we assume a 60-day delay in release to guarantee data availability for a real-time information set. For each of the seven operating items, a "deviation" is defined as the difference between the most recent quarterly release and the average over the preceding three quarters, scaled by total assets.[6] Each deviation item is assigned a percentile relative to all stocks' deviations that period (one minus percentile for invested capital and inventories). Deviations are then equally weighted across the seven items to construct a composite monthly index, $PDI$.

While $PDI$ is formed based on a parsimonious set of operating performance measures, investors may anchor on other accounting items and possibly even financial ratios. Therefore, we generalize this measure and construct a comprehensive Fundamental Deviation Index ($FDI$). This index is based on deviations for all Compustat accounting variables plus 14 common accounting ratios. The list of such items appears in Appendix B. Deviations in accounting variables are defined similarly to $PDI$ as the difference between current values and preceding means scaled by total assets, while deviations in accounting ratios are unscaled.

The $FDI$ index is calculated every month from all available data up to that month using the standard least absolute shrinkage and selection (LASSO) procedure of Tibshirani (1996).[7] In particular, consider month $J$. We run a LASSO panel regression of monthly stock returns realized up to month $J$ on previous-months' deviations. Slope coefficients from the panel regression reflect sources of both time-series and cross-sectional return predictability from deviation variables. $FDI$ is computed as the fitted value of the panel regression using time $J$ realizations of deviation variables. Thus, on the one hand, $FDI$ is the conditional expectation of the return in month $J + 1$. On the other hand, $FDI$ serves as an index as it weights all deviations based on their strength in predicting future returns (recall that

[6]An extended index that includes income before extraordinary items leads to similar results. Computing deviations from means in the most recent two quarters also leaves the conclusions unchanged.

[7]LASSO is implemented via Python module LassoLarsIC, with a lambda penalty parameter to minimize the BIC information criterion.

deviation variables are formulated as percentiles).

We require a minimum of 18 monthly observations to calculate the first set of stock-level $FDI$s (namely, the first time-series observation for each stock). Hence, the index starts in January 1979. Then, we employ an expanding scheme to regenerate a (firm month) panel of $FDI$ measures based on LASSO regressions. That is, denoting $K$ as the first month for which $FDI$ is available, the second set of $FDI$ observations are based on a LASSO panel regression of returns realized up to month $K+1$ on previous months' deviation variables, and so on. Collectively, $FDI$ differs from $PDI$ in two ways. First, it is based on a comprehensive list of accounting items and financial ratios. Second, it weights deviations based on their predictive strength, while $PDI$, like many other scores in finance and accounting, employs equal weights.

Note that LASSO implements model selection retaining a set of explanatory variables while discarding the complementary set. Appendix B summarizes the number of months each deviation variable is retained in constructing $FDI$. Higher figures indicate stronger prominence in predicting future returns. Starting with a universe of 159 accounting variables and 14 accounting ratios, about 113 deviation variables are retained at least once in constructing $FDI$. In addition, only 25 deviations are retained at least 230 times (about 50% of the sample months) suggesting that the number of variables that are consistently weighted in forming $FDI$ is considerably smaller than the initial universe. Based on the anchoring rationale to be developed below, this reduced set is something to be expected as investors should follow (and possibly underreact to) only the most representative items that have implications for equity valuations.

We note several other key findings from the LASSO regressions described in Appendix B. Observe that the list of 25 most prominent predictors does not include any accounting ratio. While this finding could go counter to prior expectations, it essentially implies that the information content of financial ratios is mostly absorbed by deviation variables. In addition, the most pronounced deviation variables are related to income taxes payable (positive weight), retained earnings (positive weight), cash and short-term investments (positive weight), inventories (negative weight), and interest and related expenses (negative weight). Understanding the precise rationales of each of these key variables is beyond the scope of this work. Instead, we consider a plausible anchoring-based rationale for the predictive power of the composite indexes $PDI$ and $FDI$ within Section 4 to follow.

Appendix C further illustrates the construction of $FDI$ over time. It is apparent that the weights of the most pronounced 25 predictors tend to be large and stable throughout the sample period. The next prominent 20 predictors are retained frequently over the sample period, while the retention of all other deviation variables is clustered and sporadic.

To ensure that $PDI$ or $FDI$ does not merely capture well-established phenomena, throughout the analysis we control for 30 predictive characteristics that are described below. The first group of control variables accounts for the usual style characteristics. Specifically, the market value of equity ($ME$) accounts for the negative size-return relation (Banz, 1981; Reinganum, 1981; Fama and French, 1992). The book-to-market ratio ($BE/ME$) captures the value effect (Fama and French, 1992).

The next group of controls considers characteristics that are associated with past prices. The 52-week high (*52-HIGH*) and the all-time maximum price ($Xmax$) measure current price relative to the maximum price during the last 52 weeks and during the entire history of stock prices as proposed by George and Hwang (2004) and Li and Yu (2012), respectively. The Recency Ratio ($RR$) of Bhootra and Hur (2013) accounts for the time elapsed since the maximum price in the last 52 weeks. The trend ($TREND$) variable 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. Three past return variables are used to incorporate price reversals and intermediate-term momentum (Jegadeesh, 1990; DeBondt and Thaler, 1985; Jegadeesh and Titman, 1993). The Information Discreteness ($ID$) variable of Da, Gurun and Warachka (2014) measures the pace with which information is accumulated over the momentum period.

The third group consists of fundamental quantities. The fundamental mispricing characteristic, termed $BG$, of Bartram and Grinblatt (2018) estimates the difference between firm's actual value and median predicted fair value from 28 most common firm-level accounting variables. The $F$-score ($F$-$S$) measures the ability to serve future debt and operating efficiency, per Piotroski (2000). The $G$-score ($G$-$S$) is based on fundamentals such as earnings stability, growth stability, and intensity of R&D, capital expenditure and advertising, as in Mohanram (2005). 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). Standardized unexpected revenue growth ($SURGE$) of Jegadeesh and Livnat (2006) controls for post-revenue announcement drift; it is calculated similarly to $SUE$ but using revenues instead of EPS. The variable representing analysts' upgrades-downgrades ($RUD$) is calculated as the number of upgrades minus downgrades divided by the total number of outstanding recommendations. $RUD$ accounts for the potential effect of recommendation revisions (Stickel, 1992; Womack, 1996). Net stock issues ($NS$) controls for high returns following stock repurchases (Ikenberry, Lakonishok, and Vermaelen, 1995) and low returns following stock issues (Loughran and Ritter, 1995; Daniel and Titman, 2006; Pontiff and Woodgate, 2008).

As in Fama and French (2008), we construct asset growth ($dA/A$) as the previous year's annual change in assets per split-adjusted share. Following Haugen and Baker (1996), Cohen, Gompers, and Vuolteenaho (2002), and Fama and French (2006), we control for firm profitability ($Y/B$), which is computed as equity income divided by book equity. The investment-to-assets ratio ($I/A$) is formed as in Fairfield, Whisenant, and Yohn (2003), Titman, Wei, and Xie (2004), and Xing (2008). Return on equity ($ROE$) is calculated as income before extraordinary items divided by the most recent quarter's book equity.

Among the list of fundamental controls, we also consider gross profitability, accruals, return on assets, new operating assets, and credit risk. In particular, Novy-Marx (2013) argues that gross profits scaled by assets ($GP$) are associated with higher future returns, Sloan (1996) finds a negative relation between accruals ($Ac/A$) and returns, Chen, Novy-Marx, and Zhang (2011) show that return on assets ($ROA$) is positively associated with future stock returns, and Hirshleifer et al. (2004) argue that net operating assets scaled by total assets ($NOA$) are a strong negative predictor of returns. To account for the credit risk effect, we consider the Ohlson (1980) distress $O$-score ($O$-$S$), as in Campbell, Hilscher, and Szilagyi (2008).

The last group of controls considers variables concerning limits to arbitrage. Turnover ($TURN$) is constructed as the ratio of trading volume to shares outstanding (Haugen and Baker, 1996; Hu, 1997; Datar, Naik, and Radcliffe, 1998; Rouwenhorst, 1998; Chordia, Roll, and Subrahmanyam, 2011). The Amihud (2002) illiquidity measure ($ILLIQ$) is the monthly average of daily absolute return per dollar of daily trading volume. Idiosyncratic volatility is based on the volatility of residuals from Fama-French time-series regressions as per Ang et al. (2006).

Table 1 displays descriptive statistics for stock returns and all control variables. The first two columns report the sample means and standard deviations. The last two columns report the correlations between $PDI/FDI$ and each of the predictive characteristics. Almost all correlations are near zero, with a maximum correlation below 0.2, indicating that the information content of $PDI$ and $FDI$ is markedly different from existing predictors. In the same vein, the correlation between $PDI$ and $FDI$ is modest. In the analyses that follow, we show that the predictive power of the fundamental deviation index, $PDI$, and to a larger extent $FDI$, is economically significant and incremental to momentum, earnings momentum, the fundamental mispricing characteristic ($BG$), other prominent anomalies, and other fundamental variables.

# 2 The $PDI$-Return Relation

In this section, we explore the ability of $PDI$ to predict the cross-section of future stock returns. In brief, the analysis shows that unlike the vast majority of market anomalies, the $PDI$ effect is not confined to small or microcap stocks and viable in the long-leg, in recent years, as well as across various economic states reflecting high versus low investor sentiment, market volatility, cumulative market return, and aggregate liquidity.

## 2.1 Cross-Sectional Regressions

We employ the Fama and MacBeth (1973) cross-sectional regression setup. For each month, we regress monthly stock returns on $PDI$ and the above-described predictive characteristics. Table 2 reports slope coefficients for $PDI$, past returns over months 2 to 12 ($MOM$), and the fundamental mispricing characteristic ($BG$) of Bartram and Grinblatt (2018). Estimated slope coefficients for all other control variables are reported in Appendix D.

Panel A of Table 2 reports results from raw returns. The $PDI$ coefficient in the first test, with one-month-ahead return as the dependent variable, is economically large at 2.17% and highly significant ($t = 13.83$). The momentum ($MOM$) and the fundamental mispricing ($BG$) variables are also highly significant. The $PDI$ effect is incremental to well-known cross-sectional effects.

Moving to an investment horizon of 2-6 months, the $PDI$ coefficient is large (2.84%) and highly significant ($t = 7.73$). It remains large (3.17% and 2.14%) and significant ($t = 7.41$ and 3.37) for investment horizons of 7-12 months and 13-24 months, respectively. Interestingly, momentum displays significantly negative slope coefficients for investment horizons longer than six months, consistent with longer-run reversals. $BG$ turns insignificant for longer investment horizons. The major takeaway is that the $PDI$ effect does not reverse and its predictive ability remains viable horizons well beyond a month.

In a recent paper, Hou, Xue, and Zhang (2017) argue that abnormal profits from investing in anomalies attenuate when the impact of microcap stocks is mitigated by value weighting returns. Also, Fama and French (2015) observe that the most serious challenges to neoclassical asset pricing models characterize small cap stocks. To mitigate the impact of small stocks we already exclude stocks with end-of-month price below or equal to \$5. Also excluded are stocks in their first year post initial public offering and stocks that do not have daily trading activity. While these filters lessen the impact of microcaps, we also consider an investment universe that excludes all microcaps, defined as stocks below the NYSE cutoff for bottom 20%.

In line with Hou, Xue, and Zhang (2017) several coefficients (presented in the appendix) including the recency ratio, illiquidity, and gross probability turn insignificant upon excluding microcaps. In addition, other effects including $BG$ and momentum in earnings and revenue ($SUE$ and $SURGE$) substantially attenuate. In contrast, The $PDI$ slope coefficient remains large and significant for all investment horizons. For the one-month investment horizon, for example, the slope coefficient is 2.16 ($t = 11.81$) excluding microcaps. For perspective, the initial universe of stocks yields a coefficient of 2.17 ($t = 13.83$). Thus, excluding microcaps has only a marginal impact on the results. This evidence distinguishes the robustness of $PDI$ from that of a comprehensive set of variables studied in Hou, Xue, and Zhang (2017).

We next examine the $PDI$ effect for the recent 2001-2017 period. The most recent period is especially important because Chordia, Subrahmanyam, and Tong (2014) as well as McLean and Pontiff (2016) show that anomalies have declined in significance during recent years. Consistent with these studies, the results in Table 2 demonstrate that over the 2001-2017 period, momentum, $BG$, and several other variables, reported in Appendix D, such as trend, information discreteness, and gross profitability, considerably attenuate. In contrast, $PDI$ produces a positive and significant coefficient of 1.81% ($t = 7.20$) in the most recent years. In addition, the exclusion of microcaps has only a minor impact on the $PDI$ coefficient which remains at 1.88% and is highly significant ($t = 6.98$).

In Panel B of Table 2, the dependent variable is one-month-ahead returns adjusted to the three Fama-French market, size, and value factors, along with the cross-sectional momentum factor ($UMD$) based on Jegadeesh and Titman (1993). The results show that $PDI$-based predictability easily survives risk adjustment for both the entire universe of stocks as well as for the universe that excludes microcaps.

We further analyze the predictive power of $PDI$ across different market states. We follow the vast literature on momentum. For example, Antoniou, Doukas, and Subrahmanyam (2013) and Stambaugh, Yu, and Yuan (2012) show that momentum profitability obtains more strongly during high sentiment periods. Moreover, Cooper, Gutierrez, and Hameed (2004) show that momentum is stronger following positive market returns, Avramov, Cheng, and Hameed (2016) show the same when markets are highly liquid, and Wang and Xu (2015) consider the impact of market volatility on momentum. Accordingly, we perform cross-sectional regressions for high-versus-low sentiment, volatility, and liquidity (stratified by medians), and high-versus-low market depending on past returns. The sentiment index follows Baker and Wurgler (2006), market illiquidity is per Amihud (2002), market volatility is the monthly standard deviation of daily returns, and market condition is based on past market returns as in Cooper, Gutierrez, and Hameed (2004). In Panel C of Table 2, we confirm the notion that the $PDI$ effect is large and significant in all sentiment, volatility, liquidity, and market states.

We next consider several potential sources for the $PDI$-based predictability by boosting the set of controls. The results of these tests are reported in Appendix E. The first test considers seasonality as a potential source for $PDI$ predictability. Heston and Sadka (2008) find that stocks with above-average return in a given month tend to record above-average returns at annual intervals. To control for any monthly pattern in returns, in the first test we replace the momentum variable with 12 separate monthly past return controls. The next two tests consider the level of major accounting variables as a source of $PDI$ predictability. Specifically, Bartram and Grinblatt (2018) ($BG$) employ 28 accounting variables to construct their fundamental mispricing characteristic ($BG$). While we control for $BG$, it is still possible that $PDI$ is absorbed by those variables on a stand-alone basis. Moreover, it is possible that the $PDI$ predictability is driven by its components rather than deviations in those components. Therefore, in the next two tests, we also control for BG's 28 accounting variables and the seven components of $PDI$, and their annual changes. To complete the analysis, we also consider regressions that control for dispersion in analysts' forecasts, as in Diether, Malloy, and Scherbina (2002), and analysts' consensus EPS forecasts which proxy for expected earnings.

Strikingly, $PDI$ slope coefficients in Appendix E do not attenuate regardless of the additional set of control variables. The results show that $PDI$-based predictability is virtually unaffected by the actual components of $BG$ and $PDI$ or by a sequence of monthly past returns. This evidence indicates it is the deviations of performance components from preceding means, rather than the components themselves that drive return predictability.

Harvey, Liu, and Zhu (2016) argue that in light of the numerous attempts to detect factors that explain cross-section of expected returns higher hurdle criteria should be applied for estimating the significance of new explanatory variables. In most cases within Table 2 for the one-month horizon we obtain double-digit $t$-values, and they are always above 6.0. Thus, overall $t$-ratios for $PDI$ are considerably higher than the threshold value of 3.0 suggested by Harvey, Liu, and Zhu (2016).[8]

In sum, evidence from cross-sectional regressions indicates that $PDI$ is a strong and significant predictor of future returns. Unlike prominent anomalies that have attenuated during the most recent years, the $PDI$ effect stands out. The effect survives well-known predictive characteristics that employ accounting variables. The robustness of our proposed $PDI$ during the entire sample period, in recent years, upon excluding microcaps, in various states related to market, volatility, liquidity, and sentiment, and over long-term horizons distinguishes this variable from existing predictors.

## 2.2 Portfolio Analysis

We next assess profitability of zero-cost strategies that employ $PDI$. The $PDI$ strategy takes long (short) positions in top (bottom) $PDI$ deciles. We consider 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).

### 2.2.1 $PDI$ Payoffs

Figure 1 displays the value of a \$1 position invested at the end of June 1977 separately in the $PDI$ top and bottom decile portfolios. The figure also displays a market proxy (the value-weighted CRSP index) that rises to \$55 at the end of our sample period. The portfolios are rebalanced on a monthly basis. The top decile portfolio outperforms the market with terminal values of \$6,340, while bottom decile portfolio lags the market with a corresponding

[8]Chordia, Goyal, and Saretto (2019) suggest a normative Fama-MacBeth $t$-statistic threshold of closer to four; our strategies pass this threshold as well.

terminal value of \$7. While Stambaugh, Yu, and Yuan (2012) and Avramov et al. (2013) show that most anomalies derive their profitability principally from the short leg, Figure 1 shows that top $PDI$ stocks (comprising the long leg of $PDI$) uniformly outperform.

In Panel A of Table 3, we summarize annual alphas from the long-short extreme-decile-based $PDI$ strategy and their significance for holding periods ranging from one to 24 months. The table provides estimates from regressing top-minus-bottom portfolio payoffs on the three Fama-French factors and $UMD$ (the cross-sectional momentum factor). Reported are results for both equally-weighted and value-weighted portfolios and for portfolios that exclude microcaps.

Starting with equally-weighted portfolios, the alphas are positive and significant for all horizons ranging from 3.44% ($t = 4.77$) for the 18-month horizon and 16.24% ($t = 13.74$) for the one-month horizon. Alphas remain large upon excluding microcaps, ranging between 2.23% ($t = 2.95$) for the 18-month horizon and 13.96% ($t = 10.34$) for the one-month horizon. Considering value-weighted portfolios, the alphas range between 1.75% ($t = 1.86$) for the two-year horizon and 8.79% ($t = 4.79$) for the one-month horizon. Excluding microcaps, the corresponding figures are 1.60% ($t = 1.66$) and 8.30% ($t = 4.41$). It is worth pointing out that the $PDI$ effect is often present even after two years, and does not reveal sign of reversal.

Another notable aspect of the $PDI$ effect is the asymmetry between buy and sell sides. In untabulated results, we find that the long side of the value-weighted portfolio yields an alpha of 6.38% ($t = 5.21$) while the short-leg counterpart is only $-2.41$% ($t = -1.65$). The evidence thus indicates that unlike many other anomalies, where bottom portfolios contribute materially to the strategy's profits, the $PDI$ effect is more pronounced on the long leg.

### 2.2.2 $PDI$ and trading costs

Do investment strategies that employ $PDI$ survive reasonable transaction costs? Panel B of Table 3 reports break-even costs that would eliminate average abnormal profits of our proposed zero-cost strategies in Panel A. the figures in the table reflect transaction costs multiplied by the portfolio average turnover (for both long and short positions). The results show that break-even costs tend to increase with holding periods as longer holding periods imply less trading and thus lower transaction costs.

Focusing on the one-month holding period, cutoff costs are 205 (equally-weighted), 173 (EW excluding microcaps), 111 (value-weighted), and 103 bps (VW excluding microcaps). The corresponding figures for the 24-month holding period are 523, 365, and 266, and 238 bps. Collectively, our evidence shows that $PDI$ delivers payoffs that largely exceed 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 for trading momentum and the post-earnings announcement drift over 1963-2013 range from 10 to 40 bps.

### 2.2.3 Properties of $PDI$ portfolios

Higher $PDI$ stocks could be potentially riskier, thereby commanding higher required returns. While we do control for prominent factors in Table 2, nonetheless, in Table 4 we compare the risk profile of top versus bottom $PDI$ portfolios. Panel A (B) considers equal- (value-) weighted portfolios. The second column reports the past 200-day mean standard deviation of daily stock returns. The average standard deviation for the top $PDI$ portfolio is smaller than that for the bottom one. This relation remains intact for the monthly portfolio standard deviation in the third column. However, the differences in standard deviations across the extreme deciles are small (between 0.5%-0.8% in absolute terms). The return spread, on the other hand is the range of 8%-16% (Table 3). This makes it unlikely that we are capturing the low volatility anomaly (Baker and Haugen, 2012).[9]

We also report the loadings on the five Fama and French (2015) factors and $UMD$. We find that loadings on size are significantly smaller for the $PDI$ top versus the bottom portfolios. The loadings on market, value, and investment are indistinguishable across the portfolios. The fact that the market betas are not statistically different across the portfolios indicate that we are not picking up the low beta anomaly (Frazzini and Pedersen, 2014; Antoniou, Doukas, and Subrahmanyam, 2015) either.

We further find that the loadings on $UMD$ are larger for the top $PDI$ portfolio relative to the bottom and the differences are significant. Specifically, the top decile loads insignificantly and positively, whereas the bottom $PDI$ decile loads strongly and negatively, on the $UMD$ factor. Even if $UMD$ is a systematic risk factor, the risk interpretation would require that low $PDI$ stocks, with weaker fundamentals, are less risky (specifically, a better hedge against $UMD$ risk) than high $PDI$ ones with stronger fundamentals, which is questionable from an intuitive standpoint. Another observation is that the top (bottom) $PDI$ portfolio loads positively (negatively) on the profitability ($RMW$) factor, and the difference in the loadings is significant. Hou, Xue, and Zhang (2015) argue that all else equal, more profitable firms should have higher discount rates, because with high profitability, high discount rates are required for firms to be in a state of equilibrium where they do not want to invest more (see also Fama and French, 2015). The loadings of $PDI$ portfolios on the profitability factor accord with this interpretation. These patterns in the loadings on $RMW$ and $UMD$

[9] In unreported analysis, we confirm this finding by controlling for the total standard deviation of monthly returns (over the past 60 months) in Fama-MacBeth regressions.

notwithstanding, the intercept of the regression remains positive and highly significant for the long-short portfolio based on $PDI$. Specifically, after controlling for the five Fama and French (2015) factors, the $t$-statistic on the intercept is almost thirteen for the equally-weighted portfolio and about five for the value-weighted counterpart. The economic magnitude of the annualized intercept is about 14% (7.7%) for the equal- (value-) weighted $PDI$-based portfolio. Thus, overall, the $PDI$ effect survives risk considerations.

Hong and Stein (1999) and Hong, Lim, and Stein (2000) argue that past return effects are stronger among small cap stocks, as well as in stocks that are less covered by analysts, possibly due to their higher information acquisition costs. Hou and Moskowitz (2005) suggest that market frictions may delay information diffusion for up to several weeks. Such delay is most pronounced for less visible, smaller cap, more volatile, and more illiquid stocks. Although we find that $PDI$ predictability is robust to the exclusion of microcap stocks, we consider below whether such channels of gradual information diffusion provide explanatory power for $PDI$. We report in Panel C of Table 4 the average firm characteristics for $PDI$-sorted groups. The mean market capitalization of firms in the $PDI$ top decile is \$3 billion, 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, stocks in the top decile of $PDI$ are more liquid than bottom decile ones and have the highest turnover. Next, the average number of analysts covering the top $PDI$ stocks is 4.52 and the average share of institutional holdings is 0.39, while the corresponding values for top price-delayed stocks are 1.3 and 0.06. Finally, the $O$-score for top $PDI$ stocks is not markedly different from that for others, suggesting that the $PDI$ effect is not driven by credit risk. Comparing firm characteristics across $PDI$ deciles at the bottom of the table also does not reveal clear patterns that could point to risks associated with $PDI$.

# 3 Generalization: Fundamental Deviation Index ($FDI$)

As investors could follow a comprehensive and diversified set of accounting data that extends beyond the $PDI$ components, the $PDI$ effect can extend to other items that reflect a broad spectrum of a firm strength and financial stability. Therefore, we generalize $PDI$ and propose a comprehensive measure, $FDI$, considering deviations of all accounting items as well as common accounting ratios from their trailing means. The construction of $FDI$ is detailed in the data and methodology section above. Summary statistics are provided in Appendices B and C.

In Table 5, we first present Fama-MacBeth regressions using $FDI$ as a forecasting variable. We report slope coefficients on a large set of control variables in Appendix F. The results show that $FDI$ strongly and positively predicts returns incremental to all controls. For example, the $FDI$ slope coefficient for the full sample is 52.96% ($t$ = 17.45). The $FDI$-based predictability obtains for the 2001-2017 period, when microcaps are excluded, when returns are risk-adjusted using common factors, and in different states of the economy. Moreover, similar to $PDI$ in Table 2, $t$-values of the $FDI$ coefficient often exceed 10.0 and they are always above 5.0, thus easily clearing the hurdle of 3.0 proposed by Harvey, Liu, and Zhu (2016). Overall, the evidence shows that deviation-based underreaction to fundamentals is a broader phenomenon that goes beyond deviations from operating performance measures as per $PDI$.

Figure 2 traces the value of a $1 position invested in the end of January 1979 in $FDI$ top/bottom decile portfolios. Similar to $PDI$, the top portfolio considerably outperforms the market yielding $7,771 at the end of the sample period, whereas the bottom portfolio accumulates to only $2.43. The vast difference between the end-of-period accumulation for the top decile of $FDI$ and the market ($7,771 vs $70) clearly indicates that $FDI$ is also pronounced on the long side.

As noted earlier, modern factor models have recently emerged. Fama and French (2015, 2016) propose a five-factor model based on the market, market capitalization, and the book-to-market ratio (items in the three-factor model), as well as investment and profitability. Fama and French (2015) use comparative statics from a present value relation to justify their five-factor model, and show that this framework eliminates several persistent anomalies including market beta, net share issues, and volatility. Hou, Xue, and Zhang (2015) propose a four-factor model under which half of previously reported anomalies become insignificant. Stambaugh and Yuan (2017) suggest a four-factor mispricing model that accommodates a large set of anomalies. Finally, Daniel, Hirshleifer, and Sun (2019) develop two behavioral factors that incrementally price many factors proposed in the literature. Distinguishing between mispricing mechanisms on the basis of the time it takes investors to correct them, they construct a short-term $PEAD$ factor and a long-term $FIN$ factor. $PEAD$ captures delays in response to earning announcements known to cause the post-earnings announcement drift phenomenon. $FIN$ uses stock issues and repurchases activity as a proxy for managers exploiting long-term mispricing.

We next examine whether the $FDI$ effect clears recently proposed factor models and well-established factors. Table 6 reports alphas for the top-minus-bottom equally- and value-weighted $FDI$ portfolios for various factor models and investment horizons of one, three, and six months. Considering Fama and French three-factor and five-factor models along with momentum, alphas are economically large and significant ranging between 12.23%-20.08% ($t$ = 9.09-13.06) and 5.82%-8.08% ($t$ = 2.83-4.77) for equal- and value-weighted portfolios, respectively. Accounting for the behavioral factors of Daniel, Hirshleifer, and Sun (2019) has but a modest impact on the magnitude and significance of alphas.

In the next two tests, we regress $FDI$ portfolio payoffs on the four-factor mispricing model of Stambaugh and Yuan (2017) and the $q$-factor model of Hou, Xue, and Zhang (2015). Alphas remain large and highly significant across the board. The last test in Table

6 is a "kitchen sink" model that consists of a comprehensive list of factors. In particular, we add the Quality minus Junk ($QMJ$) factor of Asness, Frazzini, and Pedersen (2019), a Standardized Unexpected Earnings ($SUE$) factor, and the Betting Against Beta ($BAB$) factor of Frazzini and Pedersen (2014).

The magnitude and significance of the alphas are virtually unaffected by the additional factors. Alphas remain large and highly significant in the range of 14.73%-19.98% ($t = 10.13$-$11.88$) and 8.48%-8.86% ($t = 3.74$-$4.73$) for equal- and value-weighted portfolios, respectively. In untabulated tests, we record similar results when investment strategies are based on $PDI$ portfolios. Altogether, the $FDI/PDI$-based predictability goes well beyond the five factors of Fama and French, standard momentum, earnings momentum, recently proposed behavioral factors, mispricing factors, and other well-established factors.

# 4 The Anchoring Rationale

Why are $PDI$ and $FDI$ so robust in predicting future returns? One possibility is that investors exhibit a continuing overreaction to public fundamental signals that deviate from the historical average. This accords with the feedback trading modeled by De Long et al. (1990). However, if investors do overreact, we should observe long-run reversals in $PDI/FDI$ based trading strategies. In the results reported in Table 2, we find no evidence of reversals for returns up to 24 months following portfolio formation. Thus, the evidence accords with investor underreaction, rather than overreaction.

One possible rationale for underreaction is cognitive dissonance (CD). Antoniou, Doukas, and Subrahmanyam (2013) argue that CD emerges when news contradicts investors' sentiment, thereby slowing the diffusion of signals that oppose the direction of sentiment. Under CD, bottom $PDI/FDI$ stocks are expected to be underpriced during high sentiment, while top $PDI/FDI$ stocks are expected to be underpriced during low sentiment. While the latter phenomenon can be corrected by arbitrage buying, short-selling constraints should impede arbitraging of bottom $PDI/FDI$ stocks under high sentiment, causing the $PDI/FDI$ effect to be stronger during high sentiment periods. However, Tables 2 and 5 demonstrate that the $PDI/FDI$ effect delivers statistically indistinguishable payoffs across high and low sentiment states.

Hirshleifer and Teoh (2003) propose limited attention as an intriguing rationale for underreaction to new information (such as items higher up in the income statement relative to the bottom line, i.e., net income). Note that as per our evidence in Appendix E, it is the deviation of fundamentals from their rolling means that is crucial in predicting returns, as opposed to the levels of fundamentals themselves. It is hard to argue that deviations of accounting items from their previous means represent new information relative to the much more salient, and easily available, accounting figures themselves. Thus, applying limited attention to explain $PDI/FDI$ is challenging. Further, the preceding argument indicates that any explanation for $PDI/FDI$ should involve a role for the seemingly irrelevant baseline (the long-run moving average). This leads us to propose an explanation for the predictive power of $PDI/FDI$ that relies on the anchoring bias (Tversky and Kahneman, 1974).

What are reasonable anchors? Past work often proposes anchors related to market prices. For example, Welch (2000) suggests that economists' estimates of the equity premium are influenced by past market performance. George and Hwang (2004) propose an anchor based on the 52-week high price. Relying on prospect theory and mental accounting, Grinblatt and Han (2005) argue that the current price is biased in the direction of aggregate capital gains measured by a volume weighting of past returns. Kaustia, Alho, and Puttonen (2008) indicate that estimates of future market performance in the European Union are influenced by whether subjects are given a historical estimate from a rising stock market (Sweden) or a falling one (Japan). Finally, Avramov, Kaplanski, and Subrahmanyam (2019) imply that investors anchor on the 200-day moving average of equity prices. Thus, departures from long-run moving averages are predictive of future returns.

Anchors, of course, could go beyond market prices. A vast industry is devoted to fundamental analysis, and it is reasonable to conjecture, for example, that the "news-watchers" of Hong and Stein (1999) and fundamental analysts in general could anchor on past fundamentals. Along this line of argument, in the context of the credit market, Dougal et al. (2015) show that the credit spread charged on bank loans to corporations depend on past credit spreads, seemingly because banks are anchored on these historical data.

Based on the preceding arguments, we propose that investors anchor on historical rolling averages of fundamentals. Investors thus underreact to the arrival of new information that triggers a large deviation from the anchor. The anchoring bias accords with why high (low) $PDI/FDI$ stocks predict higher (lower) returns. The anchoring-based explanation also implies that investors process small amounts of information, which generate small deviations, better than large amounts of information that cause sudden large deviations from the anchor and, in turn, a significant price underreaction.

To verify this assertion, we explore the interaction between each of the deviation indexes, $FDI$ and $PDI$, and the level of "suddenness." We repeat the Fama-MacBeth regression analyses reported in Tables 2 and 5 with two additional explanatory variables that represent the interaction of the deviation index with the level of suddenness: *SuddenUp* and *SuddenDown*. For each stock with an $FDI$ above the cross-sectional median $FDI$ in the relevant month, the suddenness of positive deviations is calculated as the maximum positive monthly change in the $FDI$ during the previous two quarters. *SuddenDown* is calculated analogously for negative changes and stocks with below-median $FDI$s. Similar variables apply to $PDI$.

The results are reported in Panel A of Table 7. Focusing on $FDI$, the coefficients of *SuddenUp* and *SuddenDown* coefficients are both positive at 13.47% and 9.35%, respectively, and highly significant ($t = 3.18$ and 2.91). For $PDI$, the slope coefficients are significant at 10% ($SuddenUp$) and 1% ($SuddenDown$).[10] Overall, the results are consistent with the notion that sudden changes in $FDI/PDI$ result in stronger return predictability than gradual changes, consistent with the anchoring rationale.

To further evaluate our claim of investors' anchoring, it is useful to note that firm's prices and accounting fundamentals ultimately move due to new information that trickles in about the firm. Thus, investors may anchor on information beyond accounting fundamentals. A primary source of such information is the advice disseminated by investment analysts (Womack, 1996). The logical extension to the arguments supporting anchoring is that investors might underreact to large changes in analysts' forecasts because they are anchored to prevailing consensus measures. Further, since anchoring on fundamentals can also be based on the consensus analysts forecast, a surprise deviation can be associated with a surprise deviation of earnings from their consensus. Similarly, anchoring on retained earnings or capital expenditures (that are associated with future stock price growth) can be associated with analysts' consensus buy/sell recommendations and price targets. These arguments suggest that there may be anchoring based on accounting fundamentals as well as on analysts' advice.

We next assess whether anchoring based on analysts' advice actually occurs and whether such anchors are incremental to $FDI$ and $PDI$. Prior to conducting the analyses, we note that Bouchaud et al. (2019) assume that the marginal investor anchors on EPS forecasts. Their sticky expectations-based rationale gives rise to the profitability anomaly along with price and earnings momentum. Our main theme in this paper is that distinct investors may anchor on heterogeneous types of information. Thus far, in essence, we have expanded the Bouchaud et al. (2019) to the case where numerous accounting items and financial ratios, beyond forecasted earnings per share, can serve as plausible anchors. We now extend the anchoring set to encompass multiple sources of analysts' advice such as shorter- and longer-term EPS forecasts, price targets, and investment recommendations.

[10]The slope coefficients of control variables in the $FDI$ and $PDI$ regressions are reported in Appendix G.

In particular, we define an analysts' deviation index, $ADI$, analogously to $PDI/FDI$. $ADI$ is the average of deviation measures related to analysts' forecasts: next quarters' and next years' EPS forecasts, investment recommendations, and stock price targets. Due to data availability, prior to 1993, $ADI$ includes only earnings forecasts and between 1993 and 1998, only EPS forecasts and recommendations. We use $ADI$ as a predictor of future returns.

The findings are reported in Panel B of Table 7. Replacing $FDI$ by $ADI$ in regressions similar to those reported in Table 5, the evidence still shows a positive and highly significant slope coefficient ($t = 7.36$). The slope coefficient remains strongly significant when excluding microcaps ($t = 5.52$), when the dependent variable is returns adjusted to Fama and French three factors plus momentum ($t = 5.89$), and when considering various market states. Finally, the slope coefficient for $ADI$ remains highly significant even when $PDI$ and $FDI$ are also included in the regression ($t = 7.41$, 11.10, and 19.05, for $ADI$, $PDI$, and $FDI$, respectively) suggesting that $ADI$ does have incremental information relative to $PDI$ and $FDI$. Overall, the evidence accords with investors using multiple sources of anchors on accounting fundamentals and analysts' advice.[11] From a conceptual standpoint, we thus propose the possibility of extending the notion of market expectations beyond EPS estimation (Bouchaud et al., 2019) to a comprehensive set of analysts' advice, and to other publicly observed accounting items and financial ratios.

In sum, the evidence supports the anchoring explanation for the effect of deviations from fundamentals. For one, the effect is stronger when changes from anchors are sudden versus gradual. In addition, an analogous effect exists also in deviations from analysts' forecasts, which is in line with the hypothesis that different investors anchor on different types of information salient to stock valuation.

[11]The evidence is not inconsistent with analysts themselves anchoring on information (Bouchaud et al., 2019). If analysts anchor, then big deviations manifested in $ADI$s will only occur when analysts receive sufficiently extreme information signals. In turn, if investors underreact to such deviations, $ADI$ will predict returns.

# 5 A Factor Based on Deviations from Fundamentals-Based Anchors

We propose a new factor based on $FDI$. To level the playing field, we form this factor, termed $FDF$, in a way consistent with $UMD$. Each month, we first split all stocks into two groups by the median market capitalization of NYSE stocks. We next consider two groups of stocks based on the deviation index. The first group is above the 70th percentile of NYSE $FDI$s, while the second is below the 30th percentile. We then form a value weighted portfolio that is long stocks with above-median market capitalization and an $FDI$ above 70th percentile. The corresponding short side is formed from stocks that have above-median market capitalization and an $FDI$ below 30th percentile. This long-short portfolio then forms our first portfolio. We then repeat the same procedure but using stocks with below-median market capitalization to obtain our second long-short portfolio. The $FDF$ factor obtains as the average return across these two long-short portfolios.

To assess performance of the newly proposed factor, we implement time-series regressions of $FDF$ on the comprehensive set of factors described earlier. Panel A of Table 8 presents intercepts (alphas) and slope coefficients (factor loadings). In the first test, $FDF$ is regressed on the five Fama-French (2015) factors along with $UMD$. The monthly alpha is substantial at 0.57% and highly significant. In line with the results for $PDI$ in Table 4, the slope coefficients of $UMD$ and $RMW$ are also significant; yet, they do not materially affect the large positive alpha associated with $FDF$.

The second test considers the two behavioral factors on a stand-alone basis. While the slope coefficient of $PEAD$ is significantly positive and that of $FIN$ is significantly negative, the $FDF$ alpha remains meaningful at 0.57% ($t = 5.49$). Likewise, results are quite similar in the next four tests with all individual factors ($PEAD$, $FIN$, $QMJ$, $SUE$, and $BAB$), the HXZ and SY models, and the all-inclusive kitchen-sink test. The associated alphas are large and highly significant in the range of 0.44%-0.59% per month.

To complement the analysis, Panel B of Table 8 reports similar time-series regressions with the $PDF$ factor replacing $FDF$. The $PDF$ factor is formed in a manner similar to $FDF$, with the difference that the portfolio construction is based on $PDI$ instead of $FDI$. We find that the monthly alphas corresponding to $PDF$ are all economically large ranging between 0.52% and 0.61%, and are highly significant.

We now provide a brief discussion on Sharpe ratios generated by the proposed factors. First, the full-sample Sharpe ratios of $FDF$ and $PDF$ are 1.11 and 1.48, respectively. For perspective, $UMD$ records a Sharpe ratio of 0.48, whereas the Novy-Marx (2013) gross profitability-based ($GP$) factor generates a Sharpe ratio of 0.41. The Sharpe ratios for both $FDF$ and $PDF$ are significantly different from $UMD$ and $GP$, with $p$-values less than 0.01. MacKinlay (1995) proposes that for a factor to represent priced risk, its Sharpe ratio should be moderate (not too large). He suggests an upper bound of 0.6, based on the ratio for the value-weighted CRSP index. The Sharpe ratios of $FDF$ and $PDF$ are substantially higher than this threshold. In Figure 3, we plot the five-year trailing averages of Sharpe ratios for $UMD$, $PDF$, and $FDF$ for our entire sample period (starting in 1984). The figure clearly demonstrates that $PDF$ and $FDF$ retain their high Sharpe ratios in the post-crisis period, whereas $UMD$ does not (Daniel and Moskowitz, 2016). Further, $PDF$ retains a high Sharpe ratio in the most recent five-year period relative to both $UMD$ and $FDF$.

In sum, $FDF$, the anchoring factor based on LASSO panel regressions, survives a long list of well-known factors. In, particular, the alpha obtained from the factor remains material in the presence of commonly-used factors, the two newly-proposed behavioral factors of Daniel, Hirshleifer, and Sun (2019), and standard momentum. Similarly, the $PDF$ factor, based on seven operating efficiency-related items, stands out as well. Overall, the $FDI/PDI$ strategy produces investment payoffs above and beyond well-known effects in the cross-section of equity returns.

# 6 Conclusion

We show that a high (low) distance between current values and moving averages of fundamentals related to operating performance ($PDI$) strongly predicts high (low) equity returns and the predictability survives a host of controls, including standard momentum, the 52-week high, and a comprehensive set of other cross-sectional return predictors. We also show that machine learning approaches are effective when applied to deviations of fundamentals from preceding means. Specifically, we develop a comprehensive predictor, based on a flexible machine learning approach applied to a complete set of fundamentals' deviations from their moving averages ($FDI$). We show that $FDI$ reliably predicts returns in the cross-section by producing alphas in excess of 15% (6%) for equal- (value-) weighted portfolios after accounting for a battery of established factor models. We also find that an $FDI$-based factor survives a large set of previously-proposed factors such as the five Fama and French (2015) factors, $UMD$, the mispricing factors of Daniel, Hirshleifer, and Sun (2019), and the investment and profitability factors of Hou, Xue, and Zhang (2015).

Since profits from $PDI/FDI$ strategies do not reverse in the long-run, they indicate investor underreaction, as opposed to continuing overreaction. We propose that the predictability arises because investors are overly anchored to the long-term average and update beliefs insufficiently in the light of new information. We test a specific implication of the anchoring hypothesis: Sudden changes in accounting fundamentals from their respective moving averages (anchors) should lead to greater underreaction. We find support for this hypothesis. We also show that investors anchor on analysts' advice, and the corresponding portfolios earn abnormal returns incremental to $PDI/FDI$.

Our work suggests avenues for future research. First, our $FDI$ measure is based on a sparse LASSO representation, and it would be interesting to examine whether non-sparse representations (e.g., ridge regressions) could better characterize the dependence of returns on fundamentals' deviations from their past means. Second, it is worth considering whether the profitability we find depends on the extent to which there is material public information available on companies, which, in turn, depends on disclosure requirements across countries, and whether it depends on persistence in firm's fundamental values. Third, it would be interesting to investigate whether there are cross-effects; i.e., whether stock prices underreact to accounting-based analogs of other stocks in the same industry. These and other topics are left for future research.

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**Table 1. Descriptive statistics**

The table displays descriptive statistics for stock returns and firm characteristics defined in Appendix A. The first two columns report sample means and standard deviations. The last two columns report sample correlations between *PDI* and *FDI* and each of the predictive characteristics. *PDI* and *FDI* indexes reflect deviations of operating performance (*PDI*) and deviations of a comprehensive set of accounting items (*FDI*) from their rolling means. The sample spans the period June 1977 through October 2017. Means, standard deviations, and correlations are based on vectorizing the panel data (month/firm) of each variable into a single column.

| | **Variable** | **Mean** | **Standard Deviation** | **Correlation with *PDI*** | **Correlation with *FDI*** |
|---|---|---|---|---|---|
| Style Variables | Log Size (*ME*) | 12.862 | 1.988 | 0.04 | 0.13 |
| | Book-to-Market (*BE/ME*) | 0.631 | 0.7.39 | –0.07 | –0.04 |
| Price Variables | Return over months –12 to –2 (*MOM*) | 0.231 | 0.715 | 0.02 | 0.01 |
| | Trend (*TREND*) | 0.238 | 0.127 | –0.02 | 0.15 |
| | 52-Week High Price (*52-HIGH*) | 0.790 | 0.183 | 0.10 | –0.02 |
| | Information Discreteness (*ID*) | –0.001 | 0.058 | –0.14 | –0.02 |
| | Recency Ratio (*RR*) | 0.538 | 0.360 | 0.13 | –0.03 |
| | All time maximum price (*Xmax*) | 0.606 | 0.285 | 0.10 | –0.02 |
| Fundamental Variables | Fundamental mispricing characteristic (*BG*) | 1.060 | 19.288 | 0.00 | –0.02 |
| | Standardized Unexpected Earnings (*SUE*) | 0.071 | 1.325 | 0.19 | 0.15 |
| | Standardized unexpected revenue growth (*SURGE*) | 0.651 | 1.253 | 0.17 | 0.02 |
| | Recommendation Upgrade-Downgrade (*RUD*) | −0.041 | 0.246 | 0.03 | –0.01 |
| | Net Stock Issues (*NS*) | 0.031 | 0.135 | –0.04 | –0.03 |
| | Assets Growth (*dA/A*) | 0.090 | 0.233 | –0.01 | –0.04 |
| | Profitability (*Y/B*) | 0.020 | 14.329 | –0.00 | –0.00 |
| | Investment-to-Assets (*I/A*) | 0.090 | 0.220 | –0.05 | –0.05 |
| | Gross Profitability (*GP*) | 0.388 | 0.892 | 0.02 | 0.00 |
| | Accruals (*Ac/A*) | −0.030 | 0.087 | –0.05 | –0.06 |
| | Return on Assets (*ROA*) | 0.041 | 0.863 | 0.01 | 0.00 |
| | Return on Equity (*ROE*) | 0.002 | 1.352 | 0.00 | 0.00 |
| | Net Operating Assets (*NOA*) | 0.676 | 0.442 | –0.03 | –0.04 |
| | Distress O-Score (*DTRS*) | −0.024 | 2.090 | 0.01 | 0.00 |
| | F-score (*F-S*) | 0.866 | 1.902 | –0.05 | 0.00 |
| | G-score (*G-S*) | 0.641 | 1.461 | 0.10 | 0.04 |
| Limits-to-Arbitrage Variables | Idiosyncratic Volatility (*IVOL*) | 0.109 | 0.059 | –0.01 | 0.03 |
| | Turnover (*TURN*) | 0.129 | 0.260 | 0.02 | 0.07 |
| | Illiquidity (*ILLIQ*) | 0.972 | 11.894 | –0.01 | –0.00 |
| Deviation Indexes | Performance Deviation Index (*PDI*) | 0.500 | 0.122 | 1.00 | 0.09 |
| | Fundamental Deviation Index (*FDI*) | 0.017 | 0.015 | 0.09 | 1.00 |

**Table 2. Cross-sectional regressions based on widely-followed accounting performance items**

The table reports average slopes (multiplied by $10^4$) and their *t*-values (in parentheses) obtained from monthly cross-sectional regressions. The dependent variable is the stock returns over (i) the next month, (ii) months 2-6, (iii) months 7-12, and (iv) months 13-24, as well as stock returns adjusted by the three Fama-French and momentum factors. *PDI* and control variables are all defined in Appendix A. The analysis is implemented for the entire sample period (June 1977 to October 2017) and for the most recent years (2001-2017). In addition, we examine stock return predictability with versus without microcap stocks (below the NYSE cutoff for the bottom quintile). Finally, we also consider various market states: (a) positive versus negative sentiment per Baker and Wurgler (2006), (b) below versus above median previous months' market volatility, (c) below versus above median previous months' market illiquidity per Amihud (2002), and (d) above and below market states per Cooper, Gutierrez, and Hameed (2004). One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively. Appendix D reports slope coefficients of all other control variables.

Panel A. Raw Returns

| **Dependent Variable** | | ***PDI*** | ***MOM*** | ***BG*** | **Averaged $R^2$** |
|---|---|---|---|---|---|
| $R_{t+1}$ | | 2.17*** | 0.24*** | 0.05*** | 0.10 |
| | | (13.83) | (2.76) | (3.55) | |
| $R_{t-2:t-6}$ | | 2.84*** | 0.38* | 0.06* | 0.11 |
| | | (7.73) | (1.88) | (1.93) | |
| $R_{t-7:t-12}$ | | 3.17*** | –0.70*** | 0.01 | 0.10 |
| | | (7.41) | (–3.86) | (0.23) | |
| $R_{t-13:t-24}$ | | 2.41*** | –1.52*** | 0.06 | 0.09 |
| | | (3.37) | (–5.07) | (0.82) | |
| Without Microcap Stocks | | | | | |
| $R_{t+1}$ | | 2.16*** | 0.38*** | 0.08** | 0.14 |
| | | (11.81) | (3.00) | (2.22) | |
| $R_{t-2:t-6}$ | | 1.10*** | 1.42*** | 0.19** | 0.14 |
| | | (2.69) | (5.00) | (2.47) | |
| $R_{t-7:t-12}$ | | 3.11*** | 0.54** | –0.08 | 0.14 |
| | | (6.22) | (2.17) | (–0.63) | |
| $R_{t-13:t-24}$ | | 2.40*** | –1.46*** | –0.55*** | 0.14 |
| | | (3.41) | (–3.23) | (–2.87) | |
| Period 2001-2017 | | | | | |
| $R_{t+1}$ | | 1.81*** | 0.04 | 0.01 | 0.09 |
| | | (7.20) | (0.27) | (0.89) | |
| $R_{t+1}$ | Without Microcap | 1.88*** | 0.18 | 0.07** | 0.14 |
| | Stocks | (6.98) | (1.02) | (1.97) | |

Panel B: Returns Adjusted to Fama–French and Momentum factors

| **Dependent** | | ***PDI*** | ***MOM*** | ***BG*** | **Averaged $R^2$** |
|---|---|---|---|---|---|
| Adjusted $R_{t+1}$ | | 2.00*** | 0.19** | 0.04*** | 0.07 |
| | | (13.59) | (2.21) | (3.03) | |
| Adjusted $R_{t+1}$ | Without Microcap | 1.92*** | 0.37*** | 0.04 | 0.10 |
| | Stocks | (11.83) | (3.01) | (1.07) | |

Panel C. Next Months' Returns versus Market States

| **Market State** | ***PDI*** | ***MOM*** | ***BG*** | **Averaged $R^2$** |
|---|---|---|---|---|
| Low Sentiment | 2.23*** | 0.23 | 0.09*** | 0.11 |
| | (7.38) | (1.35) | (2.59) | |
| High Sentiment | 2.26*** | 0.32*** | 0.04** | 0.10 |
| | (12.06) | (3.23) | (2.56) | |
| Low Volatility | 2.38*** | 0.30** | 0.06** | 0.10 |
| | (10.97) | (2.33) | (2.31) | |
| High Volatility | 1.96*** | 0.19 | 0.04*** | 0.10 |
| | (8.69) | (1.55) | (3.55) | |
| Low liquidity | 1.85*** | 0.12 | 0.08*** | 0.09 |
| | (9.74) | (1.02) | (3.49) | |
| High liquidity | 2.50*** | 0.36*** | 0.03 | 0.11 |
| | (10.04) | (2.86) | (1.35) | |
| Low Market | 2.21*** | –0.19 | 0.05 | 0.11 |
| | (4.04) | (–0.55) | (1.49) | |
| High Market | 2.17*** | 0.30*** | 0.05*** | 0.10 |
| | (13.32) | (3.36) | (3.28) | |

**Table 3. Annual alphas of *PDI* portfolios and break-even transaction costs**

Panel A reports annual alphas (in %) and their *t*-values (in parentheses) obtained from regressing monthly zero-cost portfolio returns on the three Fama-French and momentum factors. Annual alphas are obtained by multiplying monthly alphas by 12 (no compounding). The *PDI* strategy takes a long (short) position in the top (bottom) *PDI* decile, where *PDI* is a performance deviation index defined in Appendix A. Panel B reports transaction costs that would zero out average abnormal returns (alpha) on zero-cost portfolios reported in Panel A. Portfolios with different time horizons are equal-weighted. The sample is from June 1977 to October 2017. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Annual alpha

| | **Holding Period (months)** | | | | | |
|---|---|---|---|---|---|---|
| | **1** | **3** | **6** | **12** | **18** | **24** |
| Equally-Weighted (EW) Portfolios | 16.24*** | 11.88*** | 6.77*** | 4.64*** | 3.44*** | 3.45*** |
| | (13.74) | (11.27) | (7.19) | (5.78) | (4.77) | (5.36) |
| EW without Microcap Stocks | 13.96*** | 9.07*** | 4.04*** | 3.26*** | 2.23*** | 2.46*** |
| | (10.34) | (7.43) | (3.76) | (3.76) | (2.95) | (3.63) |
| Value-Weighted (VW) Portfolios | 8.79*** | 6.41*** | 3.62*** | 3.60*** | 2.14** | 1.75* |
| | (4.79) | (4.01) | (2.61) | (3.05) | (2.02) | (1.86) |
| VW without Microcap Stocks | 8.30*** | 6.03*** | 3.34** | 3.43*** | 1.97* | 1.60 |
| | (4.41) | (3.66) | (2.35) | (2.85) | (1.82) | (1.66) |

Panel B. Break-even transaction costs

| | **Holding Period (months)** | | | | | |
|---|---|---|---|---|---|---|
| | **1** | **3** | **6** | **12** | **18** | **24** |
| Equally-Weighted (EW) Portfolios | 205 | 225 | 257 | 352 | 392 | 523 |
| EW without Microcap Stocks | 173 | 169 | 150 | 242 | 248 | 365 |
| Value-Weighted (VW) Portfolios | 111 | 122 | 137 | 273 | 243 | 266 |
| VW without Microcap Stocks | 103 | 112 | 124 | 255 | 219 | 238 |

**Table 4. Risk and characteristic profiles of *PDI* portfolios**

Panel A reports various risk measures for the top *PDI* decile, the bottom *PDI* decile, and top-minus-bottom equally-weighted portfolios. Panel B reports the same risk measures for value weighted portfolios. Panel C reports average firm characteristics for *PDI* decile portfolios. The second column in Panel A and B reports the past 200-day mean standard deviation of daily stock returns. The third column reports the standard deviation (*STD*) of monthly portfolio 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 the Fama and French's (2015) five-factor model plus momentum. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

| | Stock | Portfolio | Fama-French Five-Factor Model plus *UMD* | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Portfolio** | **Mean 200-Day** | **Monthly *STD*** | **Intercept** | **Market** | **Size** | ***HML*** | ***RMW*** | ***CMA*** | ***UMD*** |
| | | | Panel A. Equally-Weighted Portfolios | | | | | | |
| Top Decile | 13.4 | 5.36 | 1.14*** | 0.98*** | 0.76*** | –0.03 | 0.15*** | 0.02 | –0.02 |
| | | | (15.67) | (55.66) | (29.02) | (–0.33) | (4.36) | (0.34) | (–1.11) |
| Bottom Decile | 14.2 | 5.85 | –0.09 | 0.96*** | 0.89*** | 0.00 | –0.17** | 0.03 | –0.13*** |
| | | | (–1.20) | (53.76) | (33.80) | (0.11) | (–5.11) | (0.59) | (–7.93) |
| (Equal Slopes *t*–test) | | | (11.90) | (0.91) | (–3.51) | (−0.62) | (6.69) | (–0.18) | (4.84) |
| Top−minus–Bottom | | 2.26 | 1.23*** | 0.02 | –0.13*** | –0.03 | 0.32*** | –0.01 | 0.113*** |
| | | | (12.65) | (0.97) | (–3.73) | (–0.66) | (7.12) | (–0.19) | (5.15) |
| | | | Panel B. Value-Weighted Portfolios | | | | | | |
| Top Decile | 9.82 | 5.14 | 0.53*** | 0.99*** | 0.12*** | −0.20*** | 0.05 | –0.10 | 0.12*** |
| | | | (5.06) | (38.80) | (3.15) | (−4.05) | (1.11) | (–1.30) | (5.13) |
| Bottom Decile | 10.33 | 5.57 | –0.11 | 0.97*** | 0.25*** | –0.26 | –0.24*** | 0.09 | –0.16*** |
| | | | (–0.91) | (31.99) | (5.57) | (–4.41) | (–4.24) | (1.06) | (–5.59) |
| (Equal Slopes *t*–test) | | | (3.95) | (0.53) | (–2.23) | (0.76) | (3.96) | (–1.65) | (7.48) |
| Top−minus–Bottom | | 3.53 | 0.64*** | 0.02 | –0.13** | 0.06 | 0.29*** | –0.19 | 0.28*** |
| | | | (4.15) | (0.56) | (–2.33) | (0.80) | (4.15) | (–1.73) | (7.94) |

Panel C. Characteristics of *PDI* Portfolios

| **Portfolio** | **Market Cap ($ million)** | ***BE/ME*** | ***TURN*** | ***ILLIQ*** | ***IVOL*** | ***O-Score*** | **Share of Institutional Holdings** | **Number of Analysts** |
|---|---|---|---|---|---|---|---|---|
| *PDI* Bottom Decile | 1,712 | 0.68 | 0.13 | 1.22 | 0.12 | –0.07 | 0.37 | 4.01 |
| *PDI* Core (Deciles 2-9) | 3,665 | 0.64 | 0.13 | 0.93 | 0.11 | –0.02 | 0.40 | 4.73 |
| *PDI* Top Decile | 3,017 | 0.54 | 0.15 | 1.04 | 0.12 | –0.02 | 0.39 | 4.52 |

**Table 5. Cross-sectional regressions based on the Fundamental Deviations Index (*FDI*)**

The table reports average slopes (multiplied by $10^4$) and their *t*-values (in parentheses) obtained from monthly cross-sectional regressions. The dependent variable is next month stock returns or excess stock returns adjusted to the three Fama-French and momentum factors. The *FDI* index reflects deviations of fundamental items from their rolling means. *FDI* and the control variables are defined in Appendix A, and slope coefficients of all control variables are reported in Appendix F. The analysis is implemented for the entire sample period (January 1979 to October 2017) and for the most recent years (2001-2017). In addition, we examine stock return predictability with versus without microcap stocks (below the NYSE cutoff for the bottom 20%). Finally, we consider various market states: (a) positive versus negative sentiment per Baker and Wurgler (2006), (b) below versus above median previous months' market volatility, (c) below versus above median previous months' market illiquidity per Amihud (2002), and (d) and above and below market states as in Cooper, Gutierrez, and Hameed (2004). One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

| | ***FDI*** | ***MOM*** | ***BG*** | **Averaged $R^2$** |
|---|---|---|---|---|
| | 52.96*** | 0.28*** | 0.05*** | 0.10 |
| | (17.45) | (3.20) | (4.39) | |
| Without Microcap Stocks | 42.55*** | 0.44*** | 0.08*** | 0.14 |
| | (12.64) | (3.71) | (3.07) | |
| Period 2001−2017 | 40.93*** | 0.05 | 0.01 | 0.10 |
| | (12.19) | (0.31) | (0.87) | |
| $R_{t+1}$ Adjusted to Fama-French and momentum | 50.70*** | 0.24*** | 0.04*** | 0.07 |
| | (18.13) | (2.74) | (4.32) | |
| Low Sentiment | 41.75*** | 0.33* | 0.08*** | 0.10 |
| | (6.90) | (1.91) | (3.91) | |
| High Sentiment | 59.61*** | 0.33*** | 0.04*** | 0.10 |
| | (16.93) | (3.34) | (2.62) | |
| Low Volatility | 45.83*** | 0.18 | 0.06*** | 0.09 |
| | (10.64) | (1.50) | (3.61) | |
| High Volatility | 59.85*** | 0.38*** | 0.04*** | 0.11 |
| | (14.14) | (2.97) | (2.60) | |
| Low Liquidity | 55.15*** | 0.39*** | 0.05*** | 0.09 |
| | (11.74) | (2.98) | (2.84) | |
| High Liquidity | 50.95*** | 0.19 | 0.04*** | 0.10 |
| | (13.03) | (1.56) | (3.54) | |
| Low Market | 32.41*** | –0.16 | 0.05 | 0.11 |
| | (5.66) | (–0.47) | (1.55) | |
| High Market | 55.71*** | 0.34*** | 0.05*** | 0.09 |
| | (16.72) | (3.89) | (4.11) | |

**Table 6. Annual alphas from *FDI* portfolios and modern factor models**

The table reports annual alphas (in %) and their *t*-values (in parentheses) obtained from regressing monthly zero-cost portfolio returns on the three/five Fama-French factors, *UMD*, as well as the following factors: Long-horizon financing (*FIN*) and short-horizon inattention (*PEAD*) mispricing factors of Daniel, Hirshleifer, and Sun (2019), Quality minus Junk (*QMJ*) of Asness, Frazzini and Pedersen (2019), Standardized Unexpected Earnings (*SUE*), Betting Against Beta (*BAB*) of Frazzini and Pedersen (2014), management (*MGMT*) and performance (*PERF*) mispricing factors of Stambaugh and Yuan (2017), and investment (*IVA*) and return on equity (*ROE*) factors of Hou, Xue, and Zhang (2015). When Stambaugh and Yuan (SY) and Hou, Xue, and Zhang (HXZ) models are employed we use their versions for market and size factors. Annual alphas are obtained by multiplying monthly alphas by 12 (no compounding). The *FDI* portfolios take long (short) positions in top (bottom) deciles, where *FDI*, defined in the data section and Appendix A, is an index reflecting deviations of fundamental items from their rolling means. Portfolios with different time horizons are equal-weighted. As *FDI* starts in January 1979 the investment period starts in February 1979 through November 2017 (December 2016 in case of SY and HXZ models). One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

| | **Equally-Weighted Portfolios** | | | **Value-Weighted Portfolios** | | |
|---|---|---|---|---|---|---|
| **Investment horizon:** | **1** | **3** | **6** | **1** | **3** | **6** |
| FF Three Factors + *UMD* | 18.71*** | 15.40*** | 12.23*** | 5.82*** | 6.55*** | 6.13*** |
| | (12.24) | (10.67) | (9.09) | (2.83) | (3.60) | (3.64) |
| FF Five Factors + *UMD* | 20.08*** | 16.77*** | 13.49*** | 7.33*** | 8.08*** | 8.01*** |
| | (13.06) | (11.54) | (9.92) | (3.52) | (4.39) | (4.77) |
| FF Five Factors+ *UMD* + *PEAD* + *FIN* | 19.48*** | 16.23*** | 13.13*** | 7.66*** | 8.13*** | 7.78*** |
| | (12.02) | (10.59) | (9.16) | (3.49) | (4.20) | (4.40) |
| SY Four Factors | 18.65*** | 16.02*** | 13.84*** | 6.23*** | 7.21*** | 7.56*** |
| | (10.01) | (9.06) | (8.58) | (2.58) | (3.37) | (3.81) |
| HXZ Four Factors | 20.15*** | 16.86*** | 13.47*** | 6.96*** | 7.83*** | 7.57*** |
| | (10.71) | (9.58) | (8.50) | (2.91) | (3.71) | (3.81) |
| FF Five factors + *UMD* + *PEAD* + *FIN* + | 19.98*** | 17.28*** | 14.73*** | 8.48*** | 8.86*** | 8.55*** |
| *QMJ* + *BAB* + *SUE*+ *MGMT*+ *PERF* + *IVA* + *ROE* | (11.88) | (11.00) | (10.13) | (3.74) | (4.39) | (4.73) |

**Table 7. Tests for anchoring**

The table repeats the Fama-MacBeth regression analyses reported in Tables 2 and 5 with some modifications. Panel A adds two additional explanatory variables: SuddenUp and SuddenDown that stand for the interaction of *FDI*/*PDI* with the level of deviation suddenness. The suddenness level of positive deviations is calculated for each stock with *FDI*/*PDI* above median as the maximum positive monthly change in *FDI*/*PDI* in the preceding two quarters. SuddenDown is calculated the same way for each stock with *FDI*/*PDI* below median and with minimum negative changes. In Panel B, *FDI*/*PDI* is replaced by analysts' deviation index (*ADI*). *ADI* is the average of deviations (from recent means) of analysts' forecasts for (i) next quarter EPS, (ii) next year EPS, (iii) recommendation, and (iv) stock price target. Slope coefficients of all control variables are reported in Appendix G. The analyst subsample is from 1984 to October 2017. One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Sudden versus Gradual Deviations from Anchor

| | ***FDI/PDI*** | ***MOM*** | ***BG*** | ***SuddenUp*** | ***SuddenDown*** | **Averaged $R^2$** |
|---|---|---|---|---|---|---|
| *PDI* | 1.70*** | 0.25*** | 0.05*** | 0.36* | 0.50*** | 0.10 |
| | (6.98) | (2.87) | (3.56) | (1.74) | (2.64) | |
| *FDI* | 41.27*** | 0.32*** | 0.03*** | 13.47*** | 9.35*** | 0.10 |
| | (11.96) | (3.31) | (2.66) | (3.18) | (2.91) | |

Panel B. Cross-sectional Regressions with Analysts' Forecasts Deviation Index (*ADI*)

| **Dependent Variable** | ***ADI*** | ***MOM*** | ***BG*** | ***PDI*** | ***FDI*** | **Averaged $R^2$** |
|---|---|---|---|---|---|---|
| | 0.63*** | 0.35*** | 0.03*** | | | 0.09 |
| | (7.36) | (3.66) | (3.10) | | | |
| Without Microcap Stocks | 0.49*** | 0.49*** | 0.07*** | | | 0.14 |
| | (5.52) | (3.77) | (2.52) | | | |
| Period 2001-2017 | 0.60*** | 0.08 | 0.02 | | | 0.09 |
| | (4.83) | (0.56) | (1.18) | | | |
| Adjusted to Fama-French and momentum | 0.53*** | 0.31*** | 0.03*** | | | 0.07 |
| | (5.89) | (3.26) | (3.00) | | | |
| Low Sentiment | 0.64*** | 0.29 | 0.06*** | | | 0.09 |
| | (4.16) | (1.43) | (2.71) | | | |
| High Sentiment | 0.66*** | 0.46*** | 0.02* | | | 0.09 |
| | (6.21) | (4.50) | (1.88) | | | |
| Low Volatility | 0.34*** | 0.27** | 0.03** | | | 0.08 |
| | (2.81) | (2.00) | (2.17) | | | |
| High Volatility | 0.87*** | 0.41*** | 0.03** | | | 0.10 |
| | (7.33) | (3.09) | (2.23) | | | |
| Low Liquidity | 0.69*** | 0.48*** | 0.04* | | | 0.08 |
| | (5.26) | (3.28) | (1.83) | | | |
| High Liquidity | 0.59*** | 0.25** | 0.03*** | | | 0.10 |
| | (5.17) | (1.98) | (2.72) | | | |
| Low Market | 0.96*** | –0.14 | 0.06* | | | 0.11 |
| | (4.13) | (–0.41) | (1.69) | | | |
| High Market | 0.58*** | 0.43*** | 0.03*** | | | 0.09 |
| | (6.30) | (4.47) | (2.63) | | | |
| Control for *PDI*/*FDI* | 0.64*** | 0.29*** | 0.03*** | 1.86*** | 46.26*** | 0.10 |
| | (7.41) | (3.03) | (2.63) | (11.10) | (19.05) | |

**Table 8. Regressions for Fundamental deviations-based Factors**

The table reports alphas, factor loadings, and their *t*-values (in parentheses) obtained from separately regressing the anchoring-based factors (*FDF* and *PDF*) on the five Fama-French factors, *UMD*, and factors from the following list: Long-horizon financing (*FIN*) and short-horizon inattention (*PEAD*) mispricing factors of Daniel, Hirshleifer, and Sun (2019), Quality minus Junk (*QMJ*) of Asness, Frazzini and Pedersen (2019), Standardized Unexpected Earnings (*SUE*), Betting Against Beta (*BAB*) of Frazzini and Pedersen (2014), management (*MGMT*) and performance (*PERF*) mispricing factors of Stambaugh and Yuan (2017) and investment (*IVA*) and return on equity (*ROE*) of Hou, Xue, and Zhang (2015). When the Stambaugh and Yuan (SY) and Hou, Xue, and Zhang (HXZ) models are employed we use their versions that apply to market and size factors. *FDF* (*PDF*) is calculated from six value-weighted portfolios formed on size (using the median NYSE benchmark) and *FDF* (*PDF*) at the $30^{th}$ and $70^{th}$ NYSE percentiles. *FDF* (*PDF*) is the average return on the two high *FDF* (*PDF*) portfolios minus the average return on the two low *FDF* (*PDF*) portfolios. The sample is from June 1977 (regressions start at February 1979 when having first *FDF* observation) to October 2017 (December 2016 in case of *MGMT*, *PERF*, *IVA* and *ROE*). One, two, and three asterisks indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. *FDF* as the Dependent Variable

| $\alpha$ | Market | Size | *HML* | *RMW* | *CMA* | *UMD* | *PEAD* | *FIN* | *QMJ* | *SUE* | *BAB* | *MGMT* | *PERF* | *IVA* | *ROE* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.57*** | 2.27 | 5.57* | –9.24** | –14.48*** | 7.31 | 30.10*** | | | | | | | | | |
| (6.68) | (1.09) | (1.81) | (–2.28) | (–3.68) | (1.24) | (15.74) | | | | | | | | | |
| 0.57*** | | | | | | | 36.09*** | –8.46*** | | | | | | | |
| (5.49) | | | | | | | (6.94) | (–3.39) | | | | | | | |
| 0.57*** | | | | | | | 33.07*** | –9.96*** | 6.02 | 7.36** | –3.43 | | | | |
| (5.45) | | | | | | | (6.10) | (–2.82) | (1.14) | (2.40) | (–1.10) | | | | |
| 0.56*** | 1.45 | 20.88*** | | | | | | | | | | | | –8.77** | 25.70*** |
| (5.17) | (0.58) | (5.79) | | | | | | | | | | | | (–1.53) | (6.23) |
| 0.44*** | 7.28*** | 18.24*** | | | | | | | | | | 1.29 | 24.85*** | | |
| (4.20) | (2.78) | (4.92) | | | | | | | | | | (0.33) | (10.08) | | |
| 0.59*** | 2.08 | 11.29*** | –11.62** | –15.39** | 5.30 | 26.85*** | 0.61 | 2.01 | –18.04** | –3.39 | –13.55*** | 18.07*** | 3.41 | –6.61 | 21.17*** |
| (6.40) | (0.85) | (3.32) | (–2.19) | (–2.16) | (0.46) | (8.29) | (0.12) | (0.40) | (–2.11) | (–1.31) | (–4.96) | (2.74) | (0.75) | (–0.58) | (3.40) |

Panel B. *PDF* as the Dependent Variable

| *α* | **Market** | **Size** | ***HML*** | ***RMW*** | ***CMA*** | ***UMD*** | ***PEAD*** | ***FIN*** | ***QMJ*** | ***SUE*** | ***BAB*** | ***MGMT*** | ***PERF*** | ***IVA*** | ***ROE*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.58*** | 5.92*** | –5.81** | –3.35 | 20.32*** | –6.32 | 15.32*** | | | | | | | | | |
| (7.83) | (3.28) | (–2.18) | (–1.24) | (5.98) | (–1.24) | (9.27) | | | | | | | | | |
| 0.61*** | | | | | | | 18.45*** | 1.81 | | | | | | | |
| (6.96) | | | | | | | (4.38) | (0.90) | | | | | | | |
| 0.57*** | | | | | | | 7.61* | –11.01*** | 25.29*** | 13.12*** | 4.22* | | | | |
| (7.13) | | | | | | | (1.86) | (–4.13) | (6.33) | (5.67) | (1.79) | | | | |
| 0.52*** | 6.03*** | –0.77 | | | | | | | | | | | | –9.79** | 40.17*** |
| (7.16) | (3.55) | (–0.32) | | | | | | | | | | | | (–2.53) | (14.50) |
| 0.57*** | 8.43*** | –7.03** | | | | | | | | | | –0.25 | 22.19*** | | |
| (7.16) | (4.24) | (–2.59) | | | | | | | | | | (–0.08) | (11.83) | | |
| 0.52*** | 4.31** | –4.94* | –1.31 | 8.45 | –6.26 | 1.96 | 1.98 | –9.30** | –17.16** | 7.23*** | –1.99*** | 11.20** | 8.50** | –1.82 | 34.07*** |
| (6.85) | (2.14) | (–1.77) | (–0.30) | (1.44) | (–0.66) | (0.74) | (0.49) | (–2.26) | (–2.44) | (3.39) | (–0.89) | (2.07) | (2.28) | (–0.20) | (6.67) |

**Figure 1: *PDI*-based investing**

The figure depicts the value of $1 invested each month for the next month through buy and sell *PDI* portfolios. The *PDI* strategy takes long (short) positions in the top (bottom) *PDI*-based deciles, where the *PDI* index reflects deviations from seven measures related to firms' operating performance. Deviation is defined as the most recent quarterly release, minus the mean in the preceding three quarters, scaled by total assets. The all-market return reflects the CRSP value-weighted composite index. Gray bars represent NBER-defined recessions.

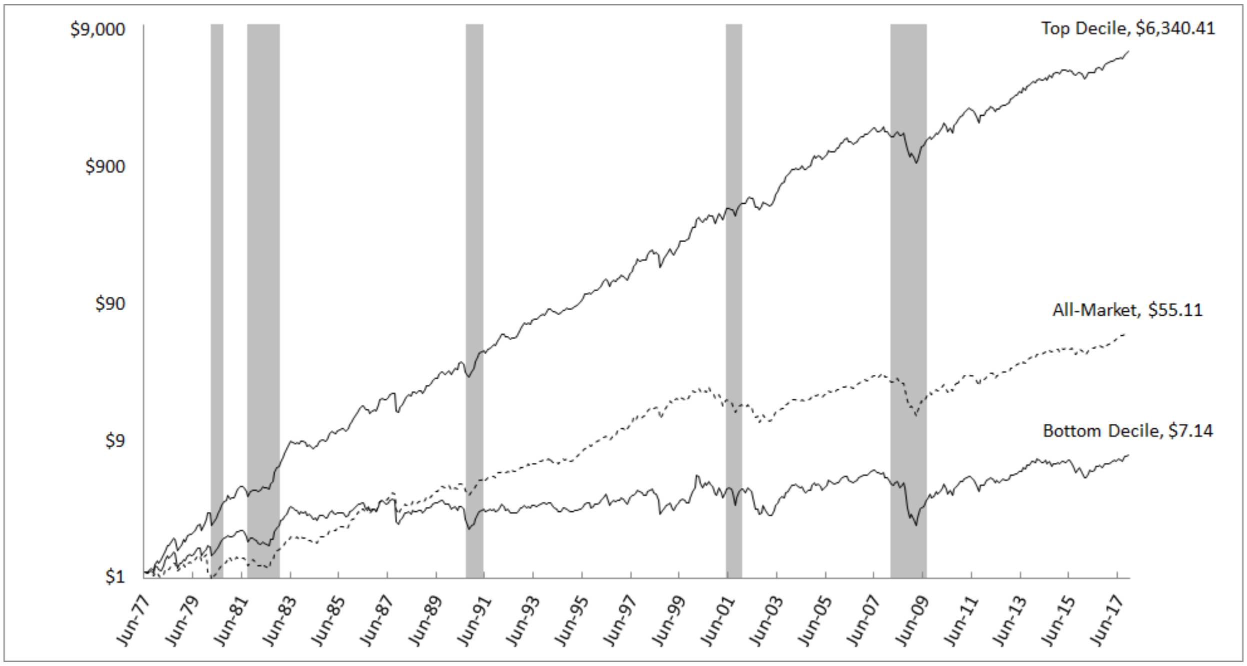


**Figure 2: *FDI*-based investing**

The figure depicts the value of $1 invested each month for the next month through buy and sell *FDI* portfolios. The *FDI* strategy takes long (short) positions in the top (bottom) *FDI* based decile, where *FDI* is an index which reflects deviations from the means of the firms' accounting variables and accounting ratios. The all-market return reflects the CRSP value-weighted composite index. Gray bars represent NBER-defined recessions.

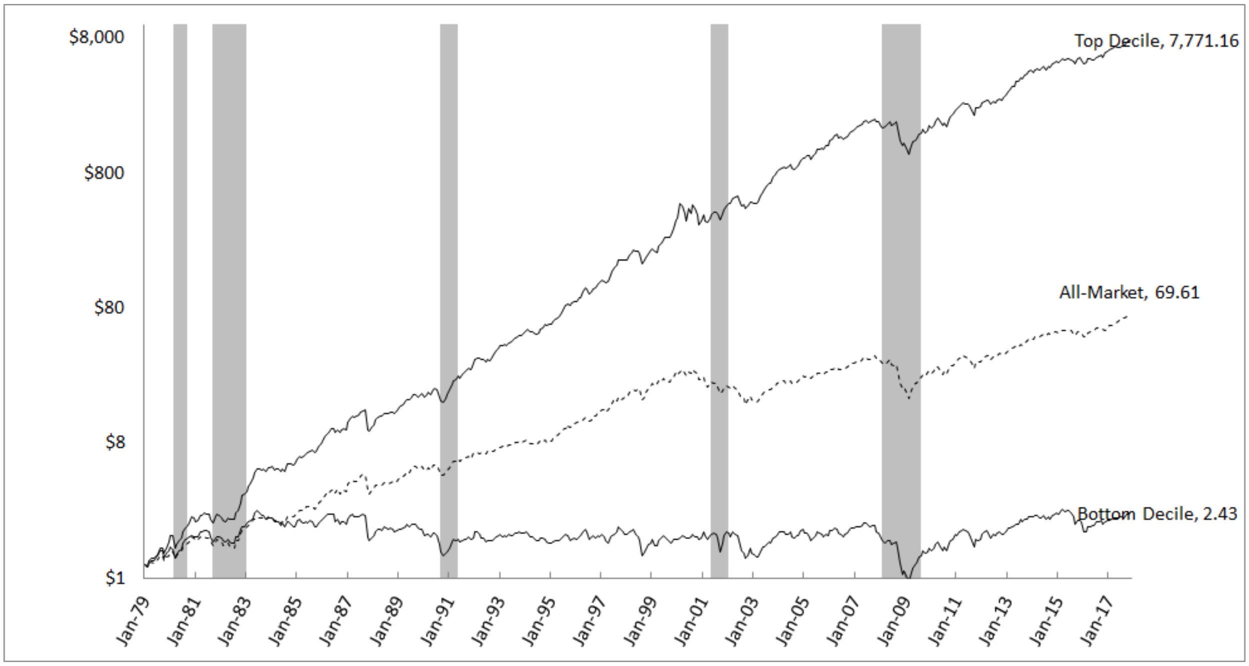
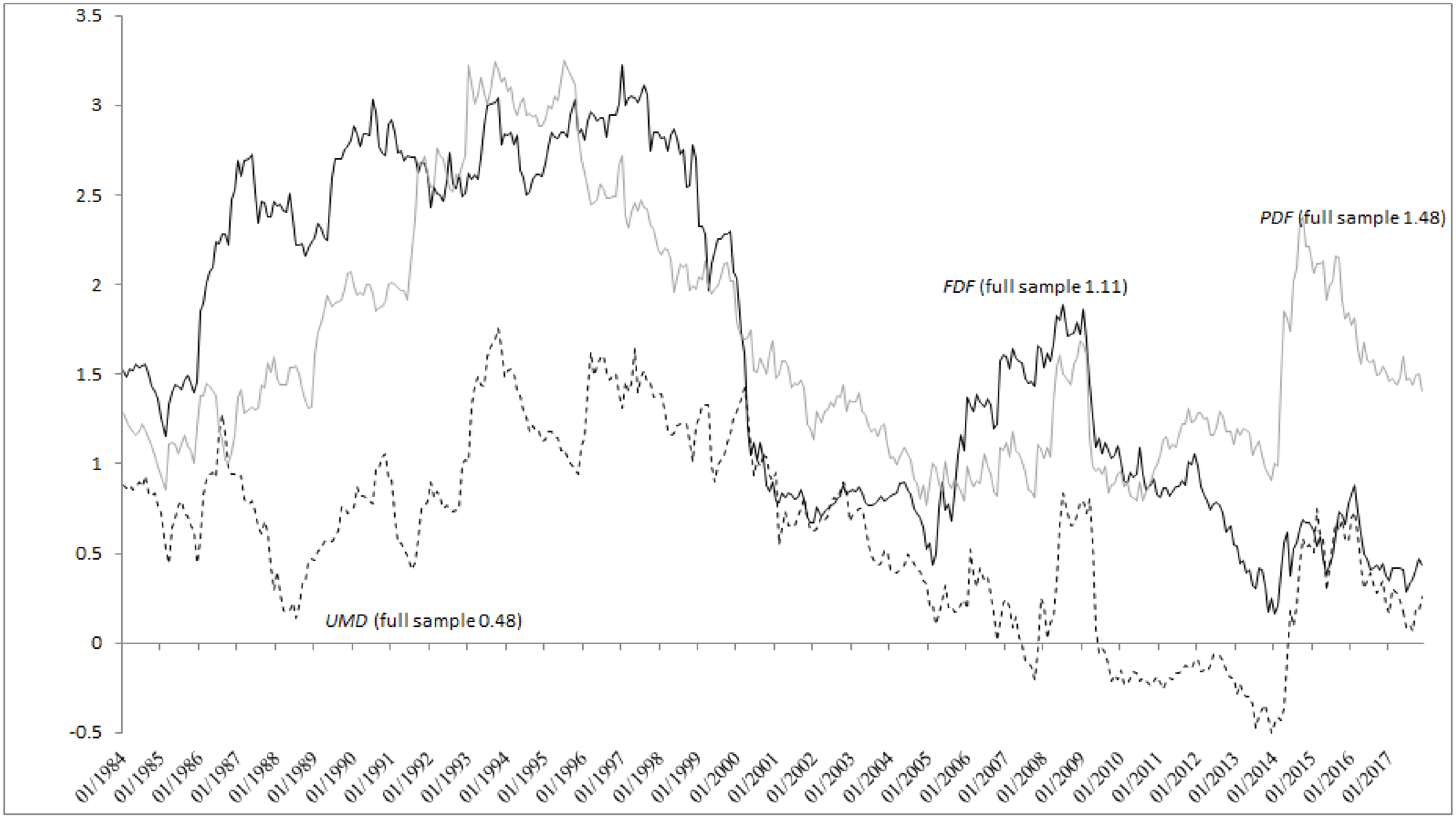


**Figure 3. Sharpe ratios for Fundamental deviation from Anchors Factor (*FDF*)**

The figure depicts five-year trailing Sharpe ratios for *FDF* and *PDF* vs the *UMD* factor. *FDF* (*PDF*) is calculated from six value-weighted portfolios formed on size (using the median NYSE cutoff) and *FDI* (*PDI*) at the 30th and 70th NYSE percentiles. *FDF* (*PDF*) is the average return on the two high *FDI* (*PDF*) portfolios minus the average return on the two low *FDI* (*PDI*) portfolios. The momentum factor, *UMD* is from Ken French's library. *FDF* starts in February 1979 and the first five-year Sharpe ratio is obtained for January 1984.



## Appendix A. Variable Definitions

Performance Deviation Index (*PDI*) = equally weighted average of seven fundamental deviation measures related to firm's operating performance: Cash and short-term investments, retained Earnings, operating Income, sales, capital expenditures, invested capital, and inventories. Deviation is defined as the most recent quarterly release, if it exists during the previous six months, minus the mean in the preceding three quarters, scaled by total assets. Each deviation is assigned a percentile value relative to all stocks' deviations in the previous year (one minus the percentile for invested capital and inventories). Deviations are equally weighted to obtain the *PDI* measure. If the release date is not available, we assume a 60-day delay in release to guarantee data availability for investors.

Fundamental Deviation Index (*FDI*) = The index is based on deviations in all Compustat accounting variables plus 14 basic accounting ratios (the list is given in Appendix B). The *FDI* index is calculated every month from all available deviation data up to that month using standard least absolute shrinkage and selection (LASSO) procedure. In particular, consider month *J*. We run a monthly LASSO panel regression of stock returns up to month *J* on previous-month deviations. Slope coefficients from that regression reflect sources of both time-series and cross-sectional return predictability by deviation variables. *FDI* is computed as the fitted value of that regression using time *t* realizations of deviation variables. Thus, *FDI* weights deviation variables based on their strength in predicting future returns. We require a minimum of 18 monthly observations to calculate the first stock-level *FDI* (the first time-series observation for each stock), hence, the index starts at January 1979. Then, we employ an expanding scheme to regenerate *FDI* variables based on LASSO panel regressions. Deviation variables are based on the most recent quarterly release, if it exists during the previous six months, minus the mean in the preceding three quarters, scaled by total assets in case of the accounting variables. There is no scaling for accounting ratios. Each deviation is assigned a percentile value relative to all stocks' deviations in the previous year. If the exact release date of the accounting reports within the month is not given, we assume a 60-day delay in release to guarantee data availability for investors.

Analysts Deviation Index (*ADI*) = equally weighted average of four deviation measures related to analysts' next quarter and the next year EPS forecasts, analysts' recommendation, and analysts' stock price target. Deviations in EPS forecasts and stock price targets are defined as the monthly mean forecast across analysts minus the mean in the preceding month scaled by stock price. The deviation in recommendations is defined as the I/B/E/S's 1 to 5 scale monthly mean minus the mean in the preceding month, multiplied by minus one to account for the I/B/E/S scale's reverse order. Each deviation is assigned a percentile value relative to all stocks' deviations in the previous year. The four deviation percentiles are equally weighted to obtain the *ADI* measure. EPS measures are from 1983 (so *ADI* starts from 1984), recommendation and stock price targets are from 1993 and 1999, respectively. Thus, prior to 1993 *ADI* includes only earnings forecasts and between 1993 and 1998, only EPS forecasts and recommendations. If a stock does not have any of the forecasts it is not included in *ADI* percentile and average calculations, and it is assigned an *ADI* value of zero.

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

Past Returns ($R_{t\text{-i}:t\text{-}j}$) = Past return control variables over one month ($R_{t\text{-}1}$), months 13-24 ($R_{t\text{-}13:t\text{-}24}$), and months 25-36 ($R_{t\text{-}25:t\text{-}36}$).

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

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

52-Week High Price (*52-HIGH*) = current price/highest price during the last 52 weeks.

Information Discreteness (*ID*) = sign(PRET)×[%neg−%pos], where %pos and %neg are the percentage of days with positive and negative returns over the past 12 months after skipping the most recent month, and PRET is defined as a firm's cumulative return over the same period, as in Da, Gurun and Warachka (2014).

All time maximum price (*Xmax*) = Current price scaled by all-rime maximum price as in Li and Yu (2012).

Recency Ratio (*RR*) = Unit minus the percentage of the year elapsed since the price was maximal in the last 52 weeks, as in Bhootra and Hur (2013).

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.

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

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

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

F-score (*F-S*) = Index for value firms within the top quartile of Book-to-Market (*BE/ME*) stocks. The index is based on fundamentals aimed to measure probability, changes in capital structure and ability to serve future debt, and operating efficiency, as in Piotroski (2000).

G-score (*G-S*) = Index for growth firms within the bottom quartile of Book-to-Market (*BE/ME*) stocks. The index is based on fundamentals such as earnings stability, growth stability and intensity of R&D, capital expenditure and advertising, as in Mohanram (2005).

Fundamental mispricing characteristic (*BG*) = The difference between firm's actual value and median predicted fair value from employs 28 most common firm-level accounting variables as in Bartram and Grinblatt (2018).

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 / lagged total assets, as in Sloan (1996).

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

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

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

Fama and French (2006).

Net Operating Assets (*NOA*) = the difference between operating assets and operating liabilities / lagged total assets, as in Hirshleifer, Hou, Teoh, and Zhang (2004).

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

Distress O-Score (*O-S*) = 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 / lagged total assets, as in Chen, Novy-Marx, and Zhang (2011).

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

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

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

**Appendix B. Construction of *FDI***

The table displays descriptive statistics for all deviation variables employed in forming the Fundamental Deviations Index (*FDI*). Each deviation variable is calculated as the most recent quarterly release minus the mean over the preceding three quarters scaled by total assets. There is no scaling of accounting ratios. The deviation variable is then assigned a percentile value relative to all stocks' deviations in the previous year. We use the LASSO procedure to construct the *FDI* index. Variables are presented in the table in descending order by the number of months they are retained in LASSO. The table reports only variables that are retained at least once out of a universe of 159 Compustat variables plus 14 accounting ratios (current, quick, cash, operating cash flow, debt, debt to equity, interest coverage, asset turnover, inventory turnover, receivable turnover, gross margin, operating margin, return on assets, and return on equity). Accounting ratios are in italics. The accounting data is from June 1976 through October 2017.

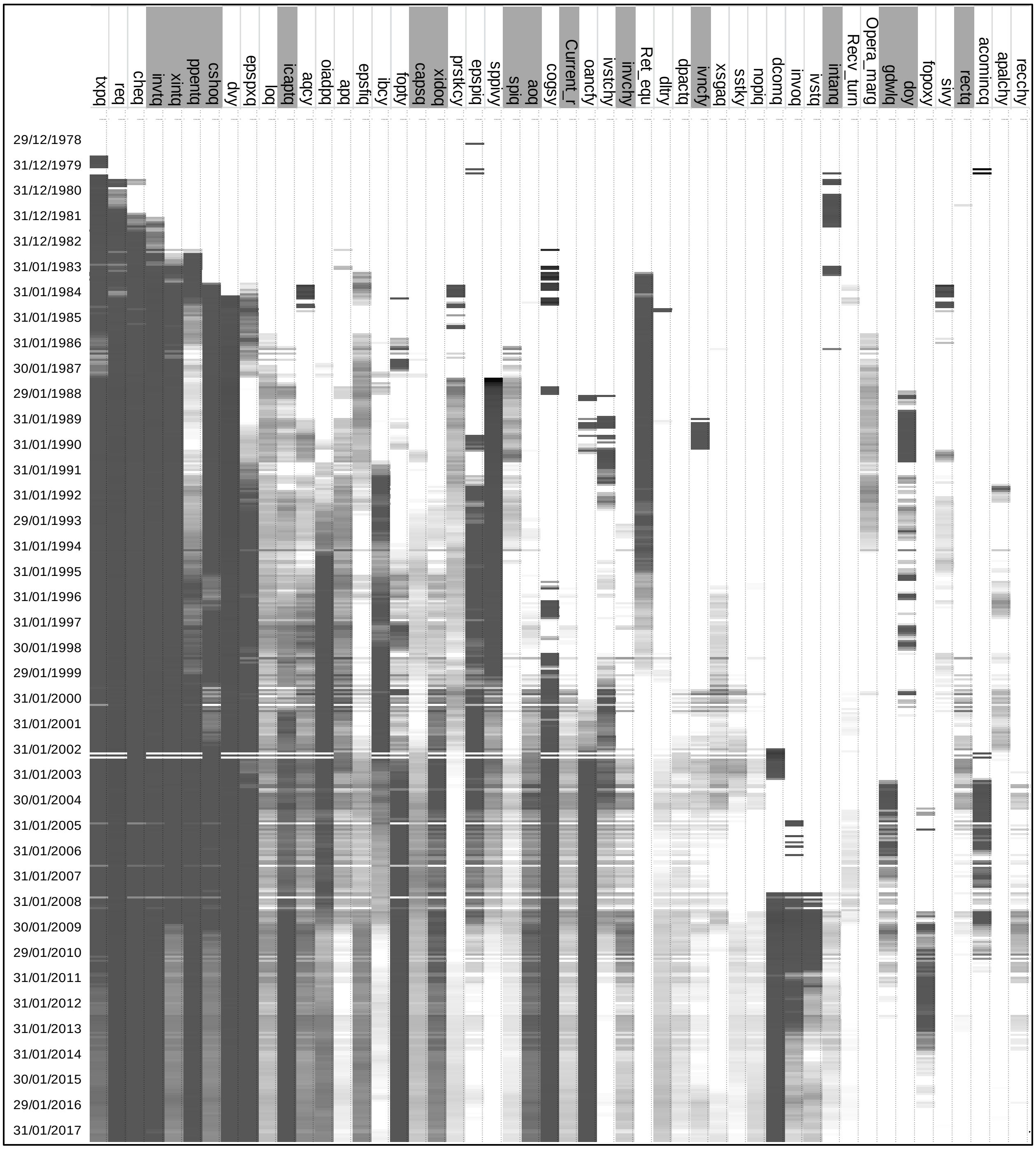
| **Deviations in variable** | **Compustat Name** | **Positive** | **Negative** | **Mean (%)** |
|---|---|---|---|---|
| 1. Income Taxes Payable | txpq | 461 | | 0.411 |
| 2. Retained Earnings | req | 452 | | 0.818 |
| 3. Cash and Short-Term Investments | cheq | 442 | | 0.373 |
| 4. Inventories - Total | invtq | | 435 | –0.448 |
| 5. Interest and Related Expense - Total | xintq | | 419 | –0.328 |
| 6. Property Plant and Equipment - Total (Net) | ppentq | | 411 | –0.302 |
| 7. Common Shares Outstanding | cshoq | | 405 | –0.295 |
| 8. Cash Dividends | dvy | 398 | | 0.795 |
| 9. Earnings Per Share (Basic) / Exc. Extraordinary | epspxq | 384 | | 0.263 |
| 10. Liabilities - Other | loq | 367 | | 0.111 |
| 11. Invested Capital / Total | icaptq | | 351 | –0.176 |
| 12. Acquisitions | aqcy | 337 | 2 | 0.164 |
| 13. Operating Income After Depreciation | oiadpq | 331 | | 0.190 |
| 14. Account Payable / Creditors - Trade | apq | 326 | | 0.095 |
| 15. Earnings Per Share (Diluted) / Inc. Extraordinary | epsfiq | 318 | | 0.101 |
| 16. Income Before Extraordinary Items - Statement of CF | ibcy | 311 | | 0.134 |
| 17. Funds From Operations / Total | fopty | 302 | | 0.217 |
| 18. Capital Surplus / Share Premium Reserve | capsq | | 298 | –0.068 |
| 19. Extraordinary Items and Discontinued Operations | xidoq | | 292 | –0.130 |
| 20. Purchase of Common and Preferred Stock | prstkcy | 288 | | 0.074 |
| 21. Earnings Per Share (Basic) / Inc. Extraordinary | epspiq | 281 | | 0.151 |
| 22. Sale of PP&E and Investments - (Gain) Loss | sppivy | 274 | | 0.456 |
| 23. Special Items | spiq | | 271 | –0.043 |
| 24. Assets - Other - Total | aoq | | 253 | –0.107 |
| 25. Cost of Goods Sold | cogsy | 243 | 20 | 0.102 |
| *26. Current Ratio* | *actq / lctq* | | 222 | –0.049 |
| 27. Operating Activities - Net Cash Flow | oancfy | 207 | 14 | 0.188 |
| 28. Short-Term Investments - Change | ivstchy | 202 | 7 | 0.070 |
| 29. Inventory - Decrease (Increase) | invchy | | 195 | –0.048 |
| *30. Return on Equity Ratio* | *ibq / seqq* | 191 | | 0.140 |
| 31. Long-Term Debt - Reduction | dltry | 188 | 2 | 0.028 |
| 32. Depreciation, Depletion and Amortization (Accum.) | dpactq | 184 | | 0.024 |
| 33. Investing Activities - Net Cash Flow | ivncfy | 14 | 164 | –0.003 |
| 34. Selling, General and Administrative Expenses | xsgaq | 161 | | 0.027 |

| Deviations in variable | Compustat Name | Positive | Negative | Mean (%) |
|---|---|---|---|---|
| 35. Sale of Common and Preferred Stock | sstky | 161 | | 0.018 |
| 36. Non-Operating Income (Expense) - Total | nopiq | 138 | | 0.015 |
| 37. Deferred Compensation | dcomq | 133 | | 0.225 |
| 38. Inventory - Other | invoq | 123 | 2 | 0.113 |
| 39. Short-Term Investments- Total | ivstq | 112 | | 0.078 |
| 40. Intangible Assets - Total | intanq | 25 | 106 | 0.036 |
| *41. Receivable Turnover Ratio* | *saleq / rectq* | 104 | | 0.007 |
| *42. Operating Margin Ratio* | *oibdpq / saleq* | 103 | | 0.027 |
| 43. Goodwill (net) | gdwlq | | 93 | –0.044 |
| 44. Discontinued Operations | doy | 1 | 92 | –0.059 |
| 45. Funds from Operations - Other excluding Option | fopoxy | 89 | 1 | 0.042 |
| 46. Sale of Investments | sivy | 85 | 3 | 0.041 |
| 47. Receivables - Total | rectq | 1 | 86 | –0.017 |
| 48. Accumulated Other Comprehensive Income (Loss) | acomincq | 80 | 4 | –0.013 |
| 49. Accounts Payable and Accrued Liabilities - Inc./Dec. | apalchy | 77 | | 0.015 |
| 50. Accounts Receivable - Decrease (Increase) | recchy | 74 | | 0.015 |
| 51. Uses of Funds - Total | fusety | 72 | | 0.010 |
| 52. Income Taxes - Total | txtq | 69 | | 0.011 |
| 53. Inventories (Util) | uinvq | 68 | | 0.024 |
| 54. Research and Development Expense | xrdq | 65 | | 0.033 |
| 55. Income Taxes Paid | txpdy | 59 | | 0.006 |
| 56. Current Deferred Tax Liability | txdbclq | | 57 | –0.152 |
| 57. Financing Activities - Other | fiaoy | 12 | 42 | 0.010 |
| 58. Total Fair Value Liabilities | tfvlq | 49 | | 0.123 |
| 59. Depreciation and Amortization - Total | dpq | 48 | | 0.005 |
| 60. Current Assets - Total | actq | 47 | 2 | 0.027 |
| 61. Deferred Taxes and Investment Tax Credit | txditcq | 46 | 1 | 0.004 |
| 62. Current Liabilities - Other - Total | lcoq | 45 | | 0.002 |
| 63. Interest Paid - Net | intpny | | 44 | –0.040 |
| 64. Sale of Property | sppey | 40 | 2 | 0.000 |
| *65. Assets Turnover Ratio* | *saleq / atq* | 40 | | 0.001 |
| 66. Other Long-term Assets | altoq | | 39 | –0.010 |
| 67. Pretax Income | piq | 36 | | 0.035 |
| 68. Earnings Per Share from Operations | opepsq | 35 | | 0.001 |
| 69. In Process R&D Expense After-tax | rdipaq | 35 | | 0.094 |
| 70. Purchase of Common Stock (Cash Flow) | prstkccy | 30 | | 0.052 |
| 71. Investing Activities - Other | ivacoy | 29 | | 0.005 |
| 72. Depreciation and Depletion (Cash Flow) | depcy | 25 | | 0.066 |
| 73. Common Shares Issued | cshiq | 24 | | 0.077 |
| 74. Net Income before Extraordinary Items | uniamiq | | 24 | –0.004 |
| *75. Cash Ratio* | *chec / lctq* | 24 | | 0.005 |
| 76. Long-Term Debt - Total | dlttq | | 20 | –0.002 |
| 77. Total Shares Repurchased - Quarter | cshopq | 4 | 19 | –0.016 |
| 78. Dividends - Preferred/Preference | dvpy | 5 | 18 | –0.011 |

| Deviations in variable | Compustat Name | Positive | Negative | Mean (%) |
|---|---|---|---|---|
| 79. Financing Activities - Net Cash Flow | fincfy | 19 | | 0.004 |
| 80. Inventory - Raw Materials | invrmq | 5 | 14 | –0.005 |
| *81. Gross Margin Ratio* | *(ibq+dpq) / saleq* | 15 | | 0.001 |
| 82. Foreign Exchange Income (Loss) | fcay | | 14 | –0.036 |
| 83. Acquisition / Merger Pretax | aqpq | | 13 | –0.040 |
| 84. Gross Income (Income Before Interest Charges) | ugiq | | 13 | –0.004 |
| 85. Common / Ordinary Stock (Capital) | cstkq | 1 | 12 | –0.005 |
| 86. Other Stockholders Equity Adjustments | seqoq | 12 | | 0.092 |
| 87. Total Long-term Investments | ivltq | 10 | | 0.015 |
| 88. Funds from Operations - Other | fopoy | 10 | | 0.001 |
| *89. Return on Assets Ratio* | *saleq / atq* | 5 | 7 | 0.000 |
| 90. Earnings Per Share / Diluted / from Operations | oepsxq | 8 | 2 | 0.001 |
| 91. Net Income (Loss) | niq | 14 | | 0.004 |
| 92. Income Taxes - Accrued - Increase (Decrease) | txachy | 8 | | 0.001 |
| 93. Stock Compensation Expense | stkcoq | | 7 | –0.003 |
| 94. Settlement (Litigation/Insurance) Pretax | setpq | 6 | | 0.005 |
| *95. Debt Ratio* | *ltq / atq* | 6 | | 0.000 |
| 96. In Process R&D | rdipq | 2 | 3 | 0.001 |
| 97. Deferred Tax Asset - Long Term | txdbaq | | 5 | –0.001 |
| 98. Cash and Cash Equivalents - Increase (Decrease) | chechy | | 5 | 0.000 |
| *99. Operating Cash Flow Ratio* | *oancfy / lctq* | | 5 | –0.002 |
| 100. Inventory - Finished Goods | invfgq | | 4 | –0.006 |
| *101. Debt to equity ratio* | *ltq / seqq* | | 4 | –0.001 |
| 102. Cost of Goods Sold | cogsq | | 3 | 0.000 |
| 103. Inventory - Work in Process | invwipq | 1 | 2 | 0.000 |
| 104. Working Capital Change / Other / Inc./Dec. | wcapcy | | 3 | –0.002 |
| 105. Dividends / Preferred/Preference | dvpq | | 2 | –0.001 |
| 106. Changes in Current Debt | dlcchy | 2 | | 0.001 |
| 107. Income Before Ext. /Adj. Common Stock Equiv. | ibadjq | 1 | | 0.000 |
| 108. Other Intangibles | intanoq | 1 | | 0.001 |
| 109. Liabilities - Total | ltq | 1 | | 0.000 |
| 110. Property, Plant and Equipment /Total (Gross) | ppegtq | | 1 | 0.000 |
| 111. Current Deferred Tax Asset | txdbcaq | | 1 | –0.004 |
| 112. Acquisition/Merger Pretax | aqpy | | 1 | –0.019 |
| 113. Gain/Loss on Sale (Core Earnings Adjusted) | glcepy | 1 | | 0.003 |

## Appendix C: Variables retained in the construction of the Fundamental Deviations Index (*FDI*)

The figure depicts the development of LASSO regression coefficients over time for the 50 most retained *FDI* components, ordered from left to right. Darkness scale represents coefficients magnitude in absolute value. A variable name in gray background represents a variable with mostly negative coefficients.



**Appendix D. Slope estimates for control variables included in the regressions of Table 2**

Panel A. Raw Returns

| | *ME* | *BE/ME* | $R_{t-1}$ | $R_{t-13:t-24}$ | $R_{t-25:t-36}$ | *52H* | *ID* | *RR* | *Xmax* | *IVOL* | *TURN* | *ILLIQ* | *TREND* | *RUD* | *NS* | *dA/A* | *Y/B* | *I/A* | *Ac/A* | *GP* | *ROA* | *ROE* | *NOA* | *O-S* | *F-S* | *G-S* | *SUE* | *SURGE* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $R_{t+1}$ | –0.09 | 0.05 | –1.65 | –0.02 | 0.01 | –0.54 | –1.12 | 0.37 | –0.03 | –1.97 | –0.74 | –0.04 | 32.27 | 0.12 | –0.60 | 0.16 | 0.14 | 0.19 | –0.46 | 0.34 | 0.73 | –0.53 | 1.25 | 0.80 | 0.09 | –0.05 | 0.18 | 0.20 |
| | (–3.32) | (0.62) | (–5.65) | (–0.30) | (0.24) | (–1.97) | (–2.34) | (4.46) | (–0.16) | (–1.98) | (–1.41) | (–4.93) | (10.33) | (1.19) | (–2.55) | (1.14) | (1.66) | (1.27) | (–1.75) | (2.68) | (1.89) | (–5.48) | (3.62) | (1.67) | (7.81) | (–2.62) | (11.36) | (10.78) |
| $R_{t+2:t+6}$ | –0.33 | 0.29 | 4.45 | –0.30 | 0.22 | 3.15 | –5.34 | 0.70 | –0.58 | –0.03 | –9.05 | –0.06 | 12.42 | 0.50 | –2.72 | 0.69 | 0.45 | 0.08 | –3.11 | 1.68 | 1.35 | –1.69 | 5.23 | 3.62 | 0.30 | –0.07 | 0.15 | 0.56 |
| | (–4.98) | (1.54) | (6.49) | (–1.98) | (1.65) | (6.12) | (–5.01) | (3.89) | (–1.68) | (–0.01) | (–7.79) | (–2.86) | (1.81) | (3.29) | (–4.99) | (1.92) | (2.45) | (0.24) | (–4.75) | (5.02) | (1.53) | (–6.25) | (5.06) | (3.81) | (9.94) | (–1.52) | (3.82) | (12.74) |
| $R_{t+7:t+12}$ | –0.25 | 0.93 | 4.26 | –0.23 | 0.18 | 1.63 | –5.90 | –0.22 | 0.61 | –1.76 | –6.75 | 0.04 | 4.46 | 0.06 | –3.34 | 0.98 | 0.46 | 0.60 | –5.18 | 2.12 | 1.19 | –1.90 | –1.36 | 2.81 | 0.14 | –0.14 | 0.15 | 0.05 |
| | (–3.32) | (2.55) | (5.51) | (–1.38) | (1.20) | (2.68) | (–5.22) | (–1.02) | (1.60) | (–0.65) | (–5.38) | (1.34) | (0.51) | (0.26) | (–5.04) | (2.57) | (2.13) | (1.40) | (–6.56) | (5.68) | (1.11) | (–6.09) | (–1.74) | (2.33) | (3.22) | (–2.41) | (3.82) | (0.86) |
| $R_{t+13:t+24}$ | –0.19 | 4.00 | 0.59 | 0.04 | –0.31 | –1.98 | –7.51 | 0.41 | –0.77 | 6.00 | –11.68 | 0.10 | 16.67 | –0.23 | –3.25 | 3.12 | 0.44 | 2.52 | –10.87 | 2.33 | –1.34 | –4.09 | –2.82 | 1.25 | –0.18 | –0.34 | 0.50 | 0.71 |
| | (–1.55) | (6.69) | (0.51) | (0.13) | (–1.32) | (–2.17) | (–4.25) | (1.27) | (–1.11) | (1.22) | (–6.17) | (2.33) | (1.11) | (–0.51) | (–2.86) | (4.16) | (1.61) | (3.06) | (–7.39) | (3.40) | (–0.67) | (–7.91) | (–2.04) | (0.48) | (–2.86) | (–3.36) | (8.98) | (8.69) |
| No Microcap Stocks | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| $R_{t+1}$ | –0.12 | 0.09 | –0.89 | –0.04 | 0.02 | –0.88 | –0.98 | 0.11 | 0.02 | –1.67 | –1.00 | 3.77 | 34.30 | 0.10 | –0.05 | 0.05 | 0.12 | 0.25 | –0.49 | 0.30 | 0.27 | 1.03 | –0.41 | 4.48 | 0.05 | –0.02 | 0.08 | 0.12 |
| | (–3.40) | (0.85) | (–2.30) | (–0.46) | (0.28) | (–3.03) | (–1.90) | (1.16) | (0.11) | (–1.14) | (–1.56) | (0.96) | (7.59) | (1.09) | (–0.14) | (0.24) | (0.63) | (1.38) | (–1.29) | (1.84) | (0.40) | (2.20) | (–3.35) | (1.42) | (2.55) | (–1.25) | (4.29) | (5.41) |
| $R_{t+2:t+6}$ | –0.43 | 0.73 | 4.15 | –0.60 | 0.09 | 1.21 | –3.67 | 0.33 | –0.18 | 2.15 | –7.79 | 16.04 | 16.68 | 0.14 | –1.06 | 0.25 | 2.01 | 0.44 | –3.29 | 1.53 | –1.58 | 4.15 | –1.26 | 16.80 | 0.17 | –0.02 | –0.01 | 0.33 |
| | (–4.72) | (2.81) | (4.68) | (–2.90) | (0.48) | (2.12) | (–3.13) | (1.41) | (–0.43) | (0.57) | (–5.82) | (1.66) | (1.76) | (0.58) | (–0.73) | (0.55) | (4.29) | (0.95) | (–4.05) | (3.82) | (–1.10) | (3.55) | (–3.63) | (2.24) | (4.40) | (–0.32) | (–0.22) | (6.08) |
| $R_{t+7:t+12}$ | –0.40 | 1.63 | 5.49 | –0.58 | 0.41 | 0.84 | –2.26 | 0.27 | 0.55 | 0.60 | –4.87 | 8.12 | 4.86 | 0.31 | –3.56 | 1.85 | 2.98 | –0.28 | –7.18 | 2.21 | –0.43 | –6.54 | –1.38 | 33.94 | –0.01 | –0.07 | –0.06 | 0.06 |
| | (–4.21) | (3.41) | (5.11) | (–2.62) | (2.30) | (1.36) | (–1.78) | (1.03) | (1.07) | (0.15) | (–2.79) | (0.68) | (0.40) | (1.59) | (–2.32) | (3.27) | (4.17) | (–0.51) | (–6.89) | (4.72) | (–0.26) | (–4.03) | (–3.83) | (3.60) | (–0.11) | (–1.35) | (–1.40) | (1.03) |
| $R_{t+13:t+24}$ | –0.27 | 4.43 | 2.53 | 0.40 | –0.04 | –0.27 | –6.93 | 0.47 | –0.17 | 10.50 | –7.95 | 47.77 | 22.24 | 0.81 | –0.65 | 4.11 | 3.07 | 0.89 | –11.12 | 3.64 | –8.47 | –0.04 | –3.51 | 85.69 | –0.04 | –0.07 | 0.46 | 0.52 |
| | (–1.94) | (6.91) | (1.55) | (1.03) | (–0.15) | (–0.25) | (–3.19) | (1.13) | (–0.26) | (1.56) | (–3.51) | (2.78) | (1.10) | (2.45) | (–0.34) | (4.54) | (2.59) | (0.88) | (–6.45) | (4.61) | (–3.02) | (–0.02) | (–6.55) | (4.93) | (–0.54) | (–0.75) | (6.01) | (6.29) |
| Period 2001-2017 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | –0.11 | –0.20 | –1.37 | –0.04 | –0.01 | –0.40 | –0.36 | 0.45 | –0.36 | –1.76 | –0.74 | –0.03 | 8.44 | –0.03 | –0.71 | 0.03 | –0.02 | 0.02 | 0.39 | 0.32 | 0.95 | 0.08 | –0.26 | 0.10 | –0.07 | 0.08 | 0.17 | –0.11 |
| | (–2.86) | (–1.80) | (–3.00) | (–0.45) | (–0.12) | (–0.87) | (–0.53) | (3.99) | (–2.07) | (–1.67) | (–2.57) | (–2.00) | (1.67) | (–0.25) | (–2.18) | (0.15) | (–0.53) | (0.08) | (0.90) | (1.60) | (2.22) | (0.36) | (–2.27) | (7.09) | (–3.00) | (3.60) | (6.27) | (–2.86) |
| No Micro | –0.10 | –0.02 | –0.60 | –0.02 | –0.01 | –0.85 | –0.65 | 0.19 | –0.20 | –1.99 | –0.60 | 9.47 | 6.98 | –0.03 | –0.58 | 0.08 | 0.04 | 0.10 | 0.90 | 0.17 | 0.10 | 0.00 | –0.23 | 12.83 | 0.03 | –0.02 | –0.01 | 0.08 |
| | (–2.10) | (–0.15) | (–1.10) | (–0.15) | (–0.11) | (–1.79) | (–0.87) | (1.63) | (–1.00) | (–1.39) | (–2.04) | (1.01) | (0.97) | (–0.20) | (–1.70) | (0.34) | (0.60) | (0.37) | (1.56) | (0.71) | (0.19) | (–0.01) | (–1.80) | (1.99) | (1.56) | (–0.78) | (–0.64) | (2.51) |

Panel B: Returns Adjusted to Fama–French and Momentum factors

| | *ME* | *BE/ME* | $R_{t-1}$ | $R_{t-13:t-24}$ | $R_{t-25:t-36}$ | *52H* | *ID* | *RR* | *Xmax* | *IVOL* | *TURN* | *ILLIQ* | *TREND* | *RUD* | *NS* | *dA/A* | *Y/B* | *I/A* | *Ac/A* | *GP* | *ROA* | *ROE* | *NOA* | *O-S* | *F-S* | *G-S* | *SUE* | *SURGE* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | –0.06 | 0.05 | –2.09 | 0.04 | 0.00 | –0.43 | –1.35 | 0.35 | 0.06 | –2.24 | –0.89 | –0.04 | 31.27 | 0.12 | –0.63 | 0.13 | 0.14 | 0.10 | –0.39 | 0.43 | 0.79 | –0.46 | 1.28 | 0.59 | 0.09 | –0.04 | 0.18 | 0.19 |
| | (–3.12) | (0.71) | (–7.67) | (0.72) | (0.06) | (–1.95) | (–3.07) | (4.55) | (0.39) | (–2.84) | (–1.78) | (–4.64) | (10.45) | (1.12) | (–2.77) | (1.04) | (1.69) | (0.69) | (–1.59) | (3.47) | (2.10) | (–5.29) | (3.63) | (1.22) | (8.46) | (–2.42) | (11.74) | (11.72) |
| No Micro | –0.07 | 0.12 | –1.47 | 0.00 | –0.01 | –0.76 | –1.17 | 0.07 | 0.09 | –2.52 | –0.98 | 3.91 | 33.52 | 0.10 | –0.06 | –0.01 | 0.13 | 0.22 | –0.52 | 0.41 | 0.32 | 1.15 | –0.33 | 3.93 | 0.05 | –0.01 | 0.07 | 0.12 |
| | (–2.87) | (1.17) | (–4.17) | (0.02) | (–0.16) | (–3.01) | (–2.38) | (0.73) | (0.58) | (–2.08) | (–1.58) | (0.98) | (7.62) | (1.08) | (–0.15) | (–0.05) | (0.72) | (1.23) | (–1.41) | (2.53) | (0.48) | (2.50) | (–2.85) | (1.23) | (2.50) | (–0.69) | (4.15) | (6.19) |

Panel B. Next month Returns and Market States

| | *ME* | *BE/ME* | $R_{t-1}$ | $R_{t-13:t-24}$ | $R_{t-25:t-36}$ | *52H* | *ID* | *RR* | *Xmax* | *IVOL* | *TURN* | *ILLIQ* | *TREND* | *RUD* | *NS* | *dA/A* | *Y/B* | *I/A* | *Ac/A* | *GP* | *ROA* | *ROE* | *NOA* | *O-S* | *F-S* | *G-S* | *SUE* | *SURGE* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| L. Sentiment | –0.09 | –0.09 | –0.99 | –0.11 | –0.04 | –1.40 | –0.11 | 0.42 | –0.55 | 0.89 | –2.18 | –0.06 | 29.73 | 0.27 | –0.29 | 0.52 | 0.12 | 0.02 | –0.78 | 0.15 | 0.71 | –0.25 | 1.44 | 1.81 | 0.10 | 0.01 | 0.22 | 0.19 |
| | (–1.90) | (–0.71) | (–1.77) | (–1.06) | (–0.45) | (–2.71) | (–0.13) | (2.73) | (–1.59) | (0.48) | (–2.00) | (–2.99) | (5.84) | (2.78) | (–0.59) | (1.94) | (0.63) | (0.09) | (–1.60) | (0.67) | (0.88) | (–1.35) | (1.74) | (1.73) | (4.32) | (0.26) | (6.81) | (5.53) |
| H. Sentiment | –0.09 | 0.13 | –1.88 | 0.03 | 0.01 | –0.17 | –1.78 | 0.33 | 0.31 | –3.51 | 0.02 | –0.04 | 36.42 | 0.07 | –0.75 | –0.01 | 0.16 | 0.30 | –0.47 | 0.50 | 0.73 | –0.71 | 1.25 | 0.27 | 0.09 | –0.09 | 0.18 | 0.20 |
| | (–2.36) | (1.29) | (–5.53) | (0.51) | (0.21) | (–0.50) | (–2.92) | (3.38) | (1.87) | (–2.89) | (0.03) | (–4.32) | (8.58) | (0.52) | (–2.94) | (–0.04) | (2.01) | (1.63) | (–1.49) | (2.99) | (1.71) | (–6.33) | (3.90) | (0.52) | (6.38) | (–3.66) | (9.83) | (9.37) |
| L. Volatility | –0.07 | 0.18 | –1.33 | 0.00 | 0.16 | –0.14 | –1.20 | 0.20 | 0.01 | –2.47 | –2.06 | –0.02 | 26.39 | –0.14 | –1.04 | 0.13 | 0.19 | 0.15 | –0.48 | 0.15 | 1.50 | –0.41 | 1.71 | 0.81 | 0.11 | –0.05 | 0.25 | 0.22 |
| | (–1.99) | (1.78) | (–3.27) | (0.02) | (2.17) | (–0.51) | (–1.96) | (1.96) | (0.05) | (–1.73) | (–2.59) | (–1.93) | (5.86) | (–0.79) | (–2.90) | (0.66) | (1.45) | (0.72) | (–1.26) | (0.96) | (2.65) | (–3.10) | (2.95) | (1.17) | (6.57) | (–2.24) | (10.79) | (8.00) |
| H. Volatility | –0.12 | –0.08 | –1.98 | –0.03 | –0.14 | –0.93 | –1.03 | 0.53 | –0.06 | –1.46 | 0.59 | –0.07 | 38.18 | 0.38 | –0.15 | 0.18 | 0.08 | 0.22 | –0.44 | 0.54 | –0.04 | –0.64 | 0.79 | 0.80 | 0.07 | –0.04 | 0.11 | 0.17 |
| | (–2.66) | (–0.74) | (–4.72) | (–0.48) | (–2.07) | (–2.00) | (–1.41) | (4.19) | (–0.28) | (–1.06) | (0.88) | (–4.90) | (8.88) | (3.66) | (–0.50) | (0.96) | (0.83) | (1.08) | (–1.22) | (2.68) | (–0.07) | (–4.64) | (2.13) | (1.19) | (4.47) | (–1.55) | (5.35) | (7.25) |
| L. liquidity | –0.09 | 0.30 | –2.06 | 0.05 | 0.04 | –0.72 | –0.82 | 0.17 | 0.14 | –2.49 | –0.46 | –0.04 | 45.23 | 0.17 | –0.47 | 0.47 | 0.26 | 0.07 | –1.04 | 0.57 | 0.71 | –0.55 | 1.72 | 0.75 | 0.09 | –0.06 | 0.20 | 0.20 |
| | (–2.32) | (3.16) | (–4.73) | (0.60) | (0.57) | (–2.21) | (–1.20) | (1.44) | (0.52) | (–1.62) | (–0.49) | (–4.01) | (11.27) | (1.00) | (–1.28) | (2.26) | (1.68) | (0.38) | (–3.08) | (3.46) | (1.06) | (–3.70) | (2.72) | (1.43) | (5.10) | (–2.36) | (9.09) | (8.54) |
| H. liquidity | –0.09 | –0.21 | –1.25 | –0.08 | –0.02 | –0.36 | –1.41 | 0.57 | –0.19 | –1.44 | –1.01 | –0.05 | 19.37 | 0.07 | –0.72 | –0.15 | 0.01 | 0.30 | 0.12 | 0.12 | 0.75 | –0.50 | 0.78 | 0.86 | 0.09 | –0.04 | 0.16 | 0.19 |
| | (–2.37) | (–1.84) | (–3.20) | (–1.17) | (–0.31) | (–0.82) | (–2.12) | (4.90) | (–1.02) | (–1.15) | (–2.20) | (–3.28) | (4.17) | (0.64) | (–2.51) | (–0.84) | (0.18) | (1.34) | (0.31) | (0.62) | (1.92) | (–4.13) | (2.84) | (1.06) | (6.09) | (–1.42) | (7.03) | (6.84) |
| L. Market | –0.11 | 0.11 | –2.24 | –0.15 | –0.28 | –2.57 | 1.01 | 0.63 | –1.24 | –1.35 | –0.30 | –0.12 | 12.03 | 0.27 | –1.42 | –0.26 | –0.07 | 0.29 | –0.82 | 0.98 | 0.53 | 0.15 | 0.37 | 2.67 | 0.09 | –0.08 | 0.14 | 0.20 |
| | (–1.28) | (0.55) | (–2.69) | (–0.80) | (–2.42) | (–2.28) | (0.69) | (2.58) | (–3.41) | (–0.64) | (–0.62) | (–2.87) | (1.60) | (1.44) | (–2.21) | (–0.73) | (–0.95) | (0.63) | (–1.11) | (2.36) | (0.62) | (0.78) | (0.68) | (0.97) | (3.03) | (–1.73) | (3.01) | (3.56) |
| H. Market | –0.09 | 0.04 | –1.58 | 0.00 | 0.05 | –0.28 | –1.39 | 0.33 | 0.13 | –2.04 | –0.80 | –0.03 | 34.86 | 0.10 | –0.49 | 0.21 | 0.16 | 0.17 | –0.41 | 0.26 | 0.76 | –0.61 | 1.37 | 0.57 | 0.09 | –0.04 | 0.22 | 0.19 |
| | (–3.06) | (0.48) | (–5.05) | (–0.00) | (0.89) | (–1.03) | (–2.77) | (3.83) | (0.76) | (–1.88) | (–1.35) | (–4.07) | (10.34) | (0.91) | (–1.97) | (1.41) | (1.76) | (1.12) | (–1.47) | (1.96) | (1.79) | (–5.84) | (3.56) | (1.37) | (7.24) | (–2.24) | (6.81) | (5.53) |

**Appendix E. Cross-sectional regressions for *PDI* with additional control variables**

| **Additional Control Variables** | ***PDI*** | ***MOM*** | ***BG*** | **Averaged $R^2$** |
|---|---|---|---|---|
| Controlling for Seasonality (past monthly returns) | 2.14*** | | 0.05*** | 0.12 |
| | (14.10) | | (3.48) | |
| Controlling for the Levels of *PDI* Components | 3.29*** | 0.27*** | 0.05*** | 0.11 |
| | (7.22) | (3.03) | (3.51) | |
| Controlling for the Levels of *GB* Components | 2.20*** | 0.24*** | 0.05*** | 0.12 |
| | (13.98) | (2.74) | (3.13) | |
| Controlling for Annual Changes in *PDI* and *GB* Components | 2.08*** | 0.25*** | 0.06*** | 0.12 |
| | (13.00) | (2.80) | (3.63) | |
| Controlling for Analysts' Dispersion and Expected Return | 2.16*** | 0.24*** | 0.05*** | 0.10 |
| | (13.75) | (2.75) | (3.59) | |

| | ***ME*** | ***BE/ME*** | $R_{t-1}$ | $R_{t-13:t-24}$ | $R_{t-25:t-36}$ | ***52H*** | ***ID*** | ***RR*** | ***Xmax*** | ***IVOL*** | ***TURN*** | ***ILLIQ*** | ***TREND*** | ***RUD*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Seasonality | –0.10 | 0.04 | –1.47 | 0.04 | 0.02 | –0.62 | –0.79 | 0.29 | 0.08 | –2.36 | –0.88 | –0.04 | 36.90 | 0.13 |
| | (–3.46) | (0.60) | (–4.76) | (0.74) | (0.43) | (–2.75) | (–1.76) | (3.61) | (0.55) | (–2.59) | (–1.66) | (–5.05) | (11.19) | (1.34) |
| *PDI* Components | –0.10 | 0.03 | –1.73 | 0.01 | 0.02 | –0.63 | –1.08 | 0.36 | 0.02 | –1.95 | –0.71 | –0.04 | 32.04 | 0.10 |
| | (–3.51) | (0.43) | (–5.95) | (0.21) | (0.38) | (–2.34) | (–2.27) | (4.36) | (0.11) | (–1.98) | (–1.36) | (–5.02) | (10.19) | (0.98) |
| *GB* Components | –0.08 | 0.04 | –1.68 | –0.01 | 0.02 | –0.52 | –1.11 | 0.37 | –0.03 | –2.03 | –0.91 | –0.04 | 32.63 | 0.13 |
| | (–2.35) | (0.47) | (–5.81) | (–0.21) | (0.45) | (–1.90) | (–2.38) | (4.59) | (–0.20) | (–2.05) | (–1.79) | (–4.83) | (10.43) | (1.35) |
| Annual Changes in *PDI* and *GB* | –0.10 | 0.06 | –1.70 | –0.02 | 0.01 | –0.49 | –1.00 | 0.34 | –0.01 | –1.98 | –0.65 | –0.04 | 32.93 | 0.11 |
| | (–3.17) | (0.77) | (–5.96) | (–0.36) | (0.29) | (–1.77) | (–2.09) | (4.24) | (–0.04) | (–2.02) | (–1.29) | (–5.02) | (10.66) | (1.09) |
| Analysts | –0.08 | 0.05 | –1.68 | –0.01 | 0.01 | –0.53 | –1.15 | 0.36 | 0.00 | –1.99 | –0.73 | –0.04 | 32.26 | 0.17 |
| | (–3.04) | (0.63) | (–5.74) | (–0.27) | (0.26) | (–1.96) | (–2.42) | (4.36) | (–0.01) | (–2.00) | (–1.39) | (–4.91) | (10.30) | (1.98) |

| | ***NS*** | ***dA/A*** | ***Y/B*** | ***I/A*** | ***Ac/A*** | ***GP*** | ***ROA*** | ***ROE*** | ***NOA*** | ***O-S*** | ***F-S*** | ***G-S*** | ***SUE*** | ***SURGE*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Seasonality | –0.53 | 0.14 | 0.13 | 0.14 | –0.50 | 0.33 | 0.83 | –0.50 | 1.32 | 0.74 | 0.09 | –0.05 | 0.18 | 0.20 |
| | (–2.20) | (1.03) | (1.62) | (0.95) | (–2.01) | (2.67) | (2.18) | (–5.36) | (3.80) | (1.58) | (8.04) | (–3.02) | (11.15) | (11.31) |
| *PDI* Components | –0.50 | 0.24 | 0.14 | 0.23 | –0.32 | 0.37 | 0.87 | –0.55 | 1.26 | 0.81 | 0.09 | –0.05 | 0.18 | 0.24 |
| | (–2.14) | (1.69) | (1.69) | (1.55) | (–1.23) | (2.93) | (2.12) | (–5.74) | (3.49) | (1.68) | (8.11) | (–2.57) | (11.12) | (12.86) |
| *GB* Components | –0.67 | 0.14 | 0.12 | 0.24 | –0.42 | 0.35 | 0.60 | –0.57 | 1.32 | 0.72 | 0.09 | –0.05 | 0.18 | 0.21 |
| | (–2.93) | (0.88) | (1.35) | (1.31) | (–1.63) | (2.75) | (1.41) | (–5.68) | (3.79) | (1.49) | (8.02) | (–2.74) | (11.07) | (11.40) |
| Annual Changes in *PDI* and *GB* | –0.65 | 0.12 | 0.22 | 0.18 | –0.43 | 0.34 | 1.02 | 1.07 | –0.50 | 0.88 | 0.09 | –0.05 | 0.18 | 0.20 |
| | (–2.70) | (0.85) | (2.30) | (1.19) | (–1.67) | (2.64) | (2.49) | (2.98) | (–5.28) | (1.80) | (7.48) | (–2.95) | (10.46) | (10.94) |
| Analysts | –0.60 | 0.16 | 0.14 | 0.19 | –0.46 | 0.35 | 0.75 | 1.29 | –0.52 | 0.82 | 0.09 | –0.05 | 0.19 | 0.20 |
| | (–2.59) | (1.15) | (1.66) | (1.26) | (–1.74) | (2.70) | (1.96) | (3.72) | (–5.47) | (1.70) | (7.78) | (–2.76) | (11.54) | (10.84) |

## Appendix F. Slope estimates for control variables included in the regressions of Table 5

| | *ME* | *BE/ME* | $R_{t-1}$ | $R_{t-13:t-24}$ | $R_{t-25:t-36}$ | *52H* | *ID* | *RR* | *Xmax* | *IVOL* | *TURN* | *ILLIQ* | *TREND* | *RUD* | *NS* | *dA/A* | *Y/B* | *I/A* | *Ac/A* | *GP* | *ROA* | *ROE* | *NOA* | *O-S* | *F-S* | *G-S* | *SUE* | *SURGE* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $R_{t+1}$ | –0.09 | –0.01 | –1.59 | –0.01 | 0.02 | –0.65 | –1.08 | 0.42 | –0.04 | –1.84 | –0.34 | –0.04 | 32.27 | 0.11 | –0.59 | 0.19 | 0.17 | 0.12 | –0.45 | 0.37 | 0.51 | 0.54 | –0.55 | 0.60 | 0.09 | –0.05 | 0.12 | 0.22 |
| | (–3.31) | (–0.16) | (–5.53) | (–0.10) | (0.40) | (–2.38) | (–2.37) | (5.23) | (–0.28) | (–1.90) | (–0.73) | (–4.73) | (10.46) | (1.05) | (–2.77) | (1.37) | (2.49) | (0.81) | (–1.75) | (2.82) | (1.43) | (2.09) | (–6.13) | (1.21) | (8.72) | (–2.67) | (7.73) | (12.49) |
| No Microcap | –0.10 | 0.08 | –0.95 | –0.01 | 0.00 | –0.96 | –0.91 | 0.15 | 0.09 | –0.79 | –0.75 | 3.49 | 34.34 | 0.09 | –0.50 | 0.12 | 0.21 | 0.18 | –0.50 | 0.27 | –0.15 | 0.69 | –0.47 | 3.87 | 0.05 | –0.02 | 0.04 | 0.14 |
| | (–3.02) | (0.73) | (–2.57) | (–0.16) | (0.05) | (–3.46) | (–1.84) | (1.71) | (0.56) | (–0.56) | (–1.52) | (0.86) | (7.73) | (1.00) | (–2.08) | (0.68) | (1.84) | (1.01) | (–1.39) | (1.65) | (–0.31) | (1.74) | (–4.24) | (1.27) | (3.70) | (–1.13) | (2.49) | (6.90) |
| 2001-2017 | –0.11 | –0.22 | –1.47 | –0.04 | 0.00 | –0.53 | –0.30 | 0.48 | –0.35 | –1.52 | –0.75 | –0.03 | 7.64 | –0.04 | –0.60 | 0.10 | –0.01 | –0.03 | 0.27 | 0.33 | 0.91 | –0.15 | –0.26 | 1.43 | 0.10 | –0.06 | 0.04 | 0.19 |
| | (–3.04) | (–1.94) | (–3.24) | (–0.44) | (–0.07) | (–1.15) | (–0.44) | (4.24) | (–1.97) | (–1.44) | (–2.58) | (–2.08) | (1.51) | (–0.33) | (–1.85) | (0.51) | (–0.33) | (–0.11) | (0.63) | (1.64) | (2.12) | (–0.70) | (–2.31) | (1.43) | (7.05) | (–2.86) | (1.76) | (7.18) |
| $R_{t+1}$ Adj. to FF and Momentum | –0.07 | –0.02 | –2.02 | 0.04 | 0.02 | –0.60 | –1.22 | 0.39 | 0.05 | –2.02 | –0.51 | –0.04 | 31.35 | 0.11 | –0.56 | 0.20 | 0.17 | 0.06 | –0.42 | 0.46 | 0.41 | 0.58 | –0.48 | 0.44 | 0.10 | –0.04 | 0.11 | 0.21 |
| | (–4.08) | (–0.33) | (–7.71) | (0.76) | (0.32) | (–2.66) | (–2.89) | (5.35) | (0.40) | (–2.64) | (–1.19) | (–4.53) | (10.73) | (0.96) | (–2.84) | (1.58) | (2.51) | (0.38) | (–1.75) | (3.55) | (1.18) | (2.27) | (–5.97) | (0.89) | (9.54) | (–2.29) | (8.18) | (13.48) |
| L. Sentiment | –0.06 | –0.26 | –0.53 | –0.11 | –0.01 | –1.58 | 0.10 | 0.55 | –0.63 | 0.96 | –1.28 | –0.06 | 30.67 | 0.29 | –0.40 | 0.54 | 0.16 | –0.17 | –0.67 | 0.23 | 0.01 | 0.64 | –0.30 | 1.27 | 0.11 | 0.01 | 0.14 | 0.21 |
| | (–1.35) | (–2.27) | (–0.98) | (–1.03) | (–0.12) | (–2.88) | (0.13) | (3.73) | (–2.44) | (0.54) | (–1.51) | (–2.68) | (6.51) | (2.64) | (–0.95) | (1.96) | (1.17) | (–0.60) | (–1.38) | (0.98) | (0.02) | (1.40) | (–1.84) | (1.12) | (5.80) | (0.42) | (4.86) | (6.67) |
| H. Sentiment | –0.10 | 0.11 | –1.96 | 0.04 | 0.01 | –0.32 | –1.77 | 0.35 | 0.30 | –3.19 | 0.10 | –0.04 | 35.75 | 0.06 | –0.67 | 0.05 | 0.19 | 0.27 | –0.54 | 0.48 | 0.75 | 0.54 | –0.71 | 0.28 | 0.09 | –0.09 | 0.12 | 0.23 |
| | (–2.69) | (1.14) | (–5.80) | (0.68) | (0.14) | (–0.96) | (–2.94) | (3.63) | (1.78) | (–2.63) | (0.16) | (–4.36) | (8.40) | (0.41) | (–2.63) | (0.29) | (2.32) | (1.48) | (–1.69) | (2.89) | (1.77) | (1.60) | (–6.30) | (0.54) | (6.43) | (–3.63) | (6.58) | (10.42) |
| L. Volatility | –0.06 | 0.06 | –1.23 | 0.01 | 0.18 | –0.24 | –1.03 | 0.23 | 0.26 | –2.65 | –1.29 | –0.02 | 27.26 | –0.15 | –1.07 | 0.14 | 0.20 | 0.11 | –0.40 | 0.21 | 1.03 | 0.88 | –0.43 | 0.46 | 0.11 | –0.05 | 0.15 | 0.21 |
| | (–1.88) | (0.62) | (–3.04) | (0.10) | (2.28) | (–0.89) | (–1.91) | (2.29) | (1.40) | (–1.93) | (–2.06) | (–1.64) | (6.25) | (–0.78) | (–3.40) | (0.70) | (2.09) | (0.54) | (–1.10) | (1.30) | (2.01) | (2.12) | (–3.56) | (0.64) | (7.61) | (–2.22) | (7.51) | (9.40) |
| H. Volatility | –0.12 | –0.08 | –1.94 | –0.02 | –0.13 | –1.05 | –1.13 | 0.60 | –0.33 | –1.06 | 0.58 | –0.07 | 37.10 | 0.36 | –0.12 | 0.24 | 0.14 | 0.12 | –0.50 | 0.52 | 0.01 | 0.21 | –0.67 | 0.73 | 0.07 | –0.05 | 0.09 | 0.22 |
| | (–2.74) | (–0.73) | (–4.76) | (–0.27) | (–1.89) | (–2.23) | (–1.55) | (4.89) | (–1.70) | (–0.78) | (0.85) | (–4.85) | (8.55) | (3.42) | (–0.41) | (1.24) | (1.45) | (0.60) | (–1.37) | (2.56) | (0.03) | (0.68) | (–5.05) | (1.07) | (4.84) | (–1.66) | (3.92) | (8.43) |
| L. liquidity | –0.07 | 0.21 | –1.86 | 0.07 | 0.06 | –0.85 | –0.84 | 0.23 | 0.11 | –2.56 | 0.39 | –0.03 | 47.06 | 0.17 | –0.53 | 0.49 | 0.33 | –0.05 | –0.96 | 0.64 | 0.29 | 0.65 | –0.61 | 0.32 | 0.10 | –0.06 | 0.18 | 0.24 |
| | (–2.06) | (2.42) | (–4.36) | (0.88) | (0.78) | (–2.59) | (–1.33) | (2.12) | (0.55) | (–1.70) | (0.47) | (–3.68) | (12.55) | (0.92) | (–1.70) | (2.36) | (2.53) | (–0.25) | (–3.01) | (3.78) | (0.48) | (1.45) | (–4.51) | (0.59) | (6.20) | (–2.45) | (9.07) | (9.61) |
| H. liquidity | –0.10 | –0.22 | –1.34 | –0.08 | –0.02 | –0.48 | –1.31 | 0.59 | –0.17 | –1.19 | –1.02 | –0.05 | 18.69 | 0.06 | –0.64 | –0.09 | 0.02 | 0.27 | 0.01 | 0.12 | 0.72 | 0.45 | –0.51 | 0.85 | 0.09 | –0.04 | 0.06 | 0.20 |
| | (–2.59) | (–1.93) | (–3.46) | (–1.10) | (–0.27) | (–1.10) | (–1.99) | (5.13) | (–0.95) | (–0.95) | (–2.20) | (–3.35) | (4.02) | (0.50) | (–2.21) | (–0.47) | (0.39) | (1.19) | (0.03) | (0.61) | (1.83) | (1.59) | (–4.16) | (1.06) | (6.13) | (–1.47) | (2.72) | (8.11) |
| L. Market | –0.11 | 0.08 | –2.27 | –0.14 | –0.27 | –2.75 | 1.12 | 0.66 | –1.19 | –1.12 | –0.31 | –0.12 | 11.21 | 0.24 | –1.35 | –0.20 | –0.06 | 0.16 | –0.90 | 1.00 | 0.52 | 0.09 | 0.14 | 2.54 | 0.09 | –0.07 | 0.12 | 0.23 |
| | (–1.34) | (0.40) | (–2.69) | (–0.76) | (–2.31) | (–2.45) | (0.77) | (2.73) | (–3.09) | (–0.53) | (–0.65) | (–2.95) | (1.50) | (1.29) | (–2.09) | (–0.55) | (–0.88) | (0.33) | (–1.23) | (2.42) | (0.62) | (0.17) | (0.74) | (0.93) | (3.06) | (–1.58) | (2.47) | (4.09) |
| H. Market | –0.09 | –0.02 | –1.50 | 0.01 | 0.06 | –0.37 | –1.38 | 0.38 | 0.12 | –1.94 | –0.35 | –0.03 | 35.08 | 0.10 | –0.48 | 0.24 | 0.20 | 0.11 | –0.39 | 0.29 | 0.51 | 0.60 | –0.65 | 0.33 | 0.09 | –0.05 | 0.12 | 0.22 |
| | (–3.03) | (–0.31) | (–4.90) | (0.21) | (1.05) | (–1.38) | (–2.88) | (4.57) | (0.81) | (–1.83) | (–0.66) | (–3.79) | (10.55) | (0.80) | (–2.16) | (1.62) | (2.62) | (0.73) | (–1.43) | (2.08) | (1.31) | (2.12) | (–6.57) | (0.80) | (8.17) | (–2.31) | (7.34) | (11.82) |

**Appendix G. Slope estimates for control variables included in the regressions of Table 7**

| | *ME* | *BE/ME* | $R_{t-1}$ | $R_{t-13:t-24}$ | $R_{t-25:t-36}$ | *52H* | *ID* | *RR* | *Xmax* | *IVOL* | *TURN* | *ILLIQ* | *TREND* | *RUD* | *NS* | *dA/A* | *Y/B* | *I/A* | *Ac/A* | *GP* | *ROA* | *ROE* | *NOA* | *O-S* | *F-S* | *G-S* | *SUE* | *SURGE* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Sudden* | –0.09 | 0.04 | –1.67 | –0.01 | 0.01 | –0.55 | –1.14 | 0.36 | –0.02 | –1.97 | –0.73 | –0.04 | 32.30 | 0.13 | –0.63 | 0.15 | 0.12 | 0.19 | –0.47 | 0.35 | 0.75 | 1.32 | –0.52 | 0.82 | 0.09 | –0.05 | 0.18 | 0.20 |
| *Deviations* | (–3.36) | (0.59) | (–5.68) | (–0.20) | (0.15) | (–2.02) | (–2.41) | (4.45) | (–0.11) | (–1.99) | (–1.39) | (–4.97) | (10.34) | (1.27) | (–2.69) | (1.06) | (1.44) | (1.28) | (–1.78) | (2.81) | (1.95) | (3.65) | (–5.44) | (1.70) | (7.80) | (–2.63) | (11.29) | (10.87) |
| *Sudden* | –0.07 | –0.06 | –1.54 | 0.02 | –0.01 | –0.59 | –1.12 | 0.43 | –0.06 | –2.14 | 0.05 | –0.03 | 29.22 | 0.10 | –0.52 | 0.19 | 0.04 | 0.14 | –0.38 | 0.36 | 0.66 | 0.21 | –0.54 | 0.58 | 0.09 | –0.05 | 0.09 | 0.22 |
| *Deviations* | (–2.34) | (–0.72) | (–5.13) | (0.28) | (–0.21) | (–1.94) | (–2.26) | (5.20) | (–0.50) | (–2.25) | (0.13) | (–3.70) | (8.65) | (0.79) | (–2.49) | (1.39) | (1.00) | (0.89) | (–1.36) | (2.59) | (2.03) | (1.05) | (–5.69) | (1.12) | (8.15) | (–2.67) | (5.60) | (11.40) |
| $R_{t+1}$ | –0.08 | –0.06 | –1.45 | 0.03 | 0.00 | –0.46 | –1.19 | 0.43 | –0.07 | –2.47 | –0.02 | –0.03 | 29.91 | 0.10 | –0.64 | 0.12 | 0.02 | 0.09 | –0.42 | 0.38 | 0.91 | 0.67 | –0.53 | 0.58 | 0.09 | –0.05 | 0.17 | 0.21 |
| | (–2.62) | (–0.76) | (–4.82) | (0.48) | (–0.03) | (–1.52) | (–2.38) | (5.05) | (–0.57) | (–2.58) | (–0.04) | (–3.41) | (8.88) | (0.77) | (–3.01) | (0.87) | (0.52) | (0.58) | (–1.50) | (2.75) | (2.79) | (3.34) | (–5.56) | (1.10) | (8.56) | (–2.42) | (10.30) | (11.00) |
| No Microcap | –0.07 | 0.05 | –0.78 | 0.01 | –0.01 | –0.99 | –1.15 | 0.14 | 0.01 | –1.70 | –0.34 | 5.07 | 29.33 | 0.10 | –0.47 | 0.04 | 0.14 | 0.04 | –0.36 | 0.22 | 0.49 | 1.20 | –0.41 | 6.20 | 0.05 | –0.01 | 0.07 | 0.13 |
| | (–2.04) | (0.44) | (–2.09) | (0.16) | (–0.15) | (–3.23) | (–2.14) | (1.47) | (0.07) | (–1.25) | (–0.87) | (1.08) | (6.18) | (0.88) | (–1.94) | (0.26) | (1.76) | (0.20) | (–0.91) | (1.31) | (1.16) | (3.46) | (–3.58) | (1.84) | (2.94) | (–0.70) | (3.92) | (5.89) |
| 2001-2017 | –0.12 | –0.21 | –1.41 | –0.02 | 0.00 | –0.47 | –0.37 | 0.46 | –0.34 | –1.91 | –0.78 | –0.03 | 8.24 | –0.07 | –0.74 | 0.02 | –0.02 | –0.08 | 0.31 | 0.34 | 1.18 | 0.08 | –0.24 | 1.38 | 0.11 | –0.06 | 0.10 | 0.18 |
| | (–3.29) | (–1.93) | (–3.11) | (–0.18) | (0.03) | (–1.01) | (–0.55) | (4.11) | (–1.89) | (–1.80) | (–2.69) | (–1.89) | (1.62) | (–0.52) | (–2.26) | (0.08) | (–0.64) | (–0.30) | (0.70) | (1.69) | (2.72) | (0.34) | (–2.16) | (1.38) | (7.28) | (–2.81) | (4.42) | (6.87) |
| $R_{t+1}$ Adj. to FF | –0.07 | –0.06 | –1.84 | 0.07 | 0.02 | –0.40 | –1.25 | 0.42 | 0.04 | –1.96 | –0.14 | –0.02 | 29.25 | 0.11 | –0.61 | 0.16 | 0.04 | 0.01 | –0.35 | 0.45 | 0.75 | 0.67 | –0.47 | 0.41 | 0.09 | –0.03 | 0.16 | 0.21 |
| and Momentum | (–3.83) | (–0.84) | (–6.70) | (1.22) | (0.34) | (–1.65) | (–2.73) | (5.49) | (0.34) | (–2.60) | (–0.41) | (–3.26) | (9.15) | (0.88) | (–3.20) | (1.25) | (0.95) | (0.07) | (–1.34) | (3.37) | (2.45) | (3.26) | (–5.60) | (0.79) | (9.19) | (–2.03) | (10.84) | (12.25) |
| L. Sentiment | –0.05 | –0.27 | –0.41 | –0.12 | –0.07 | –1.32 | 0.05 | 0.61 | –0.72 | –0.69 | –0.68 | –0.04 | 26.32 | 0.34 | –0.55 | 0.38 | 0.03 | –0.28 | –0.31 | 0.50 | 0.42 | 0.76 | –0.29 | 1.35 | 0.10 | –0.01 | 0.14 | 0.18 |
| | (–1.00) | (–2.10) | (–0.70) | (–1.06) | (–0.76) | (–2.02) | (0.06) | (3.95) | (–2.98) | (–0.41) | (–0.84) | (–1.85) | (4.93) | (2.54) | (–1.29) | (1.42) | (0.36) | (–0.92) | (–0.56) | (1.95) | (0.71) | (1.91) | (–1.70) | (1.01) | (5.39) | (–0.46) | (4.66) | (5.13) |
| H. Sentiment | –0.08 | 0.03 | –1.73 | 0.09 | 0.00 | –0.20 | –1.89 | 0.34 | 0.26 | –3.22 | 0.28 | –0.03 | 34.38 | 0.03 | –0.66 | 0.04 | 0.03 | 0.28 | –0.69 | 0.38 | 1.14 | 0.70 | –0.67 | 0.24 | 0.09 | –0.07 | 0.19 | 0.22 |
| | (–2.02) | (0.31) | (–4.94) | (1.43) | (–0.03) | (–0.55) | (–2.90) | (3.29) | (1.59) | (–2.64) | (0.56) | (–3.43) | (7.48) | (0.21) | (–2.60) | (0.26) | (0.45) | (1.48) | (–2.06) | (2.14) | (2.75) | (2.77) | (–5.62) | (0.45) | (6.49) | (–2.67) | (9.85) | (9.70) |
| L. Volatility | –0.03 | –0.05 | –1.01 | 0.05 | 0.17 | 0.05 | –1.06 | 0.28 | 0.23 | –2.77 | –1.25 | 0.00 | 20.98 | –0.29 | –1.06 | 0.00 | 0.00 | 0.03 | –0.14 | 0.18 | 1.24 | 0.65 | –0.30 | 0.16 | 0.12 | –0.04 | 0.16 | 0.19 |
| | (–0.89) | (–0.43) | (–2.39) | (0.50) | (2.05) | (0.17) | (–1.76) | (2.60) | (1.26) | (–2.14) | (–2.57) | (–0.38) | (4.17) | (–1.19) | (–3.16) | (0.02) | (0.11) | (0.15) | (–0.35) | (1.09) | (2.76) | (2.34) | (–2.29) | (0.21) | (7.16) | (–1.77) | (7.64) | (7.59) |
| H. Volatility | –0.11 | –0.07 | –1.81 | 0.01 | –0.14 | –0.87 | –1.30 | 0.55 | –0.32 | –2.22 | 0.97 | –0.05 | 37.06 | 0.41 | –0.30 | 0.21 | 0.04 | 0.14 | –0.64 | 0.54 | 0.65 | 0.69 | –0.71 | 0.90 | 0.07 | –0.05 | 0.17 | 0.22 |
| | (–2.55) | (–0.63) | (–4.26) | (0.18) | (–2.02) | (–1.76) | (–1.70) | (4.36) | (–1.72) | (–1.62) | (1.63) | (–3.99) | (8.27) | (3.57) | (–1.11) | (1.13) | (0.53) | (0.65) | (–1.69) | (2.57) | (1.40) | (2.41) | (–5.31) | (1.30) | (5.13) | (–1.75) | (7.17) | (8.07) |
| L. liquidity | –0.03 | 0.21 | –1.61 | 0.15 | 0.01 | –0.69 | –0.62 | 0.19 | 0.08 | –3.75 | 0.84 | –0.02 | 46.86 | 0.13 | –0.60 | 0.35 | 0.06 | –0.01 | –1.00 | 0.71 | 0.65 | 1.23 | –0.55 | 0.26 | 0.09 | –0.05 | 0.22 | 0.24 |
| | (–0.80) | (2.22) | (–3.47) | (1.55) | (0.15) | (–1.83) | (–0.82) | (1.58) | (0.43) | (–2.38) | (1.03) | (–3.99) | (10.97) | (0.54) | (–1.89) | (1.64) | (0.72) | (–0.03) | (–2.91) | (4.08) | (1.14) | (3.34) | (–3.75) | (0.51) | (5.23) | (–2.11) | (9.71) | (8.31) |
| H. liquidity | –0.11 | –0.27 | –1.33 | –0.06 | –0.01 | –0.29 | –1.63 | 0.61 | –0.20 | –1.49 | –0.67 | –0.04 | 17.02 | 0.07 | –0.67 | –0.06 | –0.01 | 0.16 | 0.02 | 0.13 | 1.11 | 0.25 | –0.51 | 0.82 | 0.10 | –0.04 | 0.12 | 0.18 |
| | (–2.69) | (–2.30) | (–3.36) | (–0.83) | (–0.19) | (–0.64) | (–2.43) | (5.22) | (–1.12) | (–1.27) | (–2.04) | (–2.55) | (3.55) | (0.58) | (–2.34) | (–0.30) | (–0.27) | (0.70) | (0.06) | (0.63) | (2.95) | (1.17) | (–4.11) | (0.98) | (6.81) | (–1.48) | (5.61) | (7.36) |
| L. Market | –0.13 | 0.10 | –2.26 | –0.12 | –0.25 | –2.72 | 1.03 | 0.63 | –1.14 | –1.64 | –0.37 | –0.12 | 12.09 | 0.21 | –1.47 | –0.27 | –0.07 | 0.13 | –0.91 | 1.02 | 0.69 | 0.36 | 0.16 | 2.44 | 0.09 | –0.07 | 0.16 | 0.22 |
| | (–1.56) | (0.49) | (–2.69) | (–0.64) | (–2.20) | (–2.39) | (0.70) | (2.63) | (–2.96) | (–0.77) | (–0.77) | (–2.84) | (1.61) | (1.10) | (–2.27) | (–0.75) | (–0.99) | (0.27) | (–1.24) | (2.45) | (0.81) | (0.65) | (0.85) | (0.89) | (3.14) | (–1.61) | (3.36) | (3.96) |
| H. Market | –0.07 | –0.09 | –1.33 | 0.05 | 0.04 | –0.11 | –1.54 | 0.39 | 0.09 | –2.60 | 0.04 | –0.02 | 32.71 | 0.08 | –0.51 | 0.18 | 0.04 | 0.08 | –0.34 | 0.28 | 0.95 | 0.72 | –0.64 | 0.28 | 0.09 | –0.04 | 0.17 | 0.21 |
| | (–2.18) | (–0.99) | (–4.11) | (0.84) | (0.65) | (–0.36) | (–2.91) | (4.38) | (0.69) | (–2.46) | (0.08) | (–2.13) | (8.85) | (0.56) | (–2.28) | (1.20) | (0.77) | (0.52) | (–1.13) | (1.92) | (2.68) | (3.34) | (–6.08) | (0.67) | (7.96) | (–2.02) | (9.79) | (10.27) |
| Control for | –0.08 | –0.04 | –1.54 | 0.01 | –0.01 | –0.61 | –0.91 | 0.40 | –0.09 | –2.10 | 0.00 | –0.03 | 29.37 | 0.08 | –0.50 | 0.21 | 0.04 | 0.20 | –0.26 | 0.32 | 0.45 | 0.31 | –0.54 | 0.56 | 0.09 | –0.06 | 0.08 | 0.20 |
| *PDI*/*FDI* | (–2.85) | (–0.48) | (–5.12) | (0.12) | (–0.10) | (–2.01) | (–1.83) | (4.82) | (–0.66) | (–2.20) | (–0.00) | (–3.48) | (8.67) | (0.64) | (–2.39) | (1.50) | (1.02) | (1.29) | (–0.96) | (2.32) | (1.38) | (1.55) | (–5.67) | (1.07) | (8.12) | (–2.98) | (4.86) | (10.47) |