# Using Maximum Drawdowns to Capture Tail Risk*

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ABSTRACT

We propose the use of maximum drawdown, the maximum peak to trough loss across a time series of compounded returns, as a simple method to capture an element of risk unnoticed by linear factor models: tail risk. Unlike other tail-risk metrics, maximum drawdown is intuitive and easy-to-calculate. We look at maximum drawdowns to assess tail risks associated with market neutral strategies identified in the academic literature. Our evidence suggests that academic anomalies are not anomalous: all strategies endure large drawdowns at some point in the time series. Many of these losses would trigger margin calls and investor withdrawals, forcing an investor to liquidate.

JEL Classification: G12, G14

Key words: empirical asset pricing, max drawdown, tail-risk, anomalies

Empirical asset pricing research focused on identifying anomalous returns often disregards tail-risk metrics. For example, none of the 11 academic studies identified in Stambaugh, Yu, and Yuan (2012) as the most pervasive academic anomaly studies, include an examination of tail-risk in their original analysis. In these research papers, the primary basis for proclaiming an "anomaly" is anchored on alpha estimates from linear factor models, such as the 3-factor Fama and French (1993) market, value, and size model, or the 4-factor model that includes an additional momentum factor (Carhart (1997)). The momentum anomaly originally outlined in Jegadeesh and Titman (1993) illustrates the point that asset pricing studies over rely on alpha estimates. Jegadeesh and Titman claim large alphas associated with long/short momentum strategies over the 1965 to 1989 time period. What these authors fail to mention is that the long/short strategy endures a 33.81% holding period loss from July 1970 until March 1971. When we look out of sample from 1989 to 2012, there is still significant alpha associated with the long/short momentum strategy, but the strategy endures an 86.05% loss from March 2009 to September 2009. An updated momentum study reporting alpha estimates would claim victory, an investor engaged in the long/short momentum strategy would claim bankruptcy. Tail risk matters to investors and it should matter in empirical research.

There is a well-developed theoretical literature highlighting why tail-risk matters to investors such as Rubinstein (1973) as well as Kraus and Litzenberger (1976). In Table 1 we highlight with a simple example why tail risk requires researcher attention. Table 1 shows a set of statistical measures included in many academic anomaly papers: average monthly returns, standard deviation of returns, and a laundry list of linear factor model alphas. We analyze 3 time series: 1) the value-weight CRSP index, 2) the value-weight CRSP index with 10 percent alpha injected (we simply add 10%/12 into each monthly return), and 3) the value-weight CRSP index with a 10 percent alpha injection, but the index experiences a final return of -100%, or in other words, the index goes bankrupt. The alpha estimates for the alpha injected series and the alpha injected series with an eventual bankruptcy are robust and highly significant alphas across all factor models. The author of this research study would proclaim that investing in an eventual bankrupt, high-alpha value-weight CRSP index rejects the market efficiency hypothesis. The reality is that researchers need to include measures of tail risk for a particular strategy before claiming an anomaly victory.

The literature is at no loss for measures that capture tail-risk. For example, Harvy and Siddique (2000) identify a conditional skewness measure to capture non-linear risks in asset prices, but the measure requires relatively complex calculations to compute. Conrad, Dittmar, and Ghysels (2013) propose the use of option markets to directly identify how the market prices tail-risk. This approach is sensible, but requires real-time option data and is difficult to backtest due to option data limitations. Bali and Cakici (2004) describe the use of value-at-risk, which is a step closer in the direction of identifying a *simple* way to measure tail-risk. The issue with all of the proposed tail-risk measures is that researchers rarely include these measures in their studies. We conjecture that the reasons anomaly researchers ignore tail-risk measures is due to relatively complex calculation requirements and the relative difficulty in understanding previously proposed measures.

Our first contribution to the literature is to highlight an easily measurable and intuitive tail-risk measure referred to as maximum drawdown. Maximum drawdown is defined as the maximum peak to trough loss associated with a time series. Maximum drawdown captures the worst possible performance scenario experienced by a buy and hold investor dedicated to a specific strategy. The intuition behind maximum drawdown is simple: how much can I lose?

Maximum drawdowns have received little attention in the academic literature relative to common linear factor models such as the CAPM, the 3-factor, and the 4-factor models. And yet, the use of maximum drawdown is pervasive in practice. For example, PerTrac, the investment industry leading performance analytics software, showcases drawdowns and statistics that use drawdowns (e.g., Calmar and Sterling Ratio), in their software package. Another example is from *HSBC Private Bank Hedge Weekly* newsletter, which features Maximum Drawdown alongside Annual Volatility as the only two measures of risk highlighted in the report. Of course, maximum drawdown is not perfect: the measure is an in-sample realization of the worst-case scenario, and the measure is not amiable to traditional statistical analysis. However, maximum drawdown does serve as a benchmark for how much an investor can lose by investing in a strategy.

Our second contribution to the literature is to highlight the usefulness of the simple maximum drawdown measure in the context of academic anomalies. Anomalies are proclaimed when the patterns in average stock returns cannot be explained by the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) or more sophisticated factor models, such as the Fama-French 3-Factor model or the 4-factor model (Carhart (1997)). Despite robust alpha estimates, we find significant maximum drawdowns associated with all long/short asset pricing anomalies. The drawdowns are so extreme, that in most of the long/short strategies proposed an arbitrageur would suffer margin calls via direct broker intervention or from indirect margin calls via forced liquidations by fund investors. In short, anomalies don't represent proverbial twenty dollar bills sitting on the ground; instead, they represent strategies with extreme tail risk.

The remainder of the paper is organized as follows. Section I describes drawdown calculations. Section II describes the data. Section III provides a performance analysis of long/short asset pricing anomalies. Section IV explores drawdowns in the context of long/short strategies. Section V concludes.

[Insert Table 1]

## I. Maximum Drawdown

Maximum drawdown (MDD) is defined as follows:

$$MDD = \min_{\forall t,T}\left(\prod_{t}^{T} r_{i,t} - 1\right).$$

In words, maximum drawdown measures the worst possible peak to trough performance within a time series of returns. Throughout our analysis we focus on monthly return measurements within our time series, but the technique can also be applied to daily or even intra-day data.

Investors care about MDD because it shows, historically, the worst possible scenario. Understanding worst possible scenarios is important for investors because it allows an investor to identify the required recovery rate to break even with their previous high-water mark. Investment managers with compensation contracts tied to high-water marks (e.g., hedge funds) are also focused on MDD because it directly ties into their compensation.

Despite the simplicity and intuitive nature of the MDD, the measure is far from perfect. First, MDD will mechanically increase as the sample size increases, because there is more probability for extreme return possibilities as the sample increases. One must be careful to compare similar time periods when comparing MDD across strategies. Second, MDD only measures loss extrema, but says nothing about the frequency of large losses. For example, strategy A may have a MDD of -40% and strategy B may have a MDD of -50%, but strategy A has multiple -30% drawdowns, whereas strategy B has no drawdowns, save the -50% drawdown observed. Strategy A dominates with respect to MDD, but it is unclear that it is less risky than strategy B. Conditional value-at-risk (CVAR) or expected shortfall (e.g., Rockafellar and Uryasev (2002)) can help in the analysis of the frequency of large drawdowns, but the trade-off with CVAR relative to MDD is more complication.

In Table 2 we highlight historical MDD associated with the value-weight CRSP index, the equal-weight CRSP index, and the 10-year Treasury bond. Panel A highlights the actual drawdowns associated with the benchmarks over the July 1, 1963 to December 31, 2012 period. The equal-weight CRSP index is the most risky, with a MDD of -59.81%. Panel B shows the associated recovery rates required in order to break even after experiencing a drawdown. For example, to recover from the -59.81% MDD on the equal-weight CRSP index, an investor would require a 148.79% return to reach their previous high-water mark—a heroic achievement by most investor’s standards.

[Insert Table 2]

## II. Data

Our data sample includes all firms on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and Nasdaq firms with the required data on CRSP and Compustat. We examine the time period from July 1st 1963 until December 31st 2012. We only examine firms with ordinary common equity on CRSP and eliminate all REITS, ADRS, and closed-end funds, and financial firms.[1] We incorporate CRSP delisting return data using the technique of Beaver, McNichols, and Price (2007).

To be included in the sample, all firms must have a non-zero market value of equity as of June 30th of year *t*. Stock returns are measured from July 1st 1963 through December 31st 2012. Firm size (e.g., market capitalization) is determined by the June 30th value of year *t.* Firm fundamentals are based on December 31st of year *t-1* (for firms with fiscal year ends between January 1st and March 31st we use year *t* fundamentals; for firms with fiscal year ends after March 31st we use year *t-1* fundamentals).

Stambaugh, Yu, and Yuan (2012) identify 11 academic anomalies that are the most prominent in the literature. The 11 anomalies are as follows:

- **Financial distress (DISTRESS)**. Campbell, Hilscher, and Szilagyi (2007) find that firms with high failure probability have lower subsequent returns. Their methodology involves estimating a dynamic logit model with both accounting and equity market variables as explanatory variables. Investors systematically underestimate the predictive information in the Campbell, Hilscher, and Szilagyi model, which is shown to predict future returns. DISTRESS is computed similar to Campbell, Hilscher, and Szilagyi (2007).
- **O-Score (OSCORE).** Ohlson (1980) creates a static model to calculate the probability of bankruptcy. This is computed using accounting variables. OSCORE is computed using the same methodology in Ohlson (1980).
- **Net stock issuance (NETISS).** Ritter (1991) and Loughran and Ritter (1995) show that, in post-issue years, equity issuers under-perform matching non-issuers with

[1] We perform our analysis while including financial firms and get similar results, which are available from the authors upon request.

similar characteristics. The evidence suggests that investors are unable to identify that firms prefer to raise capital by issuing stock when equity prices are overvalued. We measure net stock issues as the growth rate of the split-adjusted shares outstanding in the previous fiscal year.

- **Composite Equity Issuance (COMPISS).** Daniel and Titman (2006) study an alternative measure, composite equity issuance, defined as the amount of equity a firm issues (or retires) in exchange for cash or services. They also find that issuers under-perform non-issuers because investors overlook the signals from repurchases and issuance. We measure REP similar to Daniel and Titman (2006).

- **Total accruals (ACCRUAL).** Sloan (1996) shows that firms with high accruals earn abnormal lower returns on average than firms with low accruals. This anomaly exists because investors overestimate the persistence of the accrual component of earnings. Total accruals are computed using the same methodology as Sloan (1996).

- **Net operating assets (NOA).** Hirshleifer, Hou, Teoh, and Zhang (2004) find that net operating assets, defined as the difference on the balance sheet between all operating assets and all operating liabilities scaled by total assets, is a strong negative predictor of long-run stock returns. Investors are unable to focus on accounting profitability while neglecting information about cash profitability. NOA is computed using the methodology in Hirshleifer, Hou, Teoh, and Zhang (2004).

- **Momentum (MOM).** The momentum effect was first documented by Jagadeesh and Titman (1993). We calculate the momentum ranking monthly by looking at the cumulative returns from month -12 to month -2 similar to Fama and French (2008).

- **Gross profitability premium (GP).** Novy-Marx (2010) discovers that sorting on gross profit-to-assets creates abnormal benchmark-adjusted returns, with more profitable firms having higher returns than less profitable ones. Novy-Marx argues that gross profits divided by total assets is the cleanest accounting measure of true economic profitability and that investors overlook the investment value of the profitability of the firm. Gross profitability premium is measured by gross profits (REVT - COGS) scaled by total assets (AT).

- **Asset growth (AG).** Cooper, Gulen, and Schill (2008) find companies that grow their total asset more earn lower subsequent returns. The authors argue that investors overestimate future growth and business prospects based on observing a firm's asset growth. Asset growth is measured as the growth rate of the total assets (AT) in the previous fiscal year.
- **Return on assets (ROA).** Fama and French (2006) find that more profitable firms have higher expected returns than less profitable firms. Chen, Novy-Marx, and Zhang (2010) show that firms with higher past return on assets earn abnormally higher subsequent returns. Investors appear to underestimate the importance of ROA. ROA is computed as income before extraordinary items (IB) divided by lagged total assets (AT).
- **Investment-to-assets (INV).** Titman, Wei, and Xie (2004) and Xing (2008) show that higher past investment predicts abnormally lower future returns. The authors posit that this anomaly stems from investor's inability to identify manager empire-building behavior via investment patterns. Investment-to-assets is measured as the annual change in gross property, plant, and equipment (PPEGT) plus the annual change in inventories (INVT) scaled by the lagged total assets (AT).

We calculate monthly alphas on three different factor models. Three of the factors are described in Fama and French (1993): the return on the stock market (MKT), the return spread between small and large stocks (SMB), and the return spread between stocks with high and low book-to-market ratios (HML). The fourth factor is the spread between high and low momentum stocks (UMD), first described in Carhart (1997). We get the monthly returns to these four factors from Ken French's website.[2] In our Tables, we show the monthly alpha estimates for the 1-factor (MKT), 3-factor (MKT, SMB, HML), and 4-factor (MKT, SMB, HML, UMD) models.

For each of the anomaly strategies we use the information available on June of year *t* to sort portfolios and generate returns from July of *t* to June of year *t + 1*. The exception is the momentum variable, which is recalculated each month to sort portfolios.

## III. Results: Long/Short Strategy Performance Analysis

We look at the performance of the 11 academic anomalies in Table 3. For each strategy we go long the top decile firms ranked on the respective anomaly measure and go short the bottom decile of firms. To avoid confusion, the top decile firms are considered the "good" firms, and the bottom decile firms are considered the "bad" firms. For example, if we sort firms on accruals, high accruals are bad and the low accrual firms are good. In our rankings, the top firms are the lowest accrual firms and the bottom firms are the highest accrual firms. As per previous research, we identify strong evidence for anomalous long/short zero-investment returns. Alpha estimates across all factor models are generally positive and statistically significant.

Among the competing anomalies, we find that Financial Distress, Momentum, Gross Profits, and Return on Assets perform the best when comparing 3-factor alphas. Table 3, Panel

[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

A shows monthly 3-factor alphas of 1.52%, 2.23%, 0.87%, and 1.07%, respectively. The outperformance of these measures is robust to the 4-factor model. The monthly 4-factor alphas are 0.85% for Financial Distress, 0.64% for Momentum, 0.70% for Gross Profits, and 0.96% for Return on Assets. The momentum anomaly drops by 71% because the momentum factor included in the regression captures most of the variability associated with momentum-based returns.

Looking at the equal-weighted returns, we find that monthly alpha point estimates are generally higher. In Panel B of Table 3 (equal-weight returns), we find that 6 of our anomalies have a monthly 3-factor alpha above 1%. The 3-factor monthly alphas are as follows: Net Stock Issuance (1.06%), Composite Issuance (1.05%), Net Operating Assets (1.20%), Momentum (1.14%), Asset Growth (1.17%), and Investment to Assets (1.14%). In general, when looking at the monthly alphas, researchers conclude that these investment strategies are anomalous because they are not explained by linear factor models. The argument against the use of linear factor models is that they are unable to capture the true risk factors underlying a specific strategy. We confirm this notion in the analysis that follows.

[Insert Table 3]

## IV. Results: Strategy Drawdown Analysis

In this section we examine drawdowns for 11 long/short academic anomalies. We calculate maximum drawdowns for each anomaly and provide the dates the drawdown began and ended. For comparison, we also provide the return on the long portfolio, the short portfolio, and the S&P 500 return over this same time period. In addition, we calculate the maximum drawdown across all rolling twelve month periods. This analysis fixes the holding period to twelve months and determines the worst possible performance among all rolling twelve month periods.

Panel A of Table 4 examines the maximum drawdowns for the value-weight long/short returns. When looking at the worst drawdown in the history of the long/short return series, we find that 6 of the 11 strategies have maximum drawdowns of more than 50%. The Oscore, Momentum, and Return on Assets, endure maximum drawdowns of 83.50%, 86.05% and 84.71%, respectively! These losses would trigger immediate margin calls and liquidations from brokers. We do find that Net Stock Issuance and Composite Issuance limit maximum drawdowns, with maximum drawdowns of 29.23% and 26.27%, respectively. If a fund employed minimal leverage, a fund implementing these strategies would likely survive a broker liquidation scenario.

[Insert Table 4]

In addition to broker margin calls and liquidations, investment managers face liquidation threats from their investors. Liquidations occur for two primary reasons: there are information asymmetries between investors and investment managers, and 2)investors rely on past performance to ascertain expected future performance (Shleifer and Vishny (1997)). To understand the potential threat of liquidation from outside investors, we examine the performance of the S&P 500 during the maximum drawdown period and the twelve month drawdown period for each of our respective academic anomalies. In 9/11 cases, the S&P 500 has exceptional performance during the largest loss scenarios for the value-weighted long/short strategies. In the case of the Net Stock Issuance and the Composite Issuance anomaly—the long/short strategies with the most reasonable drawdowns—the S&P 500 returns 56.40% and 49.46% during the respective drawdown periods. One can conjecture that investors would find it difficult to maintain discipline to a long/short strategy when they are underperforming a broad equity index by over 75%. Stories about the benefits of "uncorrelated alpha" can only go so far.

One conclusion suggested by the previous analysis is that arbitrageurs trading long/short anomalies are forced to exit their trades at certain times. This forced liquidation might create a limit of arbitrage: investors are forced to liquidate positions at the exact point when expected returns are the highest. One prediction from this story is that returns to long/short anomalies are high following terrible performance. We test this prediction in Table 5. We examine the returns on the 11 academic anomalies following their maximum drawdown event. We compute three-, six-, and twelve-month compound returns to the long/short strategies immediately following the worst drawdown. The evidence suggests that performance following a maximum drawdown event is exceptional. All the anomalies experience strong positive returns over three-, six-, and twelve-month periods following the drawdown event. This evidence hints that maximum drawdowns create a limit to arbitrage: The drawdowns trigger investors to suffer large scale liquidations and this may force them out of the long/short trade at the exact time when the trade has the highest expected returns.

[Insert Table 5]

## V. Conclusions

We describe an easily measurable and intuitive tail risk measure referred to as maximum drawdown. Maximum drawdown is defined as the maximum peak to trough loss associated with a time series. Maximum drawdown captures the worst possible performance scenario experienced by a buy and hold investor dedicated to a specific strategy.

We show the usefulness of the simple maximum drawdown measure in the context of academic anomalies. Despite robust alpha estimates, we find significant maximum drawdowns associated with all long/short asset pricing anomalies. The drawdowns are so extreme, that in most of the long/short strategies proposed an arbitrageur would suffer margin calls via direct broker intervention or from indirect margin calls via forced liquidations by fund investors. We conclude that academic anomalies may not be anomalous because they suffer from a hidden tail risk. We also provide evidence that academic anomalies, even if they do represent genuine mispricing, might persist in the future because of limits to arbitrage.

**References**

Beaver, William, Maureen McNichols, and Richard Price, 2007, Delisting Returns and Their Effect on Accounting-Based Market Anomalies, *Journal of Accounting and Economics* 43, 341-368.

Bali, Turan G., and Nusret Cakici, 2004, Value at risk and expected stock returns, *Financial Analysts Journal* 60, 57-73.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899-2939.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chen, Long, Robert Novy-Marx, and Lu Zhang, 2010, An alternative three-factor model, Unpublished working paper. University of Rochester.

Conrad, Jennifer, Robert F. Dittmar, and Eric Ghysels, 2013, Ex ante skewness and expected stock returns, *Journal of Finance* 68, 85-124.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008, Asset growth and the cross-section of stock returns, *Journal of Finance* 63, 1609–1652.

Daniel, Kent D., and Sheridan Titman, 2006. Market reactions to tangible and intangible Information, *Journal of Finance* 61, 1605–1643.

Davison, Russell, and James G. MacKinnon, 1993. Estimation and Inference in Econometrics. New York: Oxford University Press.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and Kenneth R. French, 2006, Profitability, investment, and average returns, *Journal of Financial Economics* 82, 491–518.

Fama, Eugene F., and Kenneth R. French, 2008, Dissecting Anomalies, *Journal of Finance* 63, 1653–1678.

Harvy, Campbell R., and Akhtar Siddique, 2000, Conditional skewness in asset pricing tests, *Journal of Finance* 55, 1263-1295.

Hirshleifer, David A., Kewei Hou, Siew Hong Teoh, and Yinglei Zhang, 2004, Do investors overvalue firms with bloated balance sheets, *Journal of Accounting and Economics* 38, 297–331.

Jagadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling Losers: Implications for stock market efficiency, Journal of Finance 48, 65-91.

Kraus, Allen, and Robert Litzenberger, 1976, Skewness preference and the valuation of risk assets, *Journal of Finance* 31, 1085-1100.

Lintner, John, 1965, The valuation of rik assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13-37.

Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23–51.

Novy-Marx, Robert, 2010. The other side of value: good growth and the gross profitability premium. Unpublished working paper. University of Chicago.

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

Ritter, Jay R., 1991, The long-run performance of initial public offerings, *Journal of Finance* 46, 3–27.

Rockafellar, Tyrrel and Stanislav Uryasev, 2002, Conditional value-at-risk for general loss distributions, *Journal of Banking and Finance* 26, 1443-1471.

Rubinstein, Mark E., 1973, The fundamental theorem of parameter-preference security valuation, *Journal of Financial and Qualitative Analysis* 8, 61-69.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425-442.

Shleifer, Andrei, and Robert W. Vishney, 1997, The limits of arbitrage, *Journal of Finance* 52, 35-55.

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

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288–302.

Titman, Sheridan, K. C. John Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of Financial and Quantitative Analysis* 39, 677–700.

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

**Table 1: Summary Statistics for Hypothetical Alpha Portfolio**

This table reports calendar-time portfolio regression alphas and summary statistics for the value-weight CRSP index (VW CRSP), the VW CRSP index with 10% alpha (we add 10%/12 to each monthly return), and the VW CRSP with 10% alpha and a final monthly return of -100% (VW CRSP w/ alpha & bankruptcy). Portfolios for each strategy are rebalanced each year on July 1st and are held from July 1st of year *t* until June 30th of year *t+1*. The time period under analysis is from July 1, 1963, to December 31, 2012. For each portfolio (column), we show the average monthly return and the standard deviation of the monthly returns. We calculate monthly returns to the portfolios and run regressions against linear factor models. The four factors are: the return on the stock market (MKT), the return spread between small and large stocks (SMB), the return spread between stocks with high and low book-to-market ratios (HML), and the spread between high and low momentum stocks (UMD). We get the monthly factor returns from Ken French's website. We regress the monthly portfolio returns against the 1-factor model (MKT), the 3-factor model (MKT, SMB, and HML), and the 4-factor model (MKT, SMB, HML, UMD). Monthly Alphas are calculated, with p-values below the coefficient estimates, and 5% statistical significance is indicated in bold. All p-values use robust standard errors as computed in Davidson and MacKinnon (1993, 5. 553).

| | VW CRSP | VW CRSP w/alpha | VW CRSP w/alpha & Bankruptcy |
|---|---|---|---|
| Average monthly returns | 0.0088 | 0.0171 | 0.0154 |
| Standard dev. (monthly) | 0.0450 | 0.0450 | 0.0614 |
| 1-Factor alpha | **-0.0001** | **0.0082** | **0.0065** |
| | 0.0000 | 0.0000 | 0.0001 |
| 3-Factor alpha | **-0.0001** | **0.0082** | **0.0069** |
| | 0.0000 | 0.0000 | 0.0000 |
| 4-Factor alpha | **-0.0001** | **0.0082** | **0.0067** |
| | 0.0000 | 0.0000 | 0.0000 |

**Table 2: Max Drawdowns and Associated Recovery Rates**

This table reports drawdowns measured over different time periods for the value-weight CRSP index, the equal-weight CRSP index, and the 10-year Treasury bond. The time period under analysis is from July 1, 1963, to December 31, 2012. Maximum drawdown (shown in Panel A) is measured as the worst peak to trough performance over the full time series; worst 12-month drawdown is measured as the worst 12-month rolling period performance over the full times series; worst 36-month drawdown is measured as the worst 36-month rolling period performance over the full times series. Recovery rates (shown in Panel B) represent the return required in order to fully recover from a given drawdown.

| Panel A: Drawdowns | VW CRSP | EW CRSP | 10-Year Treas |
|---|---|---|---|
| Worst Monthly Drawdown | -22.54% | -27.22% | -8.41% |
| Worst Twelve-Month Drawdown | -44.21% | -47.48% | -17.10% |
| Worst Thirty Six-Month Drawdown | -41.88% | -49.74% | -17.03% |
| Worst Drawdown | -51.57% | -59.81% | -20.97% |
| Panel B: Recovery Rates | | | |
| Required Recovery (Worst Monthly) | 29.09% | 37.41% | 9.18% |
| Required Recovery (Worst 12-month) | 79.25% | 90.39% | 20.63% |
| Required Recovery (Worst 36-month) | 72.06% | 98.95% | 20.52% |
| Required Recovery (Worst Drawdown) | 106.47% | 148.79% | 26.54% |

**Table 3: Portfolio Returns to Long/Short Anomaly Strategies**

This table reports calendar-time portfolio regression alphas and summary statistics for long/short anomaly strategies. Portfolios for each strategy are rebalanced each year on July 1st and are held from July 1st of year *t* until June 30th of year *t+1*. The one exception is the Momentum strategy, which is rebalanced every month. The time period under analysis is from July 1, 1963, to December 31, 2012. Panel A shows the results for the value-weighted portfolios, and Panel B shows the results for the equal-weighted portfolios. For each long/short strategy, we show the average monthly return and the standard deviation of the monthly returns. We calculate monthly returns to the portfolios and run regressions against linear factor models. The four factors are: the return on the stock market (MKT), the return spread between small and large stocks (SMB), the return spread between stocks with high and low book-to-market ratios (HML), and the spread between high and low momentum stocks (UMD). We get the monthly factor returns from Ken French's website. We regress the monthly portfolio returns against the 1-factor model (MKT), the 3-factor model (MKT, SMB, and HML), and the 4-factor model (MKT, SMB, HML, UMD). Monthly Alphas are calculated, with p-values below the coefficient estimates, and 5% statistical significance is indicated in bold. All p-values use robust standard errors as computed in Davidson and MacKinnon (1993, 5. 553).

| Panel A: Value-Weighted L/S Deciles | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | DISTRESS | OSCORE | NETISS | COMPISS | ACCRUAL | NOA | MOM | GP | AG | ROA | INV |
| Average returns | 0.0161 | 0.0048 | 0.0131 | 0.0113 | 0.0107 | 0.0106 | 0.0223 | 0.0108 | 0.0101 | 0.0099 | 0.0110 |
| Standard dev. | 0.0612 | 0.0572 | 0.0329 | 0.0368 | 0.0426 | 0.0382 | 0.0873 | 0.0490 | 0.0422 | 0.0644 | 0.0330 |
| 1-Factor alpha | **0.0127** | 0.0025 | **0.0098** | **0.0090** | **0.0071** | **0.0063** | **0.0196** | **0.0075** | **0.0066** | **0.0079** | **0.0072** |
| | 0.0000 | 0.2379 | 0.0000 | 0.0000 | 0.0000 | 0.0001 | 0.0000 | 0.0002 | 0.0001 | 0.0013 | 0.0000 |
| 3-Factor alpha | **0.0152** | **0.0058** | **0.0086** | **0.0069** | **0.0071** | **0.0076** | **0.0223** | **0.0087** | 0.0027 | **0.0107** | **0.0046** |
| | 0.0000 | 0.0008 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0706 | 0.0000 | 0.0005 |
| 4-Factor alpha | **0.0085** | **0.0060** | **0.0079** | **0.0067** | **0.0069** | **0.0072** | **0.0064** | **0.0070** | 0.0025 | **0.0096** | **0.0043** |
| | 0.0004 | 0.0008 | 0.0000 | 0.0000 | 0.0004 | 0.0000 | 0.0005 | 0.0005 | 0.1515 | 0.0000 | 0.0017 |
| **Panel B: Equal-Weighted L/S Deciles** | | | | | | | | | | | |
| | DISTRESS | OSCORE | NETISS | COMPISS | ACCRUAL | NOA | MOM | GP | AG | ROA | INV |
| Average returns | 0.0082 | 0.0039 | 0.0152 | 0.0143 | 0.0117 | 0.0156 | 0.0134 | 0.0107 | 0.0179 | 0.0043 | 0.0169 |
| Standard dev. | 0.0612 | 0.0520 | 0.0374 | 0.0455 | 0.0256 | 0.0359 | 0.0810 | 0.0431 | 0.0386 | 0.0601 | 0.0313 |
| 1-Factor alpha | 0.0042 | 0.0003 | **0.0124** | **0.0124** | **0.0075** | **0.0115** | **0.0096** | **0.0067** | **0.0142** | 0.0009 | **0.0133** |
| | 0.1060 | 0.8807 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0044 | 0.0002 | 0.0000 | 0.6985 | 0.0000 |
| 3-Factor alpha | 0.0048 | **0.0036** | **0.0106** | **0.0105** | **0.0069** | **0.0120** | **0.0114** | **0.0062** | **0.0117** | **0.0029** | **0.0114** |
| | 0.0743 | 0.0463 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0014 | 0.0005 | 0.0000 | 0.1815 | 0.0000 |
| 4-Factor alpha | -0.0021 | 0.0026 | **0.0093** | **0.0090** | **0.0066** | **0.0112** | -0.0020 | **0.0053** | **0.0109** | 0.0013 | **0.0103** |
| | 0.5042 | 0.1908 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.5169 | 0.0044 | 0.0000 | 0.5938 | 0.0000 |

**Table 4: Drawdowns associated with L/S strategies**

This table reports drawdowns measured over different time periods for the long portfolio (Long Ret), the short portfolio (Short Ret), and the long/short portfolios (L/S) associated with different anomalies. Portfolios for each strategy are rebalanced each year on July 1st and are held from July 1st of year *t* until June 30th of year *t+1*. The one exception is the Momentum strategy, which is rebalanced every month. The time period under analysis is from July 1, 1963, to December 31, 2012. Panel A shows the results for the value-weighted portfolios, and Panel B shows the results for the equal-weighted portfolios. Maximum drawdown is measured as the worst peak to trough performance over the full time series. We also calculate the worst 12-month drawdown is measured as the worst 12-month rolling period performance over the full times series. The beginning date (Beg Date) and ending date (End Date) for the worst drawdowns and 12-month drawdowns are given in the table below. Last, we provide the performance of the S&P500 over the same time period as the worst drawdown. For example, the worst drawdown for the value-weighted Financial Distress (DISTRESS) occurs between 10/1/2002 and 5/31/2003. We show that the S&P500 return over that same time period is 19.85%. We do this for each of the long/short portfolios, given the time period of their maximum drawdown, and the time period of their worst 12-month drawdown.

| Panel A: Value-Weight | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Maximum Drawdown | | | | | | Worst 12-month Drawdown | | | | | |
| | Long Ret | Short Ret | L/S | Beg Date | End Date | S&P500 | Long Ret | Short Ret | L/S | Beg Date | End Date | S&P500 |
| DISTRESS | 6.10% | 86.88% | -54.21% | 10/1/2002 | 5/31/2003 | 19.85% | -9.77% | 38.31% | -49.99% | 7/1/2002 | 6/30/2003 | 0.85% |
| OSCORE | 19.81% | 288.08% | -83.50% | 9/1/1998 | 3/31/2004 | 29.89% | 38.36% | 128.57% | -54.77% | 5/1/1998 | 4/30/1999 | 22.03% |
| NETISS | 48.48% | 100.43% | -29.23% | 12/1/2008 | 3/31/2011 | 56.40% | 40.18% | 76.61% | -23.29% | 4/1/2009 | 3/31/2010 | 49.08% |
| COMPISS | 18.51% | 56.85% | -26.27% | 8/1/1970 | 5/31/1972 | 49.46% | 46.34% | 76.69% | -19.82% | 4/1/2009 | 3/31/2010 | 49.08% |
| ACCRUAL | -24.75% | 31.29% | -43.96% | 7/1/2005 | 8/31/2009 | -5.29% | 32.73% | 77.58% | -27.73% | 5/1/1980 | 4/30/1981 | 31.65% |
| NOA | 48.62% | 243.06% | -59.91% | 3/1/1972 | 7/31/1981 | 85.59% | -0.40% | 32.12% | -27.20% | 6/1/1979 | 5/31/1980 | 18.52% |
| MOM | 23.73% | 281.16% | -86.05% | 3/1/2009 | 9/30/2009 | 45.01% | 24.43% | 246.77% | -84.78% | 2/1/2009 | 1/31/2010 | 32.94% |
| GP | 107.52% | 325.95% | -57.56% | 9/1/1998 | 2/29/2000 | 46.47% | 46.99% | 156.04% | -48.17% | 3/1/1999 | 2/29/2000 | 12.24% |
| AG | -11.20% | 52.89% | -44.49% | 1/1/2007 | 8/31/2012 | 13.64% | -8.66% | 28.89% | -29.96% | 1/1/2007 | 12/31/2007 | 5.76% |
| ROA | 519.36% | 1580.34% | -84.71% | 5/1/1963 | 6/30/1983 | 441.71% | 60.26% | 186.18% | -59.42% | 9/1/1998 | 8/31/1999 | 39.81% |
| INV | 1.41% | 53.98% | -35.57% | 10/1/2006 | 6/30/2008 | -0.47% | -18.19% | 16.35% | -30.83% | 7/1/2007 | 6/30/2008 | -12.67% |
| Panel B: Equal-Weight | | | | | | | | | | | | |
| DISTRESS | -9.20% | 58.90% | -80.16% | 1/1/2001 | 6/30/2003 | -22.89% | 7.40% | 75.24% | -56.18% | 7/1/2002 | 6/30/2003 | 0.85% |
| OSCORE | 1207.90% | 2671.20% | -79.92% | 5/1/1964 | 7/31/1983 | 345.79% | 33.03% | 144.54% | -49.56% | 1/1/1967 | 12/31/1967 | 23.97% |
| NETISS | 48.85% | 134.87% | -42.26% | 11/1/1998 | 2/29/2000 | 27.55% | 37.40% | 98.24% | -35.83% | 3/1/1999 | 2/29/2000 | 12.24% |
| COMPISS | 45.00% | 159.48% | -50.03% | 9/1/1998 | 2/29/2000 | 46.47% | 27.80% | 100.19% | -41.65% | 3/1/1999 | 2/29/2000 | 12.24% |
| ACCRUAL | -51.39% | -37.18% | -19.33% | 11/1/2000 | 9/30/2002 | -41.11% | -0.92% | 19.30% | -17.38% | 5/1/1985 | 4/30/1986 | 36.77% |
| NOA | -29.79% | 20.97% | -41.53% | 2/1/2004 | 6/30/2008 | 23.79% | -11.25% | 12.51% | -20.81% | 3/1/2004 | 2/28/2005 | 7.02% |
| MOM | 116.06% | 132.18% | -92.99% | 1/1/2001 | 10/31/2009 | -5.70% | -4.51% | 256.39% | -83.99% | 11/1/2008 | 10/31/2009 | 9.77% |
| GP | 97.57% | 251.82% | -55.26% | 1/1/1999 | 2/29/2000 | 13.31% | 87.22% | 215.01% | -52.04% | 3/1/1999 | 2/29/2000 | 12.24% |
| AG | -65.81% | -50.16% | -31.66% | 2/1/2004 | 12/31/2008 | -10.91% | -36.20% | -21.04% | -19.38% | 7/1/2007 | 6/30/2008 | -12.67% |
| ROA | 7692.48% | 13503.07% | -88.88% | 10/1/1963 | 2/29/2000 | 6962.76% | 69.54% | 265.18% | -66.79% | 3/1/1999 | 2/29/2000 | 12.24% |
| INV | -6.54% | 37.72% | -33.02% | 2/1/2004 | 6/30/2008 | 23.79% | -30.55% | -10.32% | -22.91% | 7/1/2007 | 6/30/2008 | -12.67% |

**Table 5: Returns Following Max Drawdowns**

This table reports compound returns measured over different time periods (3-month, 6-month, and 12-month) for the long portfolio (Long Ret), short portfolio (Short Ret), and the long/short portfolios (L/S) associated with different anomalies. Portfolios for each strategy are rebalanced each year on July 1st and are held from July 1st of year *t* until June 30th of year *t+1*. The one exception is the Momentum strategy, which is rebalanced every month. The time period under analysis is from July 1, 1963, to December 31, 2012. Panel A shows the results for the value-weighted portfolios, and Panel B shows the results for the equal-weighted portfolios. Maximum drawdown is measured as the worst peak to trough performance over the full time series. The return series are calculated following the maximum drawdown experienced by the long/short portfolio. For example, the worst drawdown experienced by the Financial Distress (DISTRESS) portfolio ends on 5/31/2003 (see Table 4), so the 3-month return below shows the returns to the portfolio from 6/1/2003 – 8/31/2003. This is done similarly for the 6 and 12 month returns shown below for each long/short portfolio, based off the end date of their maximum drawdown (see Table 4).

| Panel A: Value-Weight | 3-month Return | | | 6-month return | | | 12-month return | | |
|---|---|---|---|---|---|---|---|---|---|
| | Long Ret | Short Ret | L/S | Long Ret | Short Ret | L/S | Long Ret | Short Ret | L/S |
| DISTRESS | 18.31% | 8.73% | 9.11% | 35.34% | 13.06% | 20.35% | 41.61% | 25.60% | 13.21% |
| OSCORE | 3.57% | -1.70% | 4.86% | -1.90% | -16.64% | 14.99% | 4.70% | -15.24% | 18.77% |
| NETISS | 2.70% | -2.48% | 5.15% | -8.53% | -24.58% | 19.43% | 14.37% | -11.22% | 26.48% |
| COMPISS | 4.90% | -4.54% | 9.88% | 17.60% | 0.39% | 17.15% | 14.30% | -21.60% | 43.86% |
| ACCRUAL | 10.65% | 4.93% | 5.31% | 19.02% | 9.87% | 8.45% | 26.16% | 3.54% | 21.53% |
| NOA | -6.44% | -10.74% | 3.60% | -5.24% | -17.41% | 12.73% | -8.47% | -36.04% | 38.77% |
| MOM | 13.61% | -1.06% | 13.59% | 26.63% | 4.73% | 20.00% | 30.01% | -0.77% | 28.93% |
| GP | -4.22% | -40.03% | 48.56% | 10.26% | -30.47% | 43.25% | -16.18% | -68.10% | 104.54% |
| AG | 1.07% | -5.65% | 6.89% | 4.50% | -8.58% | 13.84% | 4.50% | -8.58% | 13.84% |
| ROA | -2.67% | -11.57% | 9.70% | -6.67% | -18.94% | 14.23% | -15.90% | -37.63% | 31.83% |
| INV | -12.33% | -31.14% | 23.56% | -34.90% | -56.03% | 38.55% | -28.50% | -45.96% | 20.19% |
| Panel B: Equal-weight | | | | | | | | | |
| DISTRESS | 27.45% | 20.56% | 6.15% | 57.05% | 39.72% | 13.31% | 56.12% | 54.33% | 2.42% |
| OSCORE | -9.35% | -19.46% | 11.72% | -9.54% | -22.82% | 15.94% | -21.05% | -42.40% | 34.51% |
| NETISS | -4.97% | -27.72% | 27.23% | 3.54% | -20.82% | 24.04% | 13.11% | -51.02% | 68.99% |
| COMPISS | -2.60% | -28.06% | 30.65% | 5.40% | -21.69% | 26.74% | 17.38% | -52.71% | 72.57% |
| ACCRUAL | 24.06% | 9.30% | 15.68% | 24.76% | 10.49% | 15.06% | 151.50% | 85.01% | 41.50% |
| NOA | -14.53% | -21.54% | 7.94% | -35.14% | -53.02% | 30.01% | 7.52% | -29.41% | 40.00% |
| MOM | 10.61% | 6.26% | 3.72% | 44.34% | 28.12% | 12.51% | 39.72% | 13.17% | 23.55% |
| GP | -21.07% | -39.56% | 25.59% | -9.56% | -28.02% | 17.37% | -18.53% | -60.54% | 69.27% |
| AG | 12.09% | 6.16% | 4.51% | 74.70% | 61.09% | 7.67% | 173.43% | 96.30% | 40.49% |
| ROA | -11.11% | -44.31% | 47.13% | 2.56% | -34.82% | 41.04% | -11.96% | -65.29% | 64.41% |
| INV | -14.43% | -26.00% | 13.56% | -43.02% | -56.68% | 22.64% | -17.63% | -35.24% | 15.14% |