WHICH ANOMALIES ARE MORE POPULAR? AND WHY?

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We explore why certain anomalies documented by prior literature are more popular among arbitrageurs than others. We infer arbitrageurs' involvement via abnormal changes in short interest when a security falls into the "short leg." We find that the variation in anomaly popularity is related to an anomaly's upside potential, but not its downside-risk. Anomaly popularity also relates to the corresponding anomalies being discussed in academic outlets, suggesting that academic research helps to disseminate knowledge about anomalous returns.

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1. Introduction

In recent years, the financial marketplace has seen a proliferation of investment companies that freely use strategies involving any combination of leverage and long/short positions in securities (e.g., Bausano and Nemes (2012)). The immense price impact that these investors can exert has led to scrutiny by public authorities and the popular press, frequently pointing to the potential harm such investors cause (e.g., Garbaravicius and Dierick, 2005). Their net effect on financial markets, however, is far from obvious. In particular, arbitrageurs thrive on price inefficiencies and, by simultaneously taking long- and short positions, these investors have the potential to eliminate anomalous price differences and contribute to the price discovery process, ultimately making markets more efficient.

Our purpose in this study is to explore a set of anomaly-based strategies documented by prior literature, test whether arbitrageurs trade on these anomalies and examine whether some anomalies are more popular than others, and, if so, why. Our analysis follows Stambaugh, Yu, and Yuan (2012) and examines 11 anomalies based on measures of financial distress, equity issuance, accruals, net operating assets, profitability, asset growth, and investment ratio. Each anomaly represents a pattern in stock returns that is difficult to explain with traditional asset-pricing models.[1]

We find that in our sample period from 1988 to 2010, the majority of anomaly-based strategies, which goes long on the stocks expected to outperform (long leg) and short on those expected to underperform (short leg), continue to produce high raw returns and strong positive alphas relative to the Fama-French (1993) three-factor model. The performance is far from steady, however, with abnormal returns on long-short portfolios being positive in only 56% of the months. Long-short portfolios also exhibit substantial negative skewness. For instance, in its six worst-performing months, the long-short portfolio based on the momentum effect lost an average of 18.76% per month; across all 11 anomalies, the six worst-performing months produced an average loss of 13.02% per month.

To examine the central proposition of this study, we rely on arbitrageurs' constructing portfolios becoming reflected in the short interest of a security. To illustrate by example, prior literature finds that

[1] Such as the Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965).

when forming portfolios based on accruals at the end of each June in year *t*, the portfolio of stocks with less positive accruals (long leg) outperforms the portfolio of stocks with more positive accruals (short leg) over the ensuing one-year holding period. To assess whether arbitrageurs attempt to capitalize on the return differential, we examine whether securities entering the short leg in June of year *t* experience a disproportionate rise in short interest relative to securities entering the long leg.

Our results suggest that arbitrageurs do trade on anomalies. We find that when a security falls into the short leg, its short interest increases abnormally; the reverse applies when a security leaves the short leg. This pattern is stronger for some anomalies than others, however. In particular, we observe the strongest disproportionate rise in the short interest of short-leg securities for strategies based on accruals, asset growth, and investment-over-assets. A cross-sectional comparison of anomaly performance and our proxy for anomaly popularity reveals a strong negative correlation. That is, strategies more popular among arbitrageurs, on average, exhibit lower abnormal returns, consistent with arbitrageurs trading away parts of the anomalous returns.[2]

The evidence suggests that arbitrageurs' preferences for certain strategies are driven by differences in the upside of the corresponding long-short portfolios, irrespective of differences in downside risk. Specifically, a strategy's popularity strongly depends on the 95th or 99th percentile of past benchmark-adjusted returns of the long-short portfolio; however, its popularity is unrelated to the 5th or 1st percentile (or even the median) of past benchmark-adjusted return. This pattern is consistent with the notion that the convexity of fee structures common in the investment industry encourages managers to employ strategies with high upside, with little regard for the associated downside risk.

Anomaly popularity also relates to the respective anomalies being discussed in academic journals. Our evidence suggests that trading activity grounded in anomaly-based strategies increases notably subsequent to their being covered in academic outlets. To illustrate some of the economic significance, we find that the extent to which short interest rises disproportionally when a security enters the short leg increases by 41% following the publication of Sloan (1996). Combined with the observed negative

[2] Parts of the remaining anomalous returns may be attributed to transaction costs.

correlation between anomaly performance and arbitrage efforts, this finding lends itself to the interpretation that academic research helps to disseminate knowledge of seemingly anomalous returns, which, ultimately, makes markets more efficient.

Our study adds to work by Dechow, Hutton, Meulbroek, and Sloan (2001) and Hanson and Sunderam (2011), who find that short-sellers increase short positions for "growth" firms and firms with high past returns. Hirshleifer, Teoh, and Yu (2011) present evidence that investors engage in short arbitrage of the accrual anomaly and that arbitrage efforts depend on the ease of undertaking arbitrage strategies. Consistent with this stream of literature, our results based on a wide set of anomalies imply that arbitrageurs aim to capitalize on anomalous returns. We note that some anomalies are more popular than others. We identify these more popular anomalies and shed light on why they attract more arbitrage efforts. We find that two of the strongest determinants are (1) the corresponding anomaly being discussed in the academic literature and (2) the anomaly-based strategy having significant upside; measures of downside risk have no explanatory power.

That the convexity of fee structures encourages risk-taking has long been suspected by academics and regulators (Hodder and Jackwerth (2007) and Goetzmann, Ingersoll, and Ross (2003)). At the same time, the notion of "excess risk-taking" has been difficult to establish empirically, raising the possibility that its relevance to financial markets may have been overemphasized (Ross (2004) and Panageas and Westerfield (2009)). Here, we provide evidence to the contrary, namely, that a strategy's upside potential strongly enters the investment decision making process of arbitrageurs; the associated downside risk, on the other hand, does not. As such, our finding has the potential to contribute to the discussion of how fee structures incentivize managers and, more broadly, how contracts and organisational structure affect financial markets. In general, our (descriptive) evidence on anomaly profits and arbitrage efforts may prove to be helpful in furthering our understanding of how professional asset managers react to perceived market inefficiencies and influence prices.

The paper is organized as follows: Section 2 describes the data. Section 3 presents our main findings, and Section 4 concludes.

2. Data

Our sample consists of NYSE, AMEX, and NASDAQ ordinary shares during the period of 1988 through 2010 with data necessary to compute monthly abnormal short interest (to be defined below).[3] As institutions generally do not trade illiquid securities, we exclude stocks with a stock price < $5 as of portfolio formation (e.g., Jegadeesh and Titman (2001), Daniel and Titman (2006)). Our results are robust to more restrictive liquidity cutoff points based on dollar trading volume and market capitalization.[4] Following prior literature (e.g., Ohlson (1980), Titman, Wei, and Xie (2004), Fama and French (2006), Novy-Marx (2012)), we further exclude stocks with one-digit SIC code = 6.

NYSE, AMEX, and NASDAQ member firms are required to report to the exchange their short positions as of settlement on the 15th of each month, or on the preceding business day if the 15th is not a business day. For the period from January 1988 through December 2002, we obtain monthly short interest data directly from the stock exchanges. For the period of January 2003 through December 2009, we obtain monthly short interest data from the COMPUSTAT monthly securities database, which, in turn, pools data from the NYSE, AMEX, and NASDAQ exchanges.

We obtain financial-market data from the Center for Research in Security Prices (CRSP) and financial-statement data from the COMPUSTAT industrial files. We use these data sources to construct portfolio returns as well as variables to capture the following 11 anomalies (all of which are described in the Appendix and discussed in Stambaugh, Yu, and Yuan (2012)).[5]

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[3] Our sample of firm-month obervations with short interest data covers more than 60% of firm-month observations and 78% of total market capitalization in the CRSP monthly stock file during the period of 1988 through 2009.

[4] Including, but not limited to, > $100 million in market capitalization, > $1 million in daily trading volume.

[5] Also see, among others, Campbell, Hilscher, and Szilagyi (2008) for anomaly 1; Ohlson (1980) for anomaly 2; Ritter (1991) and Loughran and Ritter (1995) for anomaly 3; Daniel and Titman (2006) for anomaly 4; Sloan (1996) for anomaly 5; Hirshleifer, Hou, Teoh and Zhang (2004) for anomaly 6; Jegadeesh and Titman (1993, 2001) for anomaly 7; Novy-Marx (2010) for anomaly 8; Cooper, Gulen, and Schill (2008) for anomaly 9; Fama and French (2006) for anomaly 10; and Titman, Wei, and Xie (2004) and Xing (2008) for anomaly 11.

	Stocks Expected to Outperform (Long leg)	Stocks Expected to Underperform (Short leg)
Anomaly 1 (Failure Probability)	Low failure probability	High failure probability
Anomaly 2 (O-Score)	Low O-Score [low financial distress risk]	High O-Score [high financial distress risk]
Anomaly 3 (Net Stock Issuance)	Low net stock issuance	High net stock issuance
Anomaly 4 (Comp. Equ. Issuance)	Low composite issuance	High composite issuance
Anomaly 5 (Total Accruals)	Low total accruals	High total accruals
Anomaly 6 (Net Operating Assets)	Low net operating assets	High net operating assets
Anomaly 7 (Momentum)	High past 6-month returns	Low past 6-month returns
Anomaly 8 (Gross Profitability)	High gross profitability	Low gross profitability
Anomaly 9 (Asset Growth)	Low asset growth	High asset growth
Anomaly 10 (Profitability)	High return on assets	Low return on assets
Anomaly 11 (Investment Ratio)	Low past investment ratio	High past investment ratio

3. Main Results

3.1. Anomaly Performance

Every portfolio formation month, we sort stocks into decile portfolios based on the anomaly variables discussed above and construct value-weighted decile portfolio returns. In accordance with prior literature, for anomalies (3)-(9) and (11), we form portfolios as of the end of each June in year *t* (using accounting data from the fiscal year ending in calendar year *t*-1) and compute returns from July in year *t* to June in year *t*+1. For anomalies (1)-(2) and (10), we form portfolios as of the end of each calendar quarter *t* (using accounting data from the fiscal quarter ending in calendar quarter *t*-1) and compute returns over the ensuing calendar quarter *t*+1. For instance, when forming portfolios at the end of Mar2000 (using quarterly accounting data from the fiscal quarter ending in Oct1999, Nov1999, or Dec1999), we compute returns on those portfolios from Apr2000 to Jun2000. For the momentum anomaly (7), we form portfolios every month. We skip one month between portfolio formation and the portfolio-holding period, and we hold portfolios for six months. Our results are robust to alternate definitions of portfolio formation/holding periods (results are available upon request).

We report excess returns, as well as benchmark-adjusted returns, for the long leg (decile 10) and the short leg (decile 1), with the long leg being the higher-performing decile, as reported in previous studies. Following Brennan, Chordia, and Subrahmanyam (1998), benchmark-adjusted returns, *Adj.Ret*, are defined as returns net of what is attributable to exposures to the market, size, and value factors constructed by Fama and French (1993):

$$Ret_{i,t} - rf_t = \alpha_i + \beta_i Mktrf_t + \gamma_i SMB_t + \delta_i HML_t + \varepsilon_{i,t}$$
$$\rightarrow Adj.Ret_{i,t} = \alpha_i + \varepsilon_{i,t}.\text{[6]} \quad (1)$$

Table 1 shows that most of the 11 strategies, each purchasing stocks in the long leg and shorting stocks in the short leg, continue to produce high raw returns and strong positive alphas relative to the Fama-French (1993) three-factor model, consistent with their being identified as anomalies for this study. The average monthly benchmark-adjusted return across all 11 long-short strategies is 0.76%. For the composite-equity-issue- and the investment-over-assets-based anomalies, the long leg does not reliably outperform the short leg in our sample comprising stocks with short interest data and a stock price of greater than $5. The performance of the asset-growth-based strategy is also weak, consistent with evidence presented by Fama and French (2006). Of the remaining strategies that produce significant positive alphas, the financial-distress- and the profitability-based strategies perform the strongest. As we will show later, the anomaly strategies with the weakest performances also tend to be the ones that attract the highest arbitrage efforts as estimated via changes in residual short interest. This pattern is consistent with arbitrageurs trading away parts of the anomalous returns.

The generally good performance of long-short portfolios is punctuated with episodes of strong negative returns (also see Daniel and Moskowitz, 2012). For instance, the return of the long-short portfolio based on the momentum effect averages -18.76% per month across its six worst-performing

[6] The return series for each anomaly is available on the authors' website at: http://web.ics.purdue.edu/~liu138/research.html.

months. The corresponding average across the remaining 10 anomalies is substantially less negative, but with -12.44% per month still economically meaningful. These highly negative average monthly returns persist when extending the window from the 6 to the 24 worst-performing months, which represent 10% of our sample period. Here, the average monthly long-short portfolio return based on the momentum effect equals -10.51%. The corresponding average across the remaining anomalies is -6.66% per month. In short, trading on anomalies is risky and accompanied with significant downside risk; the downside risk is the most severe for the momentum strategy.

3.2. Which Anomalies Are More Popular?

The goal of this study is to explore systematically whether arbitrageurs trade on anomalies and, if so, which anomalies are more popular among arbitrageurs and why. We first explain our methodology (Section 3.2.1). We then present our main results (Section 3.2.2).

3.2.1 Methodology

We infer arbitrageurs' involvement via changes in short interest. Should certain investor groups be actively involved in arbitrage activities and short securities that are expected to underperform and, perhaps simultaneously, use parts of the proceeds from those short sales to long securities that are expected to outperform, we should observe a disproportionate rise in short interest once a security falls into the short leg. For instance, prior literature finds that when forming portfolios based on total accruals at the end of each June in year t, the portfolio of stocks with less positive accruals (long leg) outperforms the portfolio of stocks with more positive accruals (short leg) over the ensuing one-year portfolio holding period, i.e., from July in year t to June in year t+1. To assess whether arbitrageurs attempt to capitalize on the return differential accrued from July in year t to June in year t+1, we examine whether, by the end of June in year t, the short leg experienced a disproportionate rise in short interest relative to the long leg.

One might object to the use of short interest as a measure of arbitrage efforts on the grounds that securities are shorted for a variety of reasons. For instance, an investor may short a security because it is perceived to be overpriced for very firm-specific (not anomaly-based) reason. Motivated by prior literature (e.g., Hong, Lim, and Stein, 2000; Baker and Wurgler, 2006; Lemmon and Portniaguina, 2006), we, therefore, construct a measure of residual short interest. Specifically, we estimate monthly cross-sectional regressions of short interest on a set of firm characteristics that have been found to relate to the level of short interest (Brent, Morse, and Stice (1990) and Francis, Venkatachalam, and Zhang (2005)). As we would rather err on the side of *understating* the magnitude of anomaly-related arbitrage efforts than on the side of overstating it, we choose our control set, *X*, to be as large as possible. *X* includes: past one-year returns, market-to-book ratio, market beta computed using monthly returns over the previous five years, idiosyncratic volatility computed using daily returns over the previous month, an indicator of whether the firm in question has convertible debt, the natural logarithm of lagged market capitalization and institutional holdings.[7]

Consistent with prior studies, we observe that the level of short interest increases in past returns, market-to-book ratio, market beta, idiosyncratic volatility, convertible debt and institutional holdings. It is unrelated to market capitalization once controlling for institutional holdings. Because we control for past returns to construct residual short interest, we do not analyze how residual short interest pertains to the momentum effect. Our analyses from this point onward are thus conducted on 10 anomaly portfolios only.

Our proxy for arbitrage efforts equals Δ*Short Interest*, which is the change in residual short interest over the portfolio formation period. In line with the horizon over which our 10 anomaly portfolios are formed, Δ*Short Interest* represents the change in residual short interest over the 12-month portfolio formation period for anomalies (3)-(9) and (11) and the 3-month portfolio formation period for anomalies (1)-(2) and (10). We note that our results are robust to alternate definitions of portfolio-formation periods (results are available upon request).

[7] The results become slightly stronger when choosing a smaller control set, suggesting that multicollinearity among *X* is of little concern.

Before presenting our main results, a few caveats are in order. First, our testing ground does not differentiate between short arbitrage (i.e., arbitrageurs being active in the short-leg only) and long-short arbitrage (i.e., arbitrageurs shorting securities that are expected to underperform and, simultaneously, using parts of the proceeds from those short sales to long securities that are expected to outperform). As the latter allows arbitrageurs to not only capture anomalous returns on the short-side, but also on the long-side, and, as constructing long-short portfolios allows arbitrageurs to hedge against industry- and market risk, it appears likely that an observed disproportionate rise in short interest would be accompanied with offsetting positions in the long leg. However, given the lack of direct evidence, we note that an observed abnormal rise in short interest is consistent with either scenario.

A second caveat concerns our focus on the short leg. In particular, one may consider replacing the fraction of shares shorted with the fraction of shares held by institutions. If institutional investors – as a whole – were acting as arbitrageurs, we should expect not only a disproportionate rise in short interest when a security enters the short-leg, but also a disproportionate rise in institutional holdings when a security enters the long-leg.

In practice, institutional investors – as a whole – are unlikely to act as arbitrageurs (Lewellen (2011)). As a result, arbitrageurs' longing securities expected to outperform need not translate to higher institutional holdings, as arbitrageurs could buy securities from other non-arbitrage institutions, resulting in no net gain in institutional holdings.

Another alternative strategy to gauge arbitrage efforts would be to directly examine the performance of hedge funds, which are often thought of as acting arbitrageurs. Should hedge-fund returns correlate with returns on certain anomaly strategies, this would indicate that hedge funds are trading on these anomalies. One drawback of this approach is that hedge-fund databases suffer from biases (e.g., Fung and Hsieh, 2009; Bhardwaj, 2010).[8] Moreover, hedge funds engage in a multitude of strategies. Teasing out which anomalies are more popular from "aggregate" hedge fund returns is thus difficult.

[8] Biases are introduced because hedge funds only report performance information to data vendors that helps them reach potential investors (e.g., Fung and Hsieh, 2009; Bhardwaj, 2010).

Our testing ground is not without its own limitations. In particular, we do not capture the extent to which arbitrageurs use derivative securities as an alternate mean by which to construct long-short portfolios. We note that as long as short-selling and the use of derivative securities are not negatively correlated, our inferences based on short interest still apply. To this end, Brent, Morse, and Stice (1990) provide evidence that short-selling and the use of derivative securities are complements, rather than substitutes, and we observe similar results when repeating our tests for the subset of securities with no listed options.[9]

3.2.2 Trading on Anomalies

The results presented in Table 2 suggest that investors trade on anomalies. That is, when a security falls into the short leg, its short interest increases abnormally. The average change in residual short interest, Δ*Short Interest,* among securities in the short leg across all 10 anomalies is +0.17%. This contrasts with an average Δ*Short Interest* among long-leg securities of +0.00%.

To put the differential change of +0.17% in perspective, the average level of short interest across all stocks in our sample is 2.33%. The increase in residual short interest of 0.17% is thus economically meaningful.[10] Moreover, because our analysis is based on residual short interest, which, to be conservative, is orthogonalized with respect to a wide set of firm characteristics, some of which correlate with anomaly-based mispricing, our results likely understate the true extent to which investors trade on the anomalies examined in this study. Consistent with this claim, we observe stronger results when repeating our analysis for raw short interest as opposed to residual short interest.

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[9] Mayhew and Mihov (2004) find that in 1996 (the end of their sample period), around 3,500 stocks were eligible for stock options, but that only around 2,000 stocks had listed options. The analyses based on the subset of no listed options thus represent tests on a meaningful subset, both in terms of number of securities and market capitalization (results available upon request).

[10] Moreover, as stocks falling into the short leg may already have a high level of short interest from having fallen into the short leg the previous formation period, our results likely understate the extent to which arbitrageurs trade on anomalies. Consistent with this notion, we observe that when focusing on "fresh short-leg" securities, i.e., securities that fall into the short leg this formation period, but were not in the short leg the previous formation period, the average Δ*Short Interest* across all eleven anomalies slightly increases from +0.17% to +0.19%.

Table 2 also reports the average Δ*Short Interest* of securities that subsequently fall out of the short leg relative to that of former long-leg securities. We observe that when a security leaves the short leg, short interest generally decreases disproportionally.

3.2.3 Differences in Anomaly Popularity: The Role of Academia

Figure 1 examines how the pattern documented in Table 2 varies through time. To construct the figure, we compute, for each of the 10 anomalies and at the end of each June in year *t*, the average Δ*Short Interest* for short-leg securities and the average Δ*Short Interest* for long-leg securities. For anomalies (3)-(9) and (11), portfolios are formed once a year, and Δ*Short Interest* therefore represents the change in residual short interest over the 12-month period from the end of July in year *t*-1 to the end of June in year *t*. For anomalies (1)-(2) and (10), portfolios are formed once a quarter. We thus compute aggregate changes in residual short interest over the previous four quarters as of the end of each June in year *t*. We plot, for each anomaly, the annual/annualized difference between the average Δ*Short Interest* among securities in the short leg and that of long-leg securities through time.

A comparison across sub-figures reveals that, generally, securities falling into the short leg experience a substantially greater increase in short interest than their long-leg counterparts and that this pattern holds even at the beginning of our sample period, which starts in 1989, before most of the anomalies examined in this study were publicized in academic outlets. Figure 1 thus implies that arbitrageurs are trading on anomalies prior to their being discussed in peer-reviewed journals.

However, we also observe that the aforementioned pattern strengthens after article publication (The sub-figures mark the year in which corresponding academic studies were published.). For instance, we observe that the relative rise in residual short interest of short-leg securities strengthens notably in the years subsequent to Sloan (1996) for the accruals-anomaly, Hirshleifer, Hou, Teoh, and Zhang (2004) for the net operating assets-anomaly, and Titman, Wei, and Xie (2004) for the investment over assets-anomaly.

Across all anomalies, for which a before/after-publication-comparison can be made, the spread in the average Δ*Short Interest* between short-leg securities and long-leg securities widens by 0.11% in the three-year period following journal publication; this increase is statistically significant at the 1% level. One interpretation of this finding is that academic studies help to publicize strategies and their seemingly anomalous returns to potential arbitrageurs.

3.2.4 Differences in Anomaly Popularity: The Role of a Strategy's Upside Potential/Downside Risk

The disproportionate rise in short interest for short-leg securities relative to long-leg securities varies across anomalies. In particular, we find that, on average, short interest rises abnormally for the following five anomalies: failure probability, accruals, net operating assets, asset growth, and investment over assets, suggesting that these anomalies are particularly popular among arbitrageurs. We detect little to no abnormal rise in short interest in the short leg for strategies based on Ohlson's O, equity issuances, and profitability.

To assess differences in popularity more generally, we compute, for each anomaly, the average Δ*Short Interest* of stocks in the short leg relative to that of long-leg securities and estimate a regression equation of the differential Δ*Short Interest* on lagged anomaly characteristics. The observations in this regression are on an anomaly/year level. For anomalies (3)-(9) and (11), we form portfolios as of the end of each June in year *t*, and Δ*Short Interest* represents the change in residual short interest over the 12-month period from the end of July in year *t*-1 to the end of June in year *t*. For anomalies (1)-(2) and (10), we form portfolios as of the end of each calendar quarter, and we compute aggregate changes in residual short interest over the previous four quarters as of the end of each June in year *t*.

The independent variables are as follows: (1) *Portion of Profits Coming from Short-Side*, which is the unsigned average monthly benchmark-adjusted return over the previous five years of the short leg divided by the sum of the unsigned average monthly benchmark-adjusted return of the short leg and the long leg; if the average abnormal return in the short leg is positive, this variable is set to zero; if the average abnormal return in the long leg is negative and the average abnormal return in the short leg is negative, this variable is set to 100%; (2) *Beta*, which is the beta coefficient estimate from a rolling five-year time-series regression of the strategy's monthly benchmark-adjusted long-short portfolio return on the monthly composite index, which represents the benchmark-adjusted return of a portfolio that invests an equal portion in each of the 11 anomaly-based long-short portfolios considered in this study.[11] The five-year window starts at the end of July in year *t*-6 and ends at the end of June in year *t*-1; (3) *Idiosyncratic Volatility,* which is the standard deviation of the residuals from the aforementioned time-series regressions; (4) *Average Return*, which is the strategy's rolling five-year average monthly benchmark-adjusted long-short portfolio return; (5) *Skewness*, which is the strategy's rolling five-year skewness of monthly benchmark-adjusted long-short portfolio returns; (6) *Return – 50th percentile*, which is the strategy's rolling five-year median monthly benchmark-adjusted long-short portfolio return; (7) *Return – 5th (1st) percentile*, which is the strategy's rolling five-year 5$^{\text{th}}$ (1$^{\text{st}}$) percentile of monthly benchmark-adjusted long-short portfolio returns; (8) *Return – 95th (99th) percentile*, which is the strategy's rolling five-year 95$^{\text{th}}$ (99$^{\text{th}}$) percentile of monthly benchmark-adjusted long-short portfolio returns.

As reported in Table 3, when regressing our measure of anomaly popularity on the corresponding strategy's *Portion of Profits Coming from Short-Side*, *Beta*, *Idiosyncratic Volatility*, and *Average Returns*, the coefficient estimates indicate that a strategy's popularity strongly *increases* in its own volatility. Relatedly, when replacing *Idiosyncratic Volatility* with *Skewness*, the coefficient estimates imply that a strategy's popularity increases in its own skewness. These results are consistent with the notion that the convexity of fee structures, common among investment companies that can freely use long/short strategies, encourages managers to employ strategies with high variance.

To expound on this claim, we estimate regressions of our measure of popularity on the strategy's *Portion of Profits Coming from Short-Side*, *Beta*, *Idiosyncratic Volatility*, and percentiles of monthly benchmark-adjusted returns over the past five years. Because the distribution of past benchmark-adjusted returns is not symmetric, the percentiles are not perfectly correlated with each other, allowing us to gauge

[11] The composite index includes the momentum strategy as arbitrageurs likely trade on the momentum effect. However, as we are unable to gauge arbitrage efforts in the momentum strategy based on residual short interest, which is orthogonalized to past returns, the remaining variables in the regression equation are based on 10 anomaly strategies only.

whether arbitrageurs pay more attention to the 5th percentile of past monthly abnormal returns or the 95th percentile.

As reported in Table 3, we observe that a strategy's popularity among arbitrageurs does not depend on the substantial negative tail risk documented in Section 3.1. The coefficient estimate on *Return – 5th percentile*, which is the strategy's rolling five-year 5th percentile of benchmark-adjusted long-short portfolio returns, is insignificant; the same statement applies to *Return – 1st percentile*. The median abnormal return also does not explain much of the difference in popularity across strategies. However, we observe strong positive coefficient estimates on *Return – 95th percentile* or *Return – 99th percentile*; the estimates equal 0.104 (*t*-statistic=2.53) and 0.051 (*t*-statistic=3.06), respectively. Together, our results imply that negative downside risk does not enter arbitrageurs' consideration; a strategy's potential upside, on the other hand, does.

The economic significance of our determinants of a strategy's popularity is substantial. For instance, the coefficient estimate on *Idiosyncratic Volatility* implies that a one-standard-deviation increase in *Idiosyncratic Volatility* is associated with a 0.13% increase in the change in abnormal short interest; a one-standard-deviation increase in *Return – 95th percentile* is associated with a 0.22% increase in the change in abnormal short interest. Compared to the average level of short interest of 2.33%, these implied differential increases in short interest are meaningful.

The differences in popularity across anomalies shed light on why some anomalies produce higher returns than others. The correlation between anomaly performance (reported in Panel B of Table 1) and arbitrage efforts as estimated via changes in residual short interest (reported in Table 2) produces a Pearson's Correlation Coefficient of -0.45. That is, strategies that are more popular among arbitrageurs, on average, yield lower abnormal returns, consistent with arbitrageurs trading away parts of the anomalous returns.

What prevents arbitrageurs from fully exploiting seemingly anomalous returns? Transaction costs and liquidity constraints likely play a role. Because our analysis is based on residual short interest, which is orthogonalized to a wide set of firm characteristics, including those that strongly relate to transaction costs and liquidity constraints (market capitalization, institutional holdings), we are unable to directly test for the role transaction costs and liquidity constraints.

In untabulated analyses, we estimate a regression of the average Δ*Raw Short Interest* of stocks in the short leg relative to that of long-leg securities on lagged anomaly characteristics. The anomaly characteristics are similar to the ones included in the regression equations reported in Table 3 (*Portion of Profits Coming from Short-Side, Beta, Idiosyncratic Volatility, Average Returns*), but now also include the following four independent variables: (a) *Turnover-Short Side* (*Turnover-Long Side*), which is the average daily turnover as of the end of June in year *t*-1 across stocks that are in the respective strategy's short leg (long leg);[12] and (b) *Log(Size-Short Side)* (*Log(Turnover-Long Side)*), which is the average of the natural log of market capitalization as of the end of June in year *t*-1 across stocks that are in the respective strategy's short leg (long leg).

We observe that a strategy's popularity increases in the average turnover and size of stocks in the short leg, but not in the long leg. The estimates on *Turnover-Short Side* and *Log(Size-Short Side)* are 0.490 (*t*-statistic = 1.44) and 0.001 (*t*-statistic = 2.15); the estimates on *Turnover-Long Side* and *Log(Size-Long Side)* are -0.118 (*t*-statistic = 0.38) and -0.000 (*t*-statistic = -0.41). These results suggest that liquidity constraints (along with transaction costs) play a role in determining anomaly popularity and help explain why anomaly "profits" remain positive in the data; interestingly, the results also imply that liquidity constraints are more binding in the short leg than in the long leg.

3.3. Can Arbitrageurs Time Anomalies?

One of the most notable patterns presented in the previous subsection is that arbitrageurs do not seem to be bothered by a strategy's potential downside. One explanation is that arbitrageurs are able to predict strings of negative returns, which, therefore, do not represent a meaningful dimension of risk. This subsection expounds on arbitrageurs' timing ability (or lack thereof).

[12] To enable comparison across NYSE/AMEX and NASDAQ securities, we divide the number of shares traded of NASDAQ securities by two.

To assess arbitrageurs' success in timing anomaly performances, we compare the average change in residual short interest among short-leg securities relative to that of long-leg securities and examine whether that difference relates to future anomaly performance. Anomaly performances are defined as the difference in benchmark-adjusted value-weighted portfolio returns between the long leg and the short leg over the subsequent portfolio-holding period. As before, the long leg and the short leg represent the two extreme deciles from sorting stocks into decile portfolios based on the anomaly variable in question.

In our first test, we regress anomaly performances on the raw difference in the average Δ*Short Interest* over the portfolio-formation period between securities in the short leg and securities in the long leg; we also estimate regressions of anomaly performances on an indicator of whether the average Δ*Short Interest* among short-leg securities exceeds that among long-leg securities. If arbitrageurs can time anomaly performances, a disproportionate rise in short interest among short-leg securities should precede high future anomaly performances.

Our second test design more directly gauges whether arbitrageurs can predict and avoid episodes of strong negative performance. We estimate a binary-response model based on the logistic function. The dependent variable equals one if anomaly performances over the portfolio-holding period are below the 25^{th} percentile of its entire distribution, and zero otherwise. The average bottom-quartile anomaly performance across all 10 anomalies is -4.16%. The independent variables are either (1) the raw difference in the average Δ*Short Interest* between securities in the short leg and securities in the long leg, or (2) an indicator whether the average Δ*Short Interest* among short-leg securities exceeds that among long-leg securities.

In short, our results suggest that arbitrageurs are unable to time anomaly performances. For the first set of regression specifications, we observe positive signs for the majority of coefficient estimates, consistent with higher relative Δ*Short Interest* among short-leg securities preceding higher anomaly performances. Only two of the estimates are statistically significant, however.

A similar conclusion can be drawn from the second set of regression specifications. Here, half of the coefficient estimates has the "wrong" sign, implying that when Δ*Short Interest* among short-leg securities exceeds that among long-leg securities, anomaly performances are more likely to be highly negative. Only one of the estimates is statistically significant and has the "correct" sign.

In an untabulated analysis, we find that 6.9% of the time, the annual performance of the long-short portfolio falls below -10%. Within this subset of subsequent anomaly-performance "crashes," we observe that, over the portfolio formation period, the change in short interest in the short leg exceeds that in the long leg 64.5% of the time. In comparison, within the subset of observations where the annual performances did not crash and were either positive or mildly negative, the change in short interest in the short leg exceeds that in the long leg 64.4% of the time. That is, arbitrageurs are just as heavily invested in anomaly-based strategies when those strategies subsequently crash as they are when the strategies subsequently do relatively well. We arrive at the same conclusion when changing the cutoff from -10% to -15% and -20%.

One (final) alternative testing ground to assess arbitrageurs' timing ability is to compare "non-timed" anomaly performances to "timed" anomaly performances. "Non-timed" anomaly performances simply represent the difference in benchmark-adjusted returns between the long leg and the short leg over the portfolio-holding period. "Timed" anomaly performances are computed as follows: For every portfolio-formation period, we compute the average Δ*Short Interest* across securities in the short leg and the average Δ*Short Interest* across securities in the long leg. If Δ*Short Interest* in the short leg exceeds Δ*Short Interest* in the long leg, we assume that arbitrageurs are actively betting on the anomaly in question and compute the average monthly anomaly performance over the ensuing portfolio-holding period. If Δ*Short Interest* in the short leg does not exceed Δ*Short Interest* in the long leg, we assume that arbitragers do not invest in the anomaly in question and instead long the market portfolio and short the risk-free asset over the ensuing portfolio-holding period. The average Δ*Short Interest* in the short leg exceeds the average Δ*Short Interest* in the long leg 75% of the time.

If arbitrageurs are able to predict and successfully escape poor anomaly performances, timed anomaly performances should have fewer "crashes" and higher average performances than their non-timed counterfactual. As reported in Table 4, and in line with evidence presented in Table 3, we observe no such differential. Timed anomaly performances, on average, are indistinguishable from non-timed anomaly performances.

4. Conclusion

The importance of arbitrageurs in ensuring market efficiency has been widely discussed and recognized in theoretical work. Here, we consider a set of well-documented and well-publicized strategies and examine, empirically, to what extent arbitrageurs capitalize on the seemingly anomalous returns offered by these strategies. We provide evidence that arbitrageurs do trade on anomalies, and, more importantly, that some anomalies are more popular than others. The popularity appears linked to the anomaly's upside, but not its downside; it also appears related to their being discussed in the academic literature. In general, we observe that anomaly performances vary significantly through time and that arbitrageurs are unable to time these fluctuations.

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Appendix

The data are from the Center for Research in Security Prices (CRSP) and Compustat. We exclude stocks with a stock price < $5 as of portfolio formation. We further exclude stocks with two-digit SIC code = 6 (financial industry). We measure most of the variables used to forecast returns once a year. Thus, we use information in June of calendar year t (incl. accounting data from the fiscal year ending in the previous calendar year t-1) to forecast the returns in July of t to June of t+1. The exception are the variables for anomaly 1, 2, and 10, which are formed quarterly and the momentum variable, which is formed monthly. In particular,

- Anomaly 1 (Failure Probability): Please see Chen, Novy-Marx, and Zhang (2010) for a detailed description.
- Anomaly 2 (O-Score): Please see Chen, Novy-Marx, and Zhang (2010) for a detailed description.
- Anomaly 3 (Net Stock Issuance): Log($Shrout_{i,t-1}/Shrout_{i,t-2}$), where $Shrout_{i,t-1}$ is the split-adjusted number of shares outstanding of stock i as of the fiscal year ending in calendar year $t-1$.
- Anomaly 4 (Comp. Equ. Issuance): Log($ME_{i,t-1}/ME_{i,t-6}$) - $ret_{i,t-6,t-1}$, , where $ME_{i,t-1}$ is the market capitalization of stock i as of the fiscal year ending in calendar year $t-1$ and $ret_{i,t-6,t-1}$ is the cumulative log daily return of stock i over the previous five years.
- Anomaly 5 (Total Accruals): $((\Delta ACT_{i,t-2,t-1} - \Delta CHE_{i,t-2,t-1}) - (\Delta LCT_{i,t-2,t-1} - \Delta DLC_{i,t-2,t-1}))/CEQ_{i,t-1}$.
- Anomaly 6 (Net Operating Assets): $NOA_{i,t-1}/AT_{i,t-2}$, where $NOA = (AT\text{-}CHE) - (AT\text{-}DLC\text{-}DLTT\text{-}MIB\text{-}PSTK\text{-}CEQ)$.
- Anomaly 7 (Momentum): $ret_{i,t-5,t}$, where $ret_{i,t-5,t}$ is the cumulative six-months return of stock i over months t-5 to t.
- Anomaly 8 (Gross Profitability): $(SALE_{i,t-1} - COGS_{i,t-1})/AT_{i,t-1}$.
- Anomaly 9 (Asset Growth): $(AT_{i,t-1} - AT_{i,t-2})/AT_{i,t-2}$.
- Anomaly 10 (Profitability): $IBQ_{i,t-1}/ATQ_{i,t-1}$.
- Anomaly 11 (Investment Ratio): $(CE_{i,t-1}/(CE_{i,t-2} + CE_{i,t-3} + CE_{i,t-4})/3) - 1$, where $CE = CAPX/SALE$.

New COMPUSTAT Data Item	Legacy COMPUSTAT Data Item	Description
ACT	4	Current Assets - Total
AT	6	Assets - Total
CAPX	128	Capital Expenditures
CEQ	60	Common/Ordinary Equity - Total
CHE	1	Cash and Short-Term Investments
COGS	41	Cost of Goods Sold
DLC	34	Debt in Current Liabilities - Total
DLTT	9	Long-Term Debt - Total
LCT	5	Current Liabilities - Total
MIB	38	Minority Interest (Balance Sheet)
PSTK	130	Preferred/Preference Stock (Capital) - Total
SALE	12	Sales/Turnover (Net)
ATQ	44	QUARTERLY: Assets - Total
IBQ	8	QUARTERLY: Income Before Extraordinary Items

Figure 1

Anomalies and Short Interest through Time: The Role of Academia

This figure plots differences in changes in abnormal short interest for portfolios based on 10 anomalies. The sample period is 1988:10-2010:06. Every portfolio formation month, we sort stocks into decile portfolios based on the anomaly variables described in the Appendix. The long- and short leg represent the two extreme deciles, with the long leg being the higher-performing decile as reported by previous studies. In accordance with prior literature, for anomalies (3)-(9) and (11), we form portfolios as of the end of each June; for anomalies (1)-(2) and (10), we form portfolios as of the end of each calendar quarter. At the end of each June of calendar year *t*, we compute Δ*Short Interest (short leg)* and Δ*Short Interest (long leg)*, where Δ*Short Interest* represents the change in abnormal short interest across securities in the long- or the short leg over the twelve-months portfolio formation period for anomalies (3)-(9) and (11), and the average *aggregate* change in short interest across securities in the long- or the short leg over the previous four quarters for the remaining anomalies. Abnormal short interest is the residual short interest of a set of firm characteristics, including past stock return performance (as described in Section 3.2.1). We plot the difference between the average Δ*Short Interest (short leg)* and the average Δ*Short Interest (long leg)*.

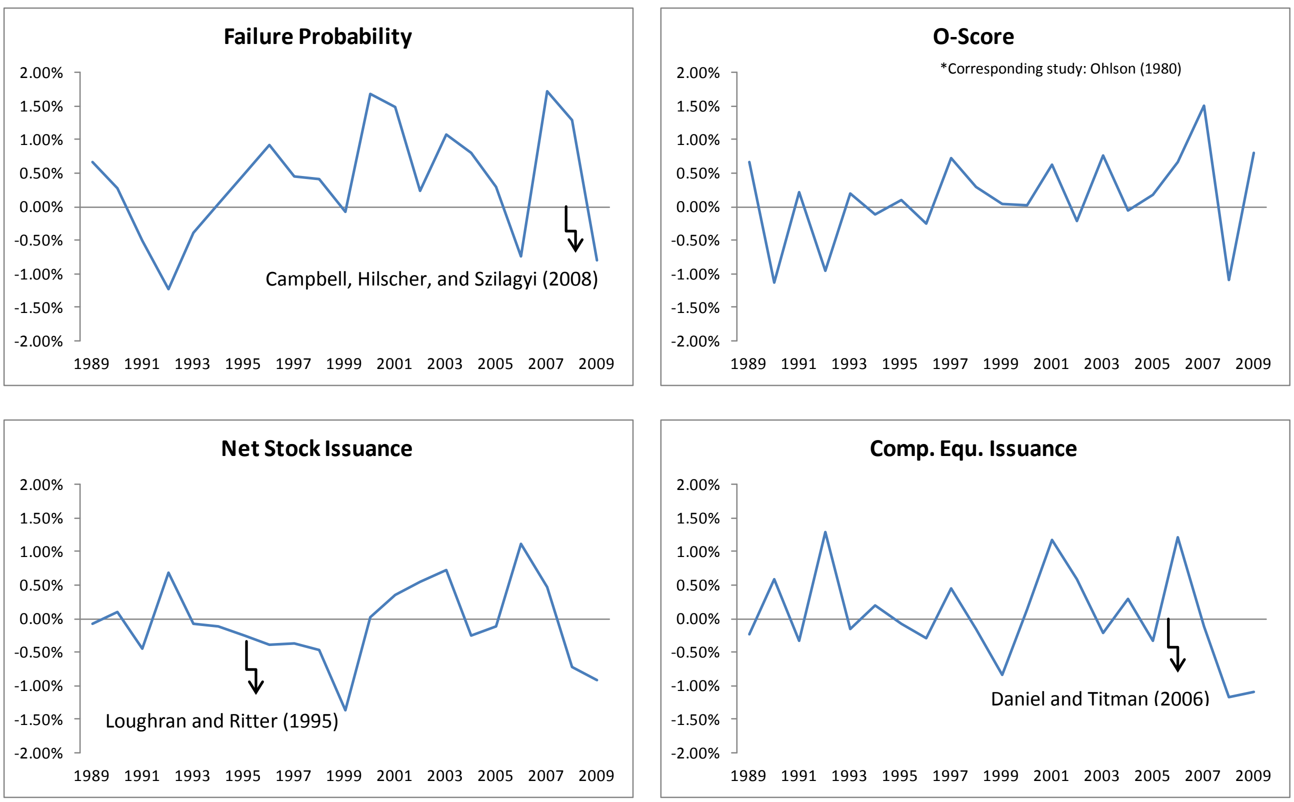

Figure 1. Continued.

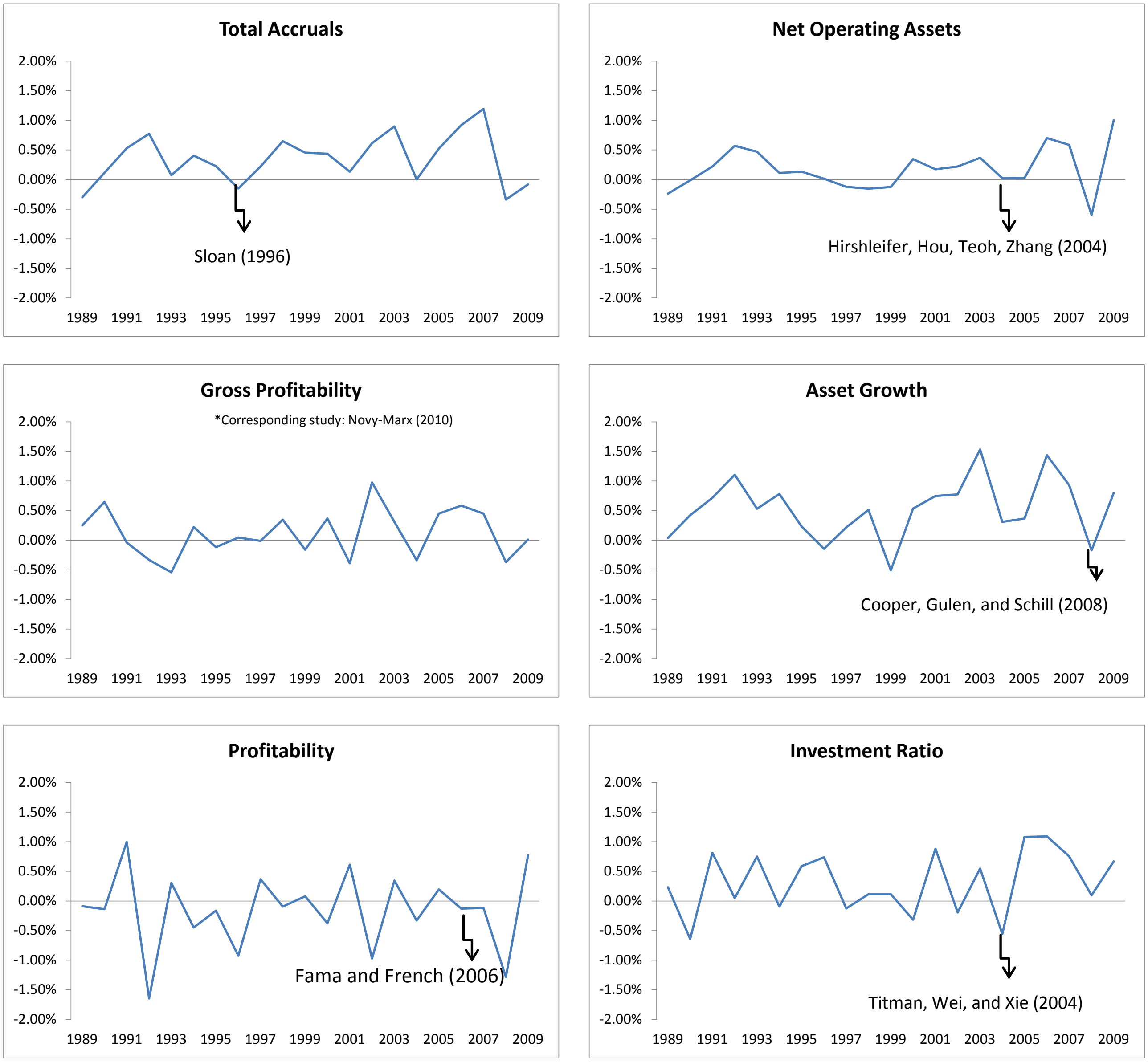

Table 1
Anomaly Returns

This table reports summary statistics of returns based on 11 anomalies. The sample period is 1988:10-2010:06. Every portfolio formation month, we sort stocks into decile portfolios based on the anomaly variables described in the Appendix and construct value-weighted portfolio returns over the portfolio holding period. The long- and short leg represent the two extreme deciles, with the long leg being the higher-performing decile as reported by previous studies. Panel A reports results for excess raw returns. Panel B reports results for benchmark-adjusted returns. The average benchmark-adjusted returns represent estimates of α_i from the following time-series regression: $(ret_{i,t} - rf_t) = \alpha_i + b_i(MKT_t\text{-}rf_t) + c_i(SMB_t) + d_i(HML_t) + \varepsilon_{i,t}$. Benchmark-adjusted returns equal $\alpha_i + \varepsilon_{i,t}$. All *t*-statistics are based on the heteroskedasticity-consistent standard errors of White (1980) and are reported in parentheses.

Anomalies	Average Long Leg	Average Short Leg	Average Long- Minus Short Leg (LS)	StDev(LS)	% Months where LS ≥ 0%	% Months where LS < 0%	Average(LS) across lowest 6 obs.
Panel A: Excess Raw Returns							
(1) Failure probability	1.39%	0.04%	1.36%	5.91%	63.57%	36.43%	-15.36%
			(3.68)				
(2) Ohlson’s O	1.17%	0.75%	0.42%	5.04%	52.71%	47.29%	-11.05%
			(1.34)				
(3) Net stock issues	1.04%	0.34%	0.70%	3.17%	56.35%	43.65%	-7.56%
			(3.51)				
(4) Composite equity issues	0.89%	0.68%	0.21%	5.22%	49.21%	50.79%	-13.97%
			(0.63)				
(5) Total accruals	0.97%	0.36%	0.61%	4.19%	56.35%	43.65%	-10.24%
			(2.32)				
(6) Net operating assets	1.27%	0.46%	0.82%	3.67%	59.13%	40.87%	-9.42%
			(3.53)				
(7) Momentum	1.59%	0.45%	1.15%	6.35%	64.34%	35.66%	-18.76%
			(2.90)				
(8) Gross profitability	0.24%	-0.19%	0.43%	7.25%	55.83%	44.17%	-18.19%
			(0.64)				
(9) Asset growth	0.99%	0.66%	0.33%	3.91%	51.98%	48.02%	-9.53%
			(1.33)				
(10) Return on assets	1.24%	0.57%	0.67%	5.26%	58.53%	41.47%	-12.93%
			(2.04)				
(11) Investment over assets	0.16%	-0.05%	0.21%	5.87%	53.33%	46.67%	-13.52%
			(0.40)				

Table 1. Continued.

Anomalies	Average Long Leg	Average Short Leg	Average Long- Minus Short Leg (LS)	StDev(LS)	% Months where LS ≥ 0%	% Months where LS < 0%	Average(LS) across lowest 6 obs.
Panel B: Benchmark-Adjusted Returns							
(1) Failure probability	0.55%	-1.17%	1.72% (5.08)	5.87%	69.77%	30.23%	-12.78%
(2) Ohlson's O	0.45%	-0.40%	0.85% (3.37)	4.05%	56.59%	43.41%	-6.85%
(3) Net stock issues	0.26%	-0.50%	0.76% (4.26)	2.84%	61.11%	38.89%	-6.10%
(4) Composite equity issues	-0.17%	-0.09%	-0.09% (-0.35)	3.96%	48.41%	51.59%	-9.66%
(5) Total accruals	0.18%	-0.54%	0.71% (2.75)	4.13%	58.73%	41.27%	-10.07%
(6) Net operating assets	0.39%	-0.40%	0.79% (3.42)	3.66%	57.94%	42.06%	-9.52%
(7) Momentum	0.68%	-0.65%	1.33% (3.57)	6.00%	64.34%	35.66%	-18.03%
(8) Gross profitability	0.10%	-0.84%	0.94% (1.95)	5.29%	62.50%	37.50%	-13.26%
(9) Asset growth	0.10%	-0.11%	0.22% (1.05)	3.28%	49.21%	50.79%	-7.83%
(10) Return on assets	0.55%	-0.44%	1.00% (3.86)	4.15%	60.85%	39.15%	-8.84%
(11) Investment over assets	-0.09%	-0.16%	0.07% (0.13)	5.49%	49.17%	50.83%	-12.84%

Table 2
Anomalies and Short Interest

This table reports changes in short interest for portfolios based on 10 anomalies. The sample period is 1988:10-2010:06. Every portfolio formation month, we sort stocks into decile portfolios based on the anomaly variables described in the Appendix. The long- and short leg represent the two extreme deciles, with the long leg being the higher-performing decile as reported by previous studies. In accordance with prior literature, for anomalies (3)-(9) and (11), we form portfolios as of the end of each June; for anomalies (1)-(2), we form portfolios as of the end of each calendar quarter. Δ*Short Interest in Long Leg (in Short Leg)* represents the average change in abnormal short interest across securities in the long- or the short leg over the twelve-months portfolio formation period for anomalies (3)-(9) and (11) [*t*-11;*t*], and the three-months portfolio formation period for anomalies (1)-(2) and (10) [*t*-2;*t*], where *t* represents the portfolio formation month. Abnormal short interest is the residual short interest of a set of firm characteristics, including past stock return performance (as described in Section 3.2.1). The final column compares the average Δ*Short Interest* of securities that, subsequent to portfolio formation, fall out of the short leg to that of former long-leg securities. All *t*-statistics are based on the heteroskedasticity-consistent standard errors of White (1980) and are reported in parentheses.

Anomalies	(1) ΔShort Interest in Long Leg	(2) ΔShort Interest in Short Leg	(2) – (1)	Subsequent relative ΔShort Interest for *former* Short-Leg Securities
Panel A: Full Sample Period				
(1) Failure probability	0.06%	-0.04%	0.10%	-0.06%
			(3.22)	(-1.55)
(2) Ohlson's O	0.04%	0.01%	0.03%	-0.15%
			(0.89)	(-1.04)
(3) Net stock issues	-0.05%	0.03%	-0.09%	0.04%
			(-0.68)	(0.29)
(4) Composite equity issues	0.17%	0.14%	0.03%	0.67%
			(0.23)	(2.35)
(5) Total accruals	0.20%	-0.15%	0.35%	0.04%
			(4.10)	(0.25)
(6) Net operating assets	0.26%	0.08%	0.18%	-0.73%
			(2.26)	(-1.53)
(7) Momentum	---	---	---	---
(8) Gross profitability	0.25%	0.05%	0.11%	1.04%
			(1.24)	(0.57)
(9) Asset growth	0.35%	-0.18%	0.53%	-0.11%
			(4.77)	(-0.65)
(10) Return on assets	0.05%	0.08%	-0.03%	-0.11%
			(-0.85)	(-2.41)
(11) Investment over assets	0.32%	-0.06%	0.39%	-0.28%
			(2.06)	(-0.90)

Table 2. Continued.

Anomalies	(1) ΔShort Interest in Long Leg	(2) ΔShort Interest in Short Leg	(2) – (1)	Subsequent relative ΔShort Interest for *former* Short-Leg Securities
Panel B: 1989 - 1999				
(1) Failure probability	0.01%	-0.03%	0.04%	-0.07%
			(1.21)	(-1.52)
(2) Ohlson's O	0.02%	0.02%	0.01%	-0.12%
			(0.13)	(-0.52)
(3) Net stock issues	-0.24%	0.02%	-0.27%	0.23%
			(-1.84)	(1.48)
(4) Composite equity issues	0.12%	0.08%	0.04%	0.85%
			(0.22)	(2.87)
(5) Total accruals	0.15%	-0.13%	0.29%	-0.12%
			(3.38)	(-0.77)
(6) Net operating assets	0.10%	0.03%	0.07%	-0.91%
			(0.94)	(-1.06)
(7) Momentum	---	---	---	---
(8) Gross profitability	0.07%	0.05%	0.02%	-3.56%
			(0.21)	(-2.05)
(9) Asset growth	0.26%	-0.08%	0.34%	-0.22%
			(2.55)	(-0.81)
(10) Return on assets	0.03%	0.05%	-0.02%	-0.13%
			(-0.48)	(-1.87)
(11) Investment over assets	0.14%	-0.08%	0.21%	0.19%
			(1.62)	(1.95)

Table 2. Continued.

Anomalies	(1) ΔShort Interest in Long Leg	(2) ΔShort Interest in Short Leg	(2) – (1)	Subsequent relative ΔShort Interest for *former* Short-Leg Securities
Panel C: 2000 - 2010				
(1) Failure probability	0.12%	-0.06%	0.17%	-0.06%
			(3.14)	(-0.85)
(2) Ohlson's O	0.06%	0.00%	0.06%	-0.16%
			(0.98)	(-0.78)
(3) Net stock issues	0.16%	0.04%	0.11%	-0.22%
			(0.55)	(-0.96)
(4) Composite equity issues	0.23%	0.20%	0.03%	0.55%
			(0.11)	(1.00)
(5) Total accruals	0.25%	-0.17%	0.42%	-0.89%
			(2.70)	(-1.60)
(6) Net operating assets	0.43%	0.14%	0.30%	-0.43%
			(2.14)	(-0.78)
(7) Momentum	---	---	---	---
(8) Gross profitability	0.25%	0.05%	0.21%	1.04%
			(1.43)	(0.57)
(9) Asset growth	0.45%	-0.29%	0.74%	0.01%
			(4.52)	(0.05)
(10) Return on assets	0.08%	0.12%	-0.04%	-0.07%
			(-0.70)	(-1.20)
(11) Investment over assets	0.32%	-0.06%	0.39%	-0.28%
			(2.06)	(-0.90)

Table 3
Determinants of "Anomaly Popularity"

This table reports estimates from regressions of the difference between the average Δ*Short Interest* in the short leg and the average Δ*Short Interest* in the long leg on various lagged anomaly characteristics. The observations are on an anomaly/year level. Every portfolio formation month, we sort stocks into decile portfolios based on the anomaly variables described in the Appendix. The long- and short leg represent the two extreme deciles, with the long leg being the higher-performing decile as reported by previous studies. In accordance with prior literature, for anomalies (3)-(9) and (11), we form portfolios as of the end of each June in year *t* and Δ*Short Interest* represents the change in abnormal short interest over the twelve-month portfolio formation period. For anomalies (1)-(2) and (10), we form portfolios as of the end of each calendar quarter and we compute aggregate changes in abnormal short interest over the previous four quarters as of the end of each June in year *t*. *Portion of Profits Coming from Short-Side* is the unsigned average benchmark-adjusted return over the previous five years of the short leg divided by the sum of the unsigned average benchmark-adjusted return of the short leg and the long leg; if the average abnormal return in the short leg is positive, this variable is set to zero; if the average abnormal return in the long leg is negative and the average abnormal return in the short leg is negative, this variable is set to 100%. *Beta* is the beta coefficient estimate from a rolling five-year time-series regression of each strategy's monthly benchmark-adjusted return on the monthly composite index, which represents the benchmark-adjusted return of a portfolio that invests an equal portion in each of the 11 anomaly-based strategies considered in this study. *Idiosyncratic Volatility* is the standard deviation of the residuals from the aforementioned time-series regressions. *Average Return* is the strategy's rolling five-year average benchmark-adjusted return. *Skewness* is the strategy's rolling five-year skewness of benchmark-adjusted return. *Return-50th percentile* is the strategy's rolling five-year median benchmark-adjusted return. *Return-5th (1st) percentile* is the strategy's rolling five-year 5th (1st) percentile of benchmark-adjusted return. *Return-95th (99th) percentile* is the strategy's rolling five-year 95th (99th) percentile of benchmark-adjusted return. All *t*-statistics are based on the heteroskedasticity-consistent standard errors of White (1980) and are reported in parentheses.

Variables	(1)	(2)	(3)	(4)
Portion of Profits Coming from Short-Side	0.017	0.015	0.016	0.019
	(2.30)	(2.00)	(2.23)	(2.68)
Beta	-0.000	0.001	-0.000	-0.001
	(-0.08)	(0.92)	(-0.27)	(-0.85)
Idiosyncratic Volatility	0.128			
	(2.36)			
Average Return	0.086			
	(0.84)			
Skewness		0.002		
		(2.11)		
Return – 50th percentile			0.017	0.001
			(0.47)	(0.05)
Return – 1st percentile			-0.052	
			(-0.66)	
Return – 99th percentile			0.104	
			(2.53)	
Return – 5th percentile				0.010
				(0.13)
Return – 95th percentile				0.051
				(3.06)
Number of Observations	150	150	150	150
Adj. R-square	9.32%	6.07%	11.74%	12.28%

Table 4
Short Interest and Future Anomaly Performances

This table reports estimates from regressions of subsequent anomaly performance on measures of the difference between the average Δ*Short Interest* in the short leg and the average Δ*Short Interest* in the long leg. The sample period is 1988:10-2010:06. Every portfolio formation month, we sort stocks into decile portfolios based on the anomaly variables described in the Appendix and construct value-weighted portfolio returns over the portfolio holding period. The long- and short leg represent the two extreme deciles, with the long leg being the higher-performing decile as reported by previous studies. In Panel A, the dependent variable is *anomaly performances* defined as the difference in benchmark-adjusted returns between the long leg and the short leg over the ensuing portfolio holding period. In Panel B, we report estimates from a binary-response model based on the logistic function. The dependent variable equals one if *anomaly performances* over the ensuing portfolio holding period are below the 25th percentile of that anomaly's performance over our entire sample period, and zero otherwise. In accordance with prior literature, for anomalies (3)-(9) and (11), we form portfolios as of the end of each June in year *t* and compute returns from July in year *t* to June in year *t*+1. For anomalies (1)-(2) and (10), we form portfolios as of the end of each calendar quarter and compute returns over the ensuing calendar quarter (e.g., portfolios are formed at the end of Mar2000 and returns on those portfolios are computed over the Apr2000:Jun2000 period). Δ*Short Interest* represents the change in abnormal short interest over the twelve-months portfolio formation period for anomalies (3)-(9) and (11) [*t*-11;*t*] and three-months portfolio formation period for anomalies (1)-(2) and (10) [*t*-2;*t*], where *t* represents the portfolio formation month. In Column (1), we regress subsequent anomaly performances on the raw difference in the average Δ*Short Interest* between securities in the short leg and securities in the long leg. In Column (2), we regress subsequent anomaly performances on an indicator variable, whether the average Δ*Short Interest* across securities in the short leg exceeds the average Δ*Short Interest* across securities in the long leg. All *t*-statistics and *p*-values are based on the heteroskedasticity-consistent standard errors of White (1980) and are reported in parentheses.

Anomalies	(1) Diff in ΔShort Interest Between Short- and Long Leg		(2) I(Diff in ΔShort Interest Between Short- and Long Leg > 0)	
	Coeff. Estimate	*t*-statistic	Coeff. Estimate	*t*-statistic
Panel A: Return of long leg minus return of short leg				
(1) Failure probability	10.97	(1.97)	0.02	(0.67)
(2) Ohlson's O	-3.37	(-1.22)	-0.04	(-1.71)
(3) Net stock issues	6.70	(1.02)	0.10	(0.97)
(4) Composite equity issues	4.49	(0.62)	0.10	(0.80)
(5) Total accruals	5.15	(0.41)	0.09	(0.98)
(6) Net operating assets	2.09	(0.33)	-0.02	(-0.32)
(7) Momentum	---	---	---	---
(8) Gross profitability	-26.10	(-1.40)	-0.25	(-1.23)
(9) Asset growth	9.35	(1.24)	0.11	(2.13)
(10) Return on assets	-2.44	(-0.68)	-0.01	(-0.44)
(11) Investment over assets	21.01	(4.13)	0.29	(5.53)

Table 4. Continued.

Anomalies	(1) Diff in ΔShort Interest Between Short- and Long Leg		(2) I(Diff in ΔShort Interest Between Short- and Long Leg > 0)	
	Coeff. Estimate	*p*-value	Coeff. Estimate	*p*-value
Panel B: I(Return of long leg minus return of short leg < 25^{th})				
(1) Failure probability	118.80	[0.17]	0.12	[0.82]
(2) Ohlson's O	-61.20	[0.40]	-0.33	[0.52]
(3) Net stock issues	-59.59	[0.56]	-0.88	[0.46]
(4) Composite equity issues	6.14	[0.95]	-0.36	[0.76]
(5) Total accruals	34.10	[0.85]	0.44	[0.75]
(6) Net operating assets	-109.10	[0.49]	-10.69	[<0.01]
(7) Momentum	---	---	---	---
(8) Gross profitability	-879.10	[<0.01]	-11.05	[<0.01]
(9) Asset growth	-44.06	[0.70]	0.92	[0.53]
(10) Return on assets	64.85	[0.39]	0.38	[0.46]
(11) Investment over assets	1565.80	[<0.01]	13.44	[<0.01]

Table 5
Timed- versus Non-Timed Anomaly Performances

This table reports summary statistics of "timed" versus "non-timed" returns based on eleven anomalies. The sample period is 1988:10-2010:06. Every portfolio formation month, we sort stocks into decile portfolios based on the anomaly variables described in the Appendix and construct value-weighted portfolio returns over the portfolio holding period. The long- and short leg represent the two extreme deciles, with the long leg being the higher-performing decile as reported by previous studies. Column (1) reports results for benchmark-adjusted returns of portfolios that are long securities in the long leg and short securities in the short leg. Column (2) reports results for portfolios resulting from the following timing strategy: Every portfolio formation period, we compute the average Δ*Short Interest* across securities in the short leg and the average Δ*Short Interest* across securities in the long leg. If Δ*Short Interest* in the short leg exceeds Δ*Short Interest* in the long leg, we assume that arbitrageurs are actively betting on the anomaly in question and compute the average monthly anomaly performance over the ensuing portfolio holding period. If Δ*Short Interest* in the short leg does not exceed Δ*Short Interest* in the long leg, we assume that arbitragers are not invested in the anomaly in question and instead long the market portfolio and short the risk-free asset over the ensuing portfolio holding period. All *t*-statistics are based on the heteroskedasticity-consistent standard errors of White (1980) and are reported in parentheses.

Anomalies	(1) Non-Timed Anomaly Performances	(2) Timed Anomaly Performances	(2) – (1)
(1) Failure probability	1.36%	1.36%	0.00%
			(0.00)
(2) Ohlson's O	0.42%	0.54%	-0.12%
			(-0.40)
(3) Net stock issues	0.70%	0.83%	-0.13%
			(-0.44)
(4) Composite equity issues	0.21%	0.62%	-0.41%
			(-1.22)
(5) Total accruals	0.61%	0.66%	-0.05%
			(-0.23)
(6) Net operating assets	0.82%	0.71%	0.10%
			(0.46)
(7) Momentum	---	---	---
(8) Gross profitability	0.43%	-0.14%	0.57%
			(0.67)
(9) Asset growth	0.33%	0.37%	-0.04%
			(-0.18)
(10) Return on assets	0.67%	0.74%	-0.08%
			(-0.22)
(11) Investment over assets	0.21%	0.47%	-0.26%
			(-0.73)