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The Limits of the Market-wide Limits of Arbitrage: Insights from the Dynamics of 100 Anomalies

Hieiko JACOBS
University of Mannheim

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Heiko Jacobs*

Abstract

Are anomalies strongest when limits of arbitrage are widely considered to be greatest? We empirically explore this theoretically deducted prediction. We first identify, categorize, and replicate 100 anomalies in the cross-section of expected equity returns. We then comprehensively study their dynamic interaction with popular proxies for time-varying market-level arbitrage conditions. Our findings reveal a surprisingly weak role of commonly employed measures of market-wide arbitrage risks and constraints. Even though this "big picture" evidence is by no means conclusive, our findings might potentially be best interpreted as supporting the growing literature which uncovers some shortcomings of the limits to arbitrage argument.

Keywords: anomalies, limits to arbitrage, return predictability, market frictions, behavioral finance

JEL Classification Codes: G12, G14

*Heiko Jacobs, Finance Department, University of Mannheim, L5,2, 68131 Mannheim, Germany. E-Mail: jacobs@bank.bwl.uni-mannheim.de. Phone: +49 621 181 3453. Financial support from the BNP Paribas Hedge Fund Centre at SMU is gratefully acknowledged.

1. Introduction

The behavioral finance view on the existence of asset pricing anomalies in the cross-section of expected equity returns is based on two building blocks (e.g. Barberis and Thaler (2003)): Investor psychology, which allows mispricings to arise, and limits to arbitrage, which prevent sophisticated market participants from quickly exploiting these inefficiencies. A testable prediction of this theoretically deducted mechanism is that abnormal returns should ceteris paribus be stronger in settings where arbitrageurs are less capable of or willing to aggressively bet against irrationality-induced mispricings (see e.g. the discussions in Brav et al. (2010) or Hanson and Sunderan (2013)). Empirical tests might help academics to enrich or challenge our understanding of the price discovery process and offer practitioners insights into ways to optimize their investment process.

However, recent work reveals that the evidence is in fact far from conclusive. We aim to revisit this controversial debate. What separates this paper from previous work is the breadth of anomalies taken into account as well as the focus on time-series (as opposed to cross-sectional) variation in market-level (as opposed to anomaly-level or stock-level) arbitrage constraints. This approach enables us to yield some novel insights into the following questions: When considered jointly, which type of phenomena yields the highest seemingly abnormal returns in which situations? To what extent do widely employed proxies for time-varying market-level limits to arbitrage have explanatory power for the magnitude of anomalous returns in the time-series?

More precisely, our contribution is twofold. First, we synthesize information from a very broad range of potential inefficiencies. We identify, categorize, and replicate 100 well-known or recently discovered anomalies related to violations of the law of one price, momentum, technical analysis, short-term reversal, long-term reversal, calendar effects, lead-lag effects among economically linked firms, pairs trading, beta, financial distress, skewness, differences of opinion, industry effects, fundamental analysis, net stock and financing decisions, capital investment and firm growth, innovation, accruals, dividend payments, or earnings surprises. We believe that these phenomena cover a reasonably representative universe of cross-sectional stock anomalies discussed in the literature.

Considering all these anomalies simultaneously in a unified framework offers a number of advantages. Most asset pricing studies concentrate on only one or few anomalies, and methodological or other differences can have a massive impact on inferences (e.g. Fama and French (2008)), making comparisons often difficult. In his literature review of predictors of cross-sectional stock returns, Subrahmanyam (2010) thus concludes that the "picture remains murky and suggests a need for clarifying studies" (p. 28). Similarly, Richardson et al. (2010) criticize the "haphazard nature" of this line of research and argue that "to date very few papers have made a serious attempt to bring some structure to the anomaly literature"(p. 422). Our approach aims at progressing on this front.

One of the most critical issues in this context appears to be the treatment of micro caps and small caps. As Fama and French (2008) highlight: "From a general economic perspective, it is important to know whether anomalous patters in returns are marketwide or limited to illiquid stocks that represent a small portion of market wealth" (p. 1655). Importantly, these stocks might also obstruct the view on the economic importance of arbitrage constraints. As the literature review in section 2 shows, several recent cross-sectional studies provide at best little support for the limits to arbitrage rationale once small stocks are controlled for. In light of these concerns, we apply the same filter rules on size and liquidity as e.g. Jegadeesh and Titman (2001). This results in excluding about 50% of the firm months of common stocks in the CRSP database, which however account for a maximum of a few percent of the total market capitalization. Our approach thus enables us to rely on a stock universe which is comparable across anomalies and which moreover represents the economically meaningful fraction of the market only. By using this common basis for a broad set of financial market phenomena, we also add to a lively debate about the real-life relevance of limits to arbitrage (see section 2).

Our second contribution is that we take a time-series perspective and focus on market-wide arbitrage constraints. In contrast, most existing tests have focused on the cross-section of specific anomalies and on stock-level constraints. In other words, this work typically compares the strength of return predictability in portfolios sorted on measures such as idiosyncratic risk, analyst coverage, firm age, or firm size. As we will show, these studies have partly arrived at conflicting findings. Alternative research designs such as ours might help to paint a more comprehensive picture.

Building on a literature review, we start by constructing a set of widely employed proxies for time-varying market-level arbitrage constraints. In our baseline analysis, these comprise the Vix, average idiosyncratic volatility, the Ted spread, the Moody's credit spread, average bid-ask spreads, and market illiquidity. We then test to what extent these popular proxies can indeed explain the magnitude of return anomalies over time.

Our main insights can be summarized as follows. From an unconditional perspective, most anomalies produce economically large abnormal returns relative to a Fama and French (1993) model. As a rough estimate, and averaged across time and anomalies, abnormal monthly returns are about 70 to 80 basis points (bp). This is noteworthy as, compared to many original studies, our data screens are often stricter. Moreover, our sample period is often longer or more recent, and thus partly out-of-sample. These findings suggest that most anomalous returns uncovered in the literature are unlikely to be primarily driven by statistical biases (see also McLean and Pontiff (2013) and Green et al. (2013)).

In line with theoretical predictions and previous empirical work (e.g. Mitchell and Pulvino (2012)), we indeed find that the few relatively unambiguous deviations from the law one price exhibit a strong positive link to market-level variables widely thought to proxy for time-varying limits of arbitrage. Strikingly, these variables turn out to be, at best, loosely related to the large time-variation of most other anomalies. In fact, anomaly returns only load sporadically on market-wide arbitrage risk factors in a statistically and economically significant matter in the direction suggested by theory. In many cases, abnormal returns on long-short anomalies are about as large in (or following) periods often argued to represent phases of high market-level limits to arbitrage as they are in (or following) periods widely considered to be characterized by only few impediments to arbitrage.

This has important implications. First, it seems that the factors that cause time-varying deviations from theoretical price parity are not necessarily the same factors that cause time variation in many cross-sectional anomalies. Thus, it appears that one cannot infer from these special cases alone to which extent market-level limits to arbitrage generally matter in stock markets. Second, our results reveal that anomalies constructed from relatively large and liquid stocks often generate highly significant abnormal returns of roughly 30 to 100 bp per month even in phases when popular proxies indicate low market frictions. This arguably presents a challenge to widely employed behavioral or rational theories aimed at explaining the existence and survival of these return patterns in the data. Behavioral theories need to explain why an economically large part of many anomaly returns does not seem to be directly related to widely used proxies for market-wide limits to arbitrage. Rational theories need to identify systematic risk factors which have a strong impact on expected returns even when overall market conditions appear calm, stocks are large and liquid, and the spectrum of return premiums appears conceptually very diverse.

Essentially, the main finding of this paper is a non-result. This raises concerns about errors-in-variables, sample selection issues, and related aspects. However, our findings survive a number of robustness checks. Among others, we use changes instead of levels, run regressions quarterly instead of monthly, use alternative proxies, and control for general time effects and outliers. Moreover, aggregate market-level arbitrage conditions also lack explanatory power for time-varying anomaly-level arbitrage popularity. We thereby draw on recent studies which propose that time-series shocks in the amount of capital and effort allocated to specific quantitative anomalies can be measured using time-series shocks in the cross-section of short interest (e.g. Hanson and Sunderan (2013), Hwang and Liu (2012)) or trading activity (e.g. McLean and Pontiff (2013)). The underlying rationale is that unobservable changes in arbitrage activity are likely to manifest themselves in observable changes in the behavior or characteristics of stocks which a specific quantitative trading strategy would typically speculate on.

It is important to put our findings into perspective and to highlight some limitations of our study. Clearly, due to the aggregate nature of our study, we are limited in our ability to consider the economic stories and arbitrage forces behind all 100 anomalies in detail. However, it is exactly the lack of comparability, consensus, or even existence of previous work regarding the impact of limits to arbitrage on individual anomalies which has motivated our large-scale analysis. We hope that our insights on the "big picture" might serve as a fruitful starting point for future research, which could explore the precise mechanism of selected issues (see e.g. the discussion below) in more depth.

We are far from claiming that limits to arbitrage in general do not matter. For instance, arbitrage constraints have extensively and convincingly been shown to be often binding for small, illiquid firms. However, these stocks are less meaningful from an economic perspective and thus less relevant for our purpose. It might also be the case that anomaly-level or stock-level arbitrage constraints are more important than market-level constraints.

Alternatively, market-level constraints might matter, but the proxies we rely on might not adequately capture impediments to arbitrage. Both arguments might be justified, even though the literature so far seems to offer little insights in this matter. However, the proxies we rely on mostly have a solid theoretical foundation, they have already been extensively employed in previous empirical studies, and they are able to explain deviations of the law of one price. On the other hand, if one assumes that the many other return phenomena covered in this study (also) represent true mispricings, then clearly some (other) forms of powerful frictions are required in order to convincingly explain their survival and time-variation in the data. Validating this assumption and identifying the precise nature of these (potentially anomaly-specific) frictions is beyond the scope of this study.

However, we do show that one often cited source of such frictions, market-wide arbitrage barriers, has, taken as a whole, surprisingly little power to explain the dynamics of a very large set of return phenomena which are often referred to as puzzling anomalies in the literature. Even though this "big picture" evidence is by no means conclusive, our findings might potentially be best interpreted as supporting the small, but growing empirical literature which uncovers some shortcomings of the limits to arbitrage argument.

2. Existing Evidence For And Against Limits To Arbitrage

There appear to be two major streams of empirical literature which document limits to arbitrage in the stock market. The first stream analyzes a set of anomalies concerned with the relative prices of assets with very similar payoffs. These settings are often referred to as (reasonably accurate) tests of the law of one price, and the literature argues that impediments to arbitrage are the major reason for the persistence of deviations from theoretical price parity. Arguably among the best documented cases are price parity deviations of dual-listed companies ("Siamese Twins") (e.g. Rosenthal and Young (1990), Froot and Dabora (1999), Scruggs (2007), Jong et al. (2009), Baker et al. (2012)). Another well documented setting is the relationship of the prices of closed-end fund shares and the per share market value of the assets held by the funds (e.g. Lee et al. (1991), Pontiff (1996), Chay and Trzcinka (1999), and Cherkes et al. (2009)). Recent evidence comes from cross-listed stocks (Gagnon and Karolyi (2010), Seasholes and Liu (2011)) and dual-class shares (Schultz and Shive (2010)). We later consider all these anomalies in our empirical tests. A drawback of these settings is that they are, by definition, special. Due to the scarcity of asset pairs with closely related payoffs, this literature typically can build only on a limited number of observations, both in the cross-section and in the time-series.

The second stream analyzes selected anomalies and thereby mostly takes a cross-sectional perspective. These studies typically argue that abnormal returns related to a specific anomaly are most pronounced for firms that are most difficult to arbitrage, proxied by e.g. firm-level idiosyncratic risk.[1] While this literature is quite large, some of its implications have recently been put into question from two sides.

First, there seem to be methodological issues. For instance, in a cross-sectional study with several anomalies, Brav et al. (2010) conclude that several previous studies which identify a positive correlation between limits to arbitrage and abnormal returns primarily do so because they rely on "research designs with non-implementable trading strategies (high frequency trading of very small cap securities and event-time analysis)" (p. 161). In their more conservative research setting, many of their tests "fail to support the limits of arbitrage argument" (p. 157). With regard to the asset growth anomaly, Lam and Wei (2011) show that value-weighted results provide only limited support for limits to arbitrage. Similarly, and "in sharp contrast" (p. 531) to previous U.S. studies, Watanabe et al. (2012) find only a very weak link to cross-country measures of limits to arbitrage.

Second, practitioners do not always seem to behave in the way predicted by academia. Influential academic work on limits to arbitrage in the cross-section is build on the long-standing, theoretically deducted argument that arbitrageurs will allocate less capital to stocks with higher idiosyncratic return volatility (e.g. Shleifer and Vishny (1997), Pontiff (2006)). However, Ben-David et al. (2010) find that hedge funds ceteris paribus actually invest more capital in these stocks, leading them to conclude: "Our results show that diversification concerns of arbitrageurs are not the primary reason why pricing anomalies are more pronounced among high idiosyncratic risk stocks" (p. 3). Similarly, Green et al. (2011) study hedge fund behavior and conclude with regard to the limits of arbitrage ar-

[1]Selected papers and anomalies include the book-to-market effect (Ali et al. (2003)), momentum (Arena et al. (2008), Zhang (2006)), accounting anomalies such as asset growth or accruals (Mashruwala et al. (2006)), Lipson et al. (2012), Li and Sullivan (2011)), or the post-earnings-announcement drift (Mendenhall (2004)).

gument: The results "substantiate statements made by key practitioners that run counter to predictions made by some academics" (p. 813).

Moreover, there is little consensus on to what extent the rapid growth of the arbitrage industry has affected anomaly returns, which to some extent might also allow to draw inferences about the impact of limits to arbitrage. For instance, Hanson and Sunderan (2013) analyze value and momentum strategies and arrive at the following conclusion: "We provide evidence that this increase in capital has resulted in lower strategy returns" (p. 29, see also Schwert (2003)). In contrast, Israel and Moskowitz (2012) conclude that there is "little evidence that size, value, or momentum premia have changed over time or are affected by changes in institutional or hedge fund participation in markets" (p. 26). Similarly, Chordia et al. (2013) show that abnormal returns for their twelve anomalies are much lower in their second subperiod, whereas Haugen and Baker (1996) do not find a pronounced time trend. Somewhere in the middle are the intriguing findings of McLean and Pontiff (2013) who analyze 72 anomalies and report on average a 35% post-publication decline in anomalous returns. We later control for time and publication effects.

In summary, one can say that the evidence is mixed. Recent work shows that the literature on limits to arbitrage does have its shortcomings, suggesting the need for clarifying studies.

3. Empirical Analysis

3.1 Anomalies

Our approach involves identifying, categorizing, and replicating stock market anomalies.[2] We consider papers published in major finance, accounting, and economics journals as well as selected working papers. Not all studies explicitly refer to their findings as anomalies. We principally take papers into account which report excess returns relative to (at least) a standard Fama and French (1993) three-factor model or comparable benchmarks, and

[2]Note that, due to e.g. our data screens, partly missing details about precise calculations in the original work, different methodologies, our own modifications, or database changes over time, we do not intend to and cannot perfectly replicate studies on specific anomalies. We can, however, at least closely follow the economic intuition, and thereby also most likely preserve the basic risk-return characteristics of the original anomaly.

which do not prominently advocate an explanation based on rational risk factors. In the following, we implicitly assume that the consensus view of quantitative arbitrageurs is that these excess returns indeed represent potentially exploitable alpha.

To keep the analysis manageable, meaningful, and of practical relevance, we impose several screens. First, the anomaly can be computed using standard databases (mostly CRSP, Compustat, and I/B/E/S). Second, the anomaly is existent at a monthly frequency in real-time. Third, the anomaly needs to yield seemingly abnormal returns when the universe of eligible stocks is restricted to firms whose market capitalization at the point of portfolio formation is larger than the first NYSE decile and whose stock price is at least 5 USD (see e.g. Jegadeesh and Titman (2001). This also implies that anomalies which historically are primarily existent among small or highly illiquid stocks do not enter our analysis.

For each anomaly, we compute the traditional long-short zero-cost portfolio approach based on some form of percentile placement. We construct a long portfolio with the seemingly most undervalued securities (in most cases decile 1 or 10, see the online appendix for details) and a corresponding short portfolio with the most overvalued stocks. Depending on the anomaly, portfolios are rebalanced every one to twelve months. We compute both equally weighted and value weighted returns for the stocks in the extreme portfolios.

Group 1: law of one price As outlined in section 2., we start with deviations of the law of one price. Specifically, we consider return phenomena related to twin stocks (1), cross-listed shares (2), dual-class shares (3), and closed-end funds (4).

Group 2: momentum Many studies have argued that the traditional momentum effect (Jegadeesh and Titman (1993), (5)) can be enhanced once one considers the interaction of formation period returns with certain stock-level variables. These characteristics are typically argued to amplify behavioral biases or information uncertainty. We thus also consider enhanced momentum strategies relying on the following variables: (6) firm age (e.g. Zhang (2006)), (7) turnover (e.g. Lee and Swaminathan (2000)), (8) market-to-book ratio (e.g. Asness (1997), Daniel and Titman (1999)), (9) credit rating (e.g. Avramov et al. (2007)), (10) market capitalization (e.g. Jegadeesh and Titman (1993), Hong et al. (2000), Zhang (2006)), (11) residual analyst coverage (e.g. Hong et al. (2000)), (12) analyst forecast dispersion (e.g. Zhang (2006)), (13) R^2 (Hou et al. (2006)), (14) formation period return consistency (Grinblatt and Moskowitz (2004)), (15) (idiosyncratic) volatility (Zhang (2006), Jiang et al. (2005)), (16) nearness to 52 week high (George and Hwang (2004)), (17) extremity of formation period returns (e.g. Bandarchuk and Hilscher (2013)), (18) weighted signed volume (Byun et al. (2013)), (19) change in mutual fund breadth of ownership (Chen et al. (2002)), (20) continuous information arrival (Da et al. (2013a)), and (21) intermediate horizon past performance (Novy-Marx (2012)).

Group 3: technical analysis Faced with the large number of potential technical trading rules, we focus on selected moving average strategies which appear to have been among the most successful historically (e.g. Huddart et al. (2009), Lo and Wang (2000), Sullivan et al. (1999)). We form portfolios based on the ratio of the current price to the moving 250 (200) day average price (22, 23). We also run trading strategies based on a dummy variable indicating whether the stock trades above or below the 250 (200) day average (24, 25). We also introduce a 25% band around the moving average to reduce the number of noisy signals (e.g. Brock et al. (1992), 26, 27).

Group 4: short-term return reversal In contrast to the aforementioned anomalies, the following phenomena are based on negative return autocorrelations. Classical studies such as Lehmann (1990) or Jegadeesh (1990) demonstrate that the previous month's return tends to reverse (28). Da et al. (2013b) show that this effect can be enhanced by relying on industry-adjusted residual returns (29).

Group 5: long-term return reversal In contrast, DeBondt and Thaler (1985) document a long-term reversal phenomenon based on a stock's past three to five year cumulative return (30). Among others, McLean (2010) shows that the effect is particularly strong among stocks with high idiosyncratic volatility (31).

Group 6: calender-based anomalies Another class of anomalies documents return predictability for recurring, calendar-based events. Heston and Sadka (2008) show that stocks tend to have relatively high (or low) returns every year in the same calendar month (32). Frazzini and Lamont (2007) uncover that firms outperform in months when they are expected to announce earnings (33). Hartzmark and Solomon (2013) show a similar phenomenon for months with expected dividend payments (34).

Group 7: lead-lag effects A small literature explores lead-lag effects between economically linked stocks. Cohen and Frazzini (2008) document return predictability across well-defined customer-supplier links (35). Cohen and Lou (2012) uncover that easy-to-analyze stand-alone firms lead the returns of more complex conglomerates (36).

Group 8: pairs trading Pairs trading (e.g. Gatev et al. (2006), Engelberg et al. (2009)) uses statistical methods to identify pairs of fundamentally linked stocks with no systematic lead-lag relationship. In essence, pairs trading bets on the future relative performance of stocks with very similar past performance. We implement four strategies (37-40) which differ in the maximum holding period of a given pairs trade and the return computation scheme. In total, we compute over 200 million possible pair combinations and, in each month, select the top 100 pairs with minimum distance between historical price paths.

Group 9: beta anomalies High-beta stocks underperform low-beta stocks (Baker et al. (2011), Frazzini and Pedersen (2013), and Hong and Sraer (2012)). We follow Frazzini and Pedersen (2013) in computing rolling pre-ranking Dimson (1979)-Betas either (41) based on daily data over one year or (42) based on monthly data over three years. Baker et al. (2011) extend the findings also to the use of volatility as a measure of risk. Consequently, we compute two similar long-short strategies (43, 44).

Group 10: distress risk anomalies Another facet of "the high risk, low return" phenomenon is related to financial distress. Campbell et al. (2008) (45) use a dynamic logit model based on a broad set of accounting and market variables to empirically quantify a firm's failure probability, and show that stocks with high (low) risk of failure underperform (outperform). We also consider the static approach of Ohlson (1980) (46) and take the bankruptcy hazard rate of Shumway (2001) into account (47). Finally, we consider the insights of e.g. Avramov et al. (2009) or Dichev and Piotroski (2001) who show that the quality of credit rating levels (48) or changes (49) positively predicts abnormal returns.

Group 11: skewness anomalies A recent, vibrant literature argues that stocks with lottery-type features tend to underperform. We follow Kumar (2009) in defining (non)-lottery stocks (50). We also replicate the related findings of Bali et al. (2011) who show that stocks with the highest daily return in the previous month underperform (51). Finally, we consider the regression-based methodology of expected idiosyncratic stock return skewness as proposed in Boyer et al. (2010) (52).

Group 12: differences of opinion Several approaches arrive at the conclusion that stocks for which differences of opinion are likely to be high tend to underperform. For instance, Diether et al. (2002) uncover that dispersion in analysts' earnings forecasts negatively predicts returns (53). Datar et al. (1998) show that turnover negatively predicts returns, which Lee and Swaminathan (2000) argue to be at least partially related to behavioral factors (54). Several studies, starting with Ang et al. (2006), suggest that idiosyncratic risk negatively predicts abnormal returns. As timing has been shown to matter, we consider three specifications: (55) monthly regressions over the preceding 36 months, (56) daily regressions over the preceding 12 months, and (57) daily regressions over the previous month.

Group 13: anomalies related to industry effects Goetzmann et al. (2012) find that procyclical stocks earn higher returns than stocks which comove less with business cycles (58). Hong and Kacperczyk (2009) uncover that stocks of firms involved in "sin" industries (alcohol, tobacco, gaming) outperform (59). We also use an alternative classification scheme based on social ratings provided by KLD (e.g. Statman and Glushkov (2009), 60).

Group 14: fundamental analysis We compute the composite measures of firm strength developed in Piotroski (2000) ("F-Score", 61) and Abarbanell and Bushee (1998) (62). Moreover, we consider some classical fundamental signals (e.g. Ou and Penman (1989), Lev and Thiagarajan (1993), Abarbanell and Bushee (1997)): the difference between the change in sales and inventories (63), the difference between the change in gross margin and sales (64), the difference between the change in selling & administrative expenses and sales (65), changes in leverage (66), and changes in the gross profit margin (67). We also consider related recent approaches. Fama and French (2006) find that more profitable firms have higher expected returns (68) and Novy-Marx (2013) argues that gross profit is the cleanest accounting measure of true economic profitability (69).

Group 15: net stock and financing anomalies A common behavioral interpretation of many of the following anomalies is that managers time equity markets by taking advantage of investor sentiment (e.g. Greenwood and Hanson (2012)) in their corporate finance decisions (successfully). We replicate the approach of Daniel and Titman (2006) (70), which synthesizes earlier work (e.g. Ikenberry et al. (1995), Loughran and Ritter (1995)) . Following Fama and French (2008) and Pontiff and Woodgate (2008), we use an approach based on the yearly change in split-adjusted shares outstanding (71). We also consider the net external finance measures of Richardson and Sloan (2004) (72) and Bradshaw et al. (2006) (73), which combine finance activities across different capital markets.

Group 16: capital investment and growth anomalies The common theme of a related set of anomalies is a negative correlation between various forms of firm growth or capital investment and future stock returns. Fairfield (2003) show that growth in net operating assets is negatively related to future stock returns (74). Similarly, Hirshleifer et al. (2004) uncover that the level of normalized net operating assets negatively predicts returns (75). Titman et al. (2004) show that capital investments scaled by total assets negatively predicts returns (76). Similarly, Anderson and Garcia-Feijoo (2006) focus on growth in capital expenditures (77), Cooper et al. (2008) on growth of total assets (78). Finally, Chemmanur and Yan (2009) and Lou (2013) find that changes in advertising expenditures negatively predict returns (79).

Group 17: anomalies related to innovation Several phenomena suggest that investors underreact to or misvalue innovation activities. Chan et al. (2001) show that firms with a high ratio of r&d to equity market value outperform (80). Similar insights are found for unexpected increases of r&d activity (Eberhardt et al. (2004), (81)). Gu (2005) shows that changes in patent citations predicts stock price behavior (82). Finally, innovative efficiency (Hirshleifer et al. (2013), (83)) and the r&d track record (Cohen et al. (2013), (84)) appear to have predictive power for abnormal returns.

Group 18: accruals anomalies Sloan (1996) finds that higher accruals predict lower returns (85). Modifications include using a broader definition of accruals (Richardson et al. (2005), 86), relying on abnormal accruals (Xie (2001), 87), or focussing on industries in which accruals are likely to be more important (Chan and Jegadeesh (2006), (88)). Thomas and Zhang (2002) argue that inventory changes scaled by total assets drive the accruals anomaly (89), whereares Belo and Lin (2012) rely on the real net growth rate of inventories (90).

Group 19: dividend anomalies Michaely et al. (1995) show that firms that initiate dividend payments for the first time tend to outperform (91). Boehme and Sorescu (2002) uncover a similar behavior after dividend resumptions (92). Moreover, Benartzi et al.

(1997) find that firms that increase dividend payments in absolute terms outperform (93). A similar result is found for changes of the dividend yield (e.g. Abarbanell and Bushee (1998), (94)).

Group 20: earnings surprises Many studies analyzing the post-earnings announcement drift (e.g. Bernard and Thomas (1989)) rely on time-series forecast of expected earnings. The resulting measure of unexpected earnings is often scaled by its historical standard deviation (e.g. Chordia and Shivakumar (2006), (95)), or by the stock price (e.g. Livnat and Mendenhall (2006), (96)). Other papers (e.g. Doyle et al. (2006), Hirshleifer et al. (2009)) base their measurement of expected earnings on consensus analysts forecasts (97). Still another approach of computing earnings surprises is the cumulative return around the day of the announcement (e.g. Chan et al. (1996), (98)). Loh and Warachka (2012) show that the market particularly underreacts to streaks of consecutive earnings surprises of the same sign (99). Finally, Balakrishnan et al. (2010) document a loss/profit post-announcement drift (100).

Table 1 displays the sample period and (where applicable) abnormal returns relative to a Fama and French (1993) model for each of the 100 computed return anomalies. More details on the construction of the anomalies are provided in the online appendix. In line with the original studies, all return phenomena yield statistically significant abnormal returns relative to a Fama and French (1993) model. Averaged across anomalies of group 2 to 20, the average equally weighted (value weighted) abnormal return is 79 (70) bp per month. Our screens on nominal share price and market capitalization might explain why the overall difference between equally weighting and value weighting returns is relatively small. Unless noted otherwise and to conserve space, we thus report results from equally weighted portfolios only.

Please insert table 1

For most parts of our empirical analysis, we group anomalies based on their underlying economic intuition as well as based on the correlation structure of their abnormal returns. By doing so it is intended to carve out the joint economic, institutional, or psychological drivers of related individual anomalies, to maximize the sample period, and to facilitate presentation. As indicated by the paragraph structure above, the procedure results in the construction of 20 “meta anomalies”, which simply correspond to the equally weighted average of the 2 to 17 constituent individual anomaly returns.

In this context, the meta anomaly concerned with deviations of the law one price is distinct in at least three ways. First, it is partly based on data from international stock markets. Second, violations of the law of one price are often considered to be among the most undisputed and obvious mispricings. Third, the absolute level of deviations from theoretical price parity is hardly comparable among the four settings which are part of this meta anomaly. We thus standardize the four anomalies so that their mean is zero and their standard deviation is one, before we aggregate them into meta anomaly 1.

Table 2 shows sample periods and selected characteristics of monthly returns for meta anomalies 2 to 20. All anomalies produce large abnormal returns relative to a Fama and French (1993) model. In line with the literature, several anomalies (momentum, short-term reversal, lead-lag effects among economically linked firms, pairs trading, earnings surprises) generate average abnormal monthly returns of at least 100 bp.

Please insert table 2

However, there is large time-series variation in the raw as well as the abnormal returns of each anomaly. The difference between the 10th percentile and the 90th percentile of monthly returns is always several hundred bp. Can these large differences at least in part be linked to time-series variation in proxies deemed to quantify market-level arbitrage constraints? We explore this question in the following sections.

3.2 Proxies for market-level arbitrage constraints

Our goal is to identify useful measures for the willingness and ability of speculators’ capital to put arbitrage capital at risk. We select these measures based on a literature survey, and start by employing the following six variables which can be divided in three groups: overall expected volatility and uncertainty, interest rate spreads, and constraints related to transaction costs. Each group consists of two proxies, out of which one is available from the 1920ies onwards, whereas the other one only covers a more recent time period.

Overall expected volatility and uncertainty We consider the Chicago Board Options Exchange Market Volatility Index (Vix), which reflects the implied volatility of S&P index options. Theoretical work suggests that higher expected volatility leads to tighter funding constraints of speculators (e.g. Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009)). During times of high Vix, arbitrageurs may have hard times to raise money from investors or to borrow it from lenders. Investors and lenders may even withdraw their money, forcing arbitrageurs to unwind potentially profitable positions prematurely (e.g. Shleifer and Vishny (1997), Gromb and Vayanos (2010)). They may also stem from increased risk aversion and subsequent flight to quality phenomena (e.g. Vayanos (2004)). There is also evidence that hedge funds reduced leverage and suffered from outflows in phases of high Vix (Ang et al. (2011), Ben-David et al. (2012)). As Ang et al. (2006), we rely on the old version of the Vix (denoted Vxo) as it starts four year earlier (in January 1986) and has been available in real time.

The Vix is highly positively correlated (.51) with an empirical estimation of aggregate idiosyncratic risk which is deemed to be related to diversification concerns of arbitrageurs (e.g. Pontiff (2006), Akbas et al. (2013)). More precisely, we first define a stock's idiosyncratic volatility for a given month as the standard deviation of the residual obtained from regressing the daily excess return in that month on a Fama and French (1993) model. We then compute the equally weighted average value of our eligible stock universe, starting in the 1920ties. This yields an aggregate monthly measure, which builds on high-frequency, non-overlapping data. Using a one factor or four-factor Carhart (1997) model generates highly correlated measures, and inferences remain unchanged.

Interest rate spreads The Ted spread is defined as the difference between the 3-month LIBOR Eurodollar rate and the 3-month T-Bill rate. Short-term US government debt is considered riskless, whereas the LIBOR rate additionally reflects perceived credit risk in interbank loans. In times of liquidity problems, the spread between both measures typically widens due to a "flight to quality" or "flight to liquidity" phenomenon (e.g Brunnermeier et al. (2008)). The Ted spread is thus by now a widely employed measure of funding liquidity (e.g. Ang et al. (2011), Asness et al. (2012), Brunnermeier and Pedersen (2009), Moskowitz et al. (2012)). Similar arguments hold for a corporate credit spread, defined as the difference between Moody's BAA corporate bond rate and Moody's AAA corporate bond rate (e.g. Akbas et al. (2013), Engelberg et al. (2009)), which on a monthly frequency is available from the 1920ties on.

Transaction costs We use the eligible stock universe to construct a monthly time-series of average bid-ask spreads using the recently proposed algorithm in Corwin and Schultz (2012). We also rely on the aggregate liquidity level as constructed in Pástor and Stambaugh (2003). We multiply values by -1 so that a high level indicates illiquidity. In times of high spreads or low liquidity, trading is likely to be more costly, which in turn might affect the magnitude of seemingly anomalous returns (see e.g. Chordia et al. (2013), Chordia et al. (2011), or Nagel (2013) for a motivation).

The upper half of figure 1 shows the time-series of each proxy. For presentation purposes, the minimum (maximum) value for each variable is set to 0 (1). High values signal high limits to arbitrage. The proxies appear to share a common component. For instance, during the recent financial crisis, they all indicate severe constraints. However, the average correlation between the proxies is only .42. Thus, each variable also seems to capture different aspects of market environments, which justifies the separate consideration of all proxies in the following tests.

Please insert figure 1

3.3 The impact of market-level arbitrage constraints on anomaly returns

Related work has relied on a broad range of regression approaches, including the use of both predictive models and contemporaneous models, the use of both raw anomaly returns and benchmark-adjusted anomaly returns, and the use of levels, changes, or (median-based) dummies for market-level conditions (e.g. Akbas et al. (2013), Ang et al. (2011), Frazzini and Pedersen (2013), Green et al. (2011), Stambaugh et al. (2012)). We consider several combinations of these approaches to test for the sensitivity of our findings.

To start as simple as possible, we run predictive regressions of the time-series of monthly raw long-short returns on a dummy variable, which takes on a value of 1 (0) if a given arbitrage proxy was above (below) its median value in the previous month. From a conceptual point of view, these regressions correspond to e.g. the baseline approach in Stambaugh et al. (2012). However, inferences are qualitatively unchanged if we construct a dummy based on rolling historical values in order to avoid any potential forward-looking bias. The lower half of figure 1 shows the proxy-specific time-series of high and low limits to arbitrage environments. The average correlation between the measures is .21.

We run univariate regressions for each pairwise combination of the 20 meta-anomalies and the six proxies for limits to arbitrage. We also construct a composite anomaly which simply is the average raw zero-cost return of all meta anomalies (2-20) available in a given month. As an alternative approach, we run a panel regression with all meta anomalies (2-20) and random fixed effects. Table 3 and 4 show the main results.

Please insert table 3 and table 4

Several findings are noteworthy. First, violations of the law of one price appear to be heavily driven by limits to arbitrage. This type of mispricing becomes more severe following months of above-median Vix, idiosyncratic volatility, Ted spread, bid-ask spreads, and illiquidity. Findings are not only statistically, but also economically significant. As a rough estimate, an above-median bid-ask spread in month t-1 is for instance associated with a 3/4 standard deviation (=0.49) increase in violations of the law of one price in month t. Similarly, an above-median level of average idiosyncratic volatility is associated with a 2/3 standard deviation increase. Untabulated findings show that a very similar pattern is also found at a daily (as opposed to monthly) frequency.

Second, however, there appears to be, at best, a weak link between the magnitude of the other meta anomalies and the dynamics of arbitrage constraints. Anomaly returns only sporadically load on arbitrage risk factors in a statistically significant matter in the direction suggested by theory. Significantly positively related to at least two proxies for arbitrage constraints are only a handful of anomalies: short-term reversal, pairs trading, innovation, and earnings surprises. With the exception of anomalies related to innovation, a common theme of these phenomena is that they tend to require frequent trading. As some proxies are directly (e.g. bid-ask spread) or indirectly related to costs of trading, these findings are in line with the limits to arbitrage argument when observed in isolation.

However, at least some of the above mentioned anomalies are not only unconditionally among the seemingly most profitable ones, but they also generate large profits in periods of low arbitrage constraints. For instance, depending on the specification, anomalies related to earnings surprises appear to yield monthly returns of 70 to 120 bp if one explicitly conditions on environments characterized by low limits to arbitrage. More generally, in about 85% of all regression estimates for meta anomalies 2 to 20, there are statistically significant excess returns even in periods when market-wide conditions suggest hardly any obstacles to arbitrage activities.

Similar insights are gained from attempts to measure the overall impact of limits to arbitrage on anomaly returns: neither the composite meta-anomaly return nor the pooled meta anomaly returns are significantly higher following months of high arbitrage constraints, as quantified by any proxy. From an economic perspective, only the estimates for idiosyncratic volatility seem meaningful, which indicate a 20 bp return difference between periods with high and low limits to arbitrage in the previous month.

However, we have relied on a simple binary variable of lagged market environments and thus potentially have neglected useful information. We therefore replicate all regressions, but now rely on the actual, continuous values of the arbitrage proxy. We moreover measure these values contemporaneously although inferences do not change if we lag them. Table 5 displays the corresponding regression coefficients.

Please insert table 5

The role of limits of arbitrage turns out to be a bit stronger, especially in case of the Vix and of the illiquidity measure. About half of the 20 meta-anomalies and also the composite anomaly measures are now significantly positively related to the level of these two variables. More specifically, violations of the law of one price and anomalies related to calendar effects, pairs trading, beta, distress, skewness, differences of opinion, net stock and financing, and capital investment and growth appear to be most pronounced in illiquid markets or when expected volatility is high.

However, these findings are based on raw returns and thus do not explain whether arbitrage proxies matter once one controls for the Fama and French (1993) factors, or, in unreported tests with similar findings, for the market factor only. We thus implement a two-stage regression as in e.g. Brennan et al. (1998) or Stambaugh et al. (2012). The approach involves regressing the monthly time-series of raw returns of anomaly i ($R_{i,t}$) on the market excess return ($RMRF$), the small-minus-big factor (SMB), and the value-minus-growth factor (HML).

$$R_{i,t} = \widehat{\alpha}_i + \widehat{\beta 1}_i RMRF_t + \widehat{\beta 2}_i SMB_t + \widehat{\beta 3}_i HML_t + \epsilon_{i,t} \tag{1}$$

Benchmark-adjusted abnormal monthly returns are then defined as the sum of $\widehat{\alpha}_i$ and the fitted value of $\epsilon_{i,t}$. The resulting series is then regressed on measures of arbitrage conditions, analogously to table 5. Table 6 displays the main findings.

Please insert table 6

The most important observation from this two-stage regression approach is that the impact of proxies for limits to arbitrage on anomaly returns becomes even weaker. For instance, neither the Vix nor market illiquidity are now significantly positively related to anomaly returns anymore. However, the link between violations of the law of one price and arbitrage conditions remains stable. These findings suggest that inferences about the impact of market frictions on these special settings cannot simply be transferred to most other anomalies and may represent a distinct phenomenon.

Table 7 shows that inferences do not change if we switch to a more disaggregated analysis. We now run the analysis of table 6 separately for each of the 100 individual anomalies and determine in each case whether the coefficient obtained on the proxies for arbitrage constraints is greater than zero and statistically significant at least at the 10% level. For presentation purposes, we aggregate these numbers within each meta anomaly. For instance, table 7 uncovers that five out of nine (56%) anomalies based on fundamental analysis load positively on aggregate idiosyncratic volatility, but only one (11%) of these anomalies does so in a statistically significant matter.

The last row of the table averages the numbers across all (meta) anomalies and reveals that the likelihood of positive coefficients on arbitrage constraints is often not much higher than the likelihood of negative coefficients. Moreover, the average fraction of statistically significant loadings is low and ranges from 8% in the case of the Ted spread to 24% in the case of idiosyncratic volatility.

Please insert table 7

Taken together, the main insight from the investigation so far thus is that widely employed proxies for market-level constraints to arbitrage activities appear to have surprisingly little power to explain the time-series variation in the magnitude of a broad range of anomalies. While previous work has sporadically revealed related findings regarding the behavior of specific anomalies and specific proxies[3], our results suggest that the lack of explanatory power is a phenomenon which is potentially far more general than commonly thought.

3.4 Robustness checks

The main inferences from the baseline analysis do not materially change after a number of sensitivity checks which we briefly describe in the following. For means of brevity, results are not tabulated.

Changes vs. levels We decompose the contemporaneous level of the arbitrage proxies (see table 5) into its value in month t-1 and its change from month t-1 to t. Alternatively, we only rely on the change of the arbitrage proxies, and either on the level or the change of anomaly returns.

Outliers We winsorize anomaly returns, arbitrage proxies, or both at the 99% level.

Value-weighted returns If we use value-weighted instead of equally weighted anomaly returns, the role of arbitrage constraints appears to become even slightly weaker.

Non-linearities We have experimented with a number of piecewise linear regressions, for instance by regressing benchmark-adjusted anomaly returns on quintile dummy variables times the arbitrage proxy under consideration.

Combined proxies We have experimented with different approaches to assess the overall impact of market-level arbitrage proxies, for instance by aggregating the dummies in tables 3 and 4 to a single variable or by running multivariate regressions with all six proxies

[3]For instance, it is well known that momentum returns are negatively related to various measures of market volatility and stress (e.g. Cooper et al. (2004), Daniel and Moskowitz (2013)). With regard to the low beta anomaly, Frazzini and Pedersen (2013) find that the lagged Ted spread negatively predicts abnormal returns which appears to be "inconsistent with the model [of leverage constraints] if a high Ted spread means a tightness of investors' funding constraints" (p. 5).

simultaneously. Performing the latter analysis analogously to the univariate approach in table 6 yields, over the time period from 1986 to 2011, an R^2 of 0.40 (0.05) for the anomalies related to the law of one price (the average remaining anomaly).

Time trends and publication effects Even though there does not seem to be consensus on this issue (see section 2.), there might be a negative time trend for anomaly returns. This could affect our findings to the extent that high and low limits to arbitrage environments are clustered over time. To explore this issue, we include a linear time trend variable in all regressions outlined so far. We have also experimented with subsamples, such as testing distinct subperiods of 25 years length or excluding the recent financial crisis. The only notable deviation from our baseline findings is that the impact of idiosyncratic volatility often becomes stronger once one focuses on a more recent time period. We also include a dummy variable which characterizes the (average) post-publication period for meta-anomalies (see McLean and Pontiff (2013)). The qualitative nature of our insights does not change.

Timing and lags It might be the case that the impact of limits to arbitrage might not show up in monthly data, but instead might matter at lower frequencies. However, most proxies for arbitrage constraints exhibit substantial autocorrelation (see figure 1) so that at least slow moving capital effects (e.g. Mitchell et al. (2007)) should partly be picked up. We have nevertheless also re-run the analysis with quarterly data. As theory does not offer a prior, we have experimented with different lag lengths between measures of arbitrage constraints and anomaly returns. Our findings remain similar.

Other proxies for market-level arbitrage constraints We have experimented with a number of proxies deemed to measure the role of institutions likely to act as arbitrageurs, the role of interest-related variables, and the role of price impact.[4]

[4] More specifically, we have constructed a proxy for overall shadow banking activity as in Adrian et al. (2010). We have also considered hedge fund index returns by following e.g. Menzly and Ozbas (2010) in relying on the Credit Suisse/Tremont Long/Short Equity Hedge Fund Index. Moreover, we have constructed an aggregated abnormal stock return measure of the nine investment banks relied on in Ang et al. (2011). Finally, we have experimented with the LIBOR, the term spread, and the Amihud (2002) illiquidity measure.

3.5 Market-level arbitrage constraints and anomaly-level arbitrage activity

Do proxies for market-level arbitrage constraints go along with changes in anomaly-level arbitrage activity? To explore this question, we build on recent work which proposes novel measures to infer arbitrage capital invested to profit from specific strategies. These variables are argued to reflect factors that drive arbitrageurs' decision making process and might be understood as anomaly-specific, time-varying arbitrage popularity barometers. We compute the following variables for each of all 96 anomalies (groups 2-20), and then aggregate them to 19 time-series at the meta anomaly level.

Changes in short interest Short interest should be most meaningful for stocks that a typical trading strategy would recommend shorting. Consequently, shocks of short interest in stocks entering the short leg of an anomaly, benchmarked against stocks in the long leg, might signal changes in arbitrage activity (e.g. Hanson and Sunderan (2013) and Hwang and Liu (2012)).We build on this intuition by constructing an arbitrage popularity measure based on short interest data for NYSE and AMEX stocks obtained from Compustat. As there is an upward trend in market-wide short selling activity over time (e.g. Hanson and Sunderan (2013)), we focus on relative measures (e.g. McLean and Pontiff (2013)). In each month, we rank all eligible stocks based on their short interest and assign a continuous value from 0 (lowest short interest) to 1 (highest short interest). We then compute the difference between the average short interest rank of the stocks contained in the short and long leg of the anomaly portfolio in a given month. An untabulated analysis shows that, with the exception of anomalies related to lead-lag effects or innovation, the difference is (often highly significantly) greater than zero on average. This suggests that there is indeed an attempt to exploit these anomalies, which in turn indicates that changes in short interest (from month t-1 to t) might help to draw a conclusion about sophisticated market participants behavior.

Trading activity Increased arbitrage activity has also been shown to manifest itself in higher turnover for those stocks that a typical anomaly would speculate on (see e.g. McLean and Pontiff (2013)). We again construct a rank-based measure as the time-series of the average rank of trading activity in the long and short leg of each anomaly. We then aggregate this variable at the meta-anomaly level and compute the monthly change.

Our regression framework mirrors the approach in table 5. The only difference is that we now use the monthly change in the average short interest rank (long portfolio-short portfolio) or the monthly change in the average turnover rank (0.5*long portfolio + 0.5*short portfolio) as dependent variable. Due to length concerns, we here only report results for the Vix, the Ted spread, and the average bid-ask spread. Using the other three proxies from the baseline analysis leads to similar results. The same holds true for a number of plausible changes in methodology.[5] The major insight from table 8 is the following: proxies for market-wide limits to arbitrage are at best only loosely related to changes in anomaly-level arbitrage activity. Virtually all regression coefficients are insignificant. In other words, the relative amount of capital invested in those anomalies does not, in the overall picture, seem to exhibit pronounced shocks in turbulent market conditions. The analysis thus appears to confirm the insights from the baseline analysis.

Please insert table 8

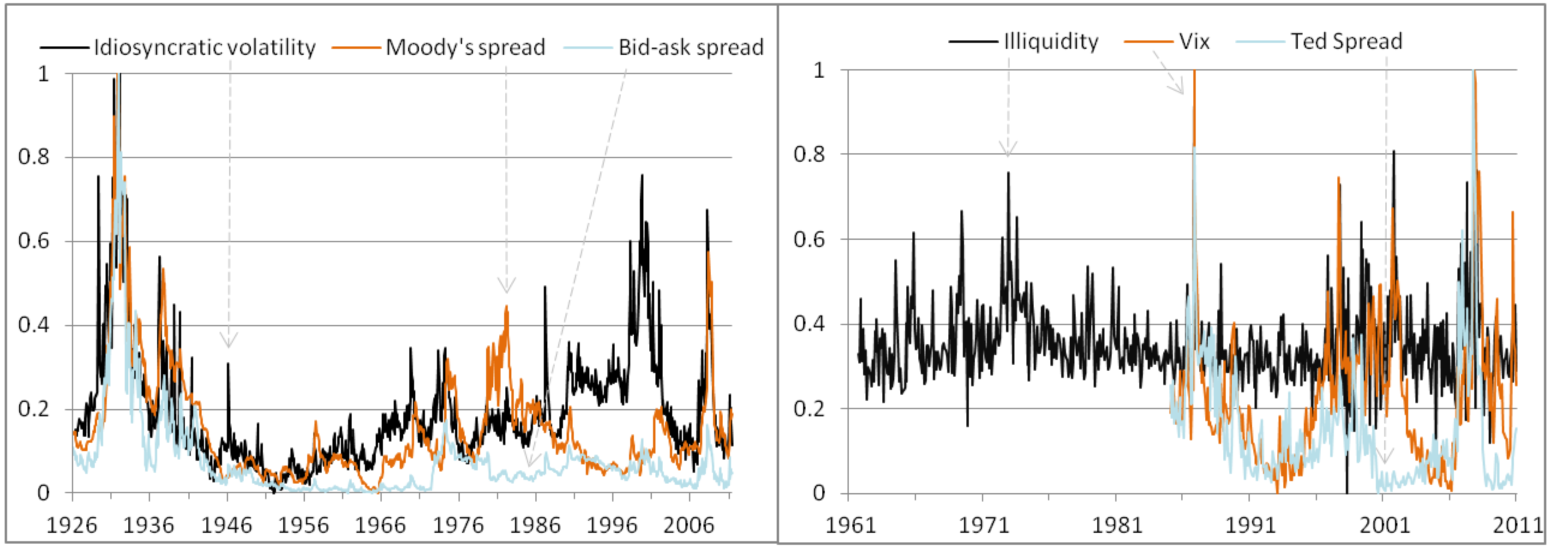
4. Conclusion

Are there market-wide economic barriers which prevent sophisticated market participants from capitalizing on abnormal returns? The idea that such limits to arbitrage are often binding and thus offer a convincing rationale for the survival of alleged mispricings has gained much interest in recent years. However, in contrast to these predictions, our findings on the dynamics of 100 cross-sectional well-known or recently discovered phenomena reveals that return anomalies appear to be surprisingly large in magnitude even in times when market wide limits to arbitrage are commonly thought to be low. The unobservability of arbitrage activities clearly make it hard to arrive at strong inferences. We believe it is nevertheless justified to conclude that our findings collectively support the emerging stream of literature which highlights some limits in the large work on limits to arbitrage.

[5] More specifically, we have experimented with relying on raw (instead of Nasdaq-adjusted) turnover or relying on short interest data also for Nasdaq stocks (from 2003 on, instead of solely relying on NYSE/AMEX). We have rerun the regressions with levels of (instead on changes) in short interest and turnover. We have also used dollar trading volume instead of turnover. We have relied on value weighted (instead of equally weighted) anomaly returns. Finally, we have also included the Fama and French (1993) factors in the regression.

Figure 1: Time-series characteristics of popular proxies for market-wide limits to arbitrage

The following graphs illustrate the behavior of the six baseline proxies for limits to arbitrage, as characterized in section 3.2. The graphs show the time-series of the level of each arbitrage proxy over the maximum time period available. The minimum (maximum) value for each variable is set to 0 (1). High values suggest high limits to arbitrage.



The figure is a graphical visualization of a dummy variable, which takes on a value of 1 (0) if a given arbitrage proxy was above (below) its overall sample median in the previous month. Thus, values of 1 (marked in black) indicate high limits to arbitrage environments, whereas values of 0 (marked in light grey) indicate low limits to arbitrage environments.

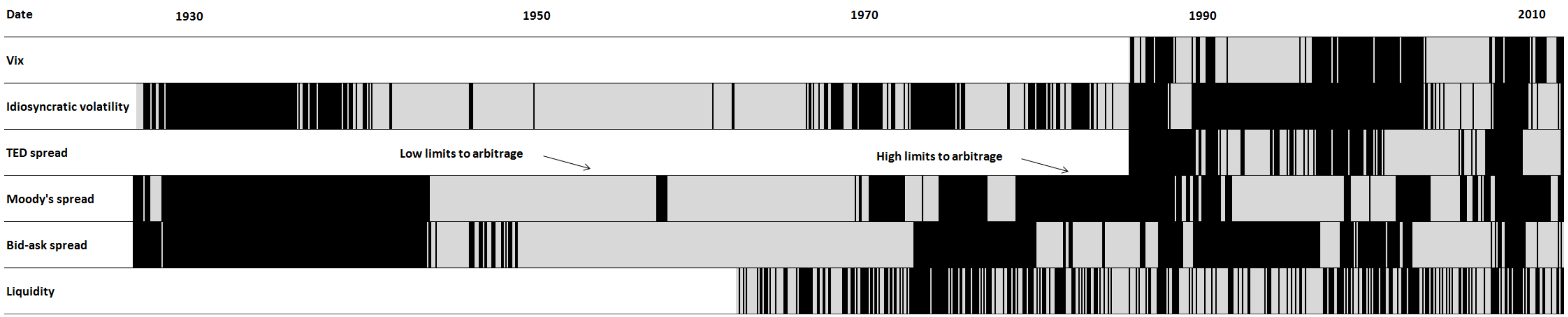


Table 1: Sample periods and abnormal returns of individual return anomalies

This table provides an overview over all 100 individual anomalies relied on in this paper. *ID* is a running number to identify anomalies in section 3.1. *Start* and *End* characterize the sample period. Where applicable, *3factor alpha* reports average monthly intercepts (in %) from time-series regressions of the long-short anomaly return on a Fama and French (1993) model. Reported are alphas for both the equally weighted (*ew*) and the value weighted (*vw*) version of anomaly returns. In the case of pairs trading, there is no distinction between equally and value weighted returns for conceptual reasons. The online appendix gives more detailed information about the construction of each anomaly. T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

ID	**Start**	**End**	**Anomaly name**	**3factor alpha (ew)**	**t-stat**	**3factor alpha (vw)**	**t-stat (vw)**
			1. Anomalies related to violations of the law of one price				
1	Aug-91	Sep-02	Twin stock anomaly	Anomalies related to the law of one price			
2	Jan-90	Dec-08	Cross-listed shares anomaly	are standardized so that their mean			
3	Jan-87	Dec-11	Dual-class shares anomaly	is zero and their standard deviation is one			
4	Jul-65	Feb-11	Closed-end fund anomaly	(see section 3.1)			
			2. Momentum anomalies				
5	Aug-26	Dec-11	Standard momentum	1.014***	(8.08)	0.915***	(6.64)
6	Sep-26	Dec-11	Age-enhanced momentum	1.232***	(9.52)	1.305***	(8.90)
7	Aug-26	Dec-11	Turnover-enhanced momentum	1.179***	(9.10)	1.207***	(8.38)
8	Jan-72	Dec-11	Market-to-book ratio-enhanced momentum	1.457***	(6.75)	1.301***	(5.44)
9	Feb-86	Dec-11	Credit rating-enhanced momentum	1.520***	(4.22)	1.292***	(3.40)
10	Sep-26	Dec-11	Size-enhanced Momentum	0.714***	(4.61)	0.768***	(4.80)
11	Jan-80	Dec-11	(Residual) analyst coverage-enhanced momentum	1.002***	(4.46)	0.790***	(2.87)
12	Jan-80	Dec-11	Forecast dispersion-enhanced momentum	1.071***	(4.14)	0.983***	(3.51)
13	Mar-29	Dec-11	R^2-enhanced momentum	0.926***	(7.17)	0.973***	(6.01)
14	Aug-26	Dec-11	Return consistency-enhanced momentum	1.520***	(8.82)	1.444***	(8.23)
15	Jul-28	Dec-11	(Idiosyncratic) volatility-enhanced momentum	1.034***	(8.31)	1.154***	(7.37)
16	Aug-26	Dec-11	52 week high-enhanced momentum	1.442***	(9.70)	1.349***	(8.45)
17	Aug-26	Dec-11	Formation period return-enhanced momentum	1.334***	(8.73)	1.327***	(7.87)
18	Oct-26	Dec-11	Signed volume-enhanced momentum	0.732***	(7.70)	0.544***	(5.33)
19	Apr-80	Dec-11	Change in breadth of ownership-enhanced momentum	1.010***	(4.03)	0.924***	(3.61)
20	Aug-26	Dec-11	Continuous information-enhance momentum	1.455***	(9.10)	1.304***	(7.95)
21	Jan-27	Dec-11	Intermediate momentum	0.714***	(6.28)	0.863***	(6.23)
			3. Technical analysis anomalies				
22	Oct-26	Dec-11	250 day moving average anomaly (deciles)	0.602***	(2.99)	0.606***	(2.75)
23	Oct-26	Dec-11	200 day moving average anomaly (deciles)	0.388**	(1.99)	0.392*	(1.84)
24	Oct-26	Dec-11	250 day moving average anomaly (dummy)	0.357***	(3.55)	0.205**	(2.04)
25	Oct-26	Dec-11	200 day moving average anomaly (dummy)	0.238**	(2.42)	0.113	(1.18)
26	Feb-69	Dec-11	250 day moving average anomaly (25% band)	1.464***	(5.23)	1.299***	(4.09)
27	Feb-69	Dec-11	200 day moving average anomaly (25% band)	1.350***	(4.52)	1.274***	(3.69)
			4. Short-term reversal anomalies				
28	Jul-26	Dec-11	Short-term reversal	1.116***	(7.35)	0.541***	(3.08)
29	Aug-28	Dec-11	Industry residual return-enhanced short-term reversal	1.715***	(15.08)	1.282***	(9.34)
			5. Long-term reversal anomalies				
30	Mar-31	Dec-11	Long-term reversal	0.177*	(1.82)	0.002	(0.02)
31	Mar-31	Dec-11	Idiosyncratic volatility enhanced-long term reversal	0.499***	(4.57)	0.481***	(3.40)
			6. Calendar-based anomalies				
32	Jan-31	Dec-11	Seasonality momentum	0.700***	(7.47)	0.705***	(5.50)
33	Sep-72	Dec-11	Earnings announcement premium	0.555***	(6.54)	0.663***	(4.79)
34	Jan-65	Dec-11	Dividend month anomaly	0.563***	(7.33)	0.438***	(4.17)
			7. Anomalies related to lead-lag effects among economically linked firms				
35	Jan-81	Dec-05	Customer-supplier anomaly	0.975***	(3.77)	1.032**	(2.35)
36	Jan-77	Dec-11	Complicated firms anomaly	1.252***	(5.52)	0.665***	(2.77)
			8. Pairs trading anomaly				
37	Jan-62	Dec-08	Pairs trading (6 months, conservative)	0.716***	(9.99)	0.716***	(9.99)
38	Jan-62	Dec-08	Pairs trading (6 months)	0.874***	(11.78)	0.874***	(11.78)
39	Jan-62	Dec-08	Pairs trading (1 month, conservative)	1.227***	(13.65)	1.227***	(13.65)
40	Jan-62	Dec-08	Pairs trading (1 month)	1.542***	(16.64)	1.542***	(16.64)
			9. Beta anomalies				
41	Jul-27	Dec-11	Low beta anomaly (high frequency)	0.890***	(6.81)	0.814***	(5.26)
42	Aug-29	Dec-11	Low beta anomaly (low frequency)	0.685***	(5.48)	0.590***	(4.13)
43	Dec-26	Dec-11	Low volatility anomaly (high frequency)	0.984***	(7.54)	0.827***	(4.86)
44	Dec-28	Dec-11	Low volatility anomaly (low frequency)	0.819***	(6.64)	0.737***	(4.81)

[continued overleaf]

			10. Distress risk anomalies				
45	Oct-72	Dec-11	Distress risk (Campbell et al. (2008)) anomaly	1.405***	(7.15)	1.347***	(5.10)
46	Nov-71	Dec-11	Distress risk (Ohlson (1980)) anomaly	0.787***	(7.31)	0.678***	(5.19)
47	Jul-51	Dec-11	Distress risk (Shumway (2001)) anomaly	1.067***	(6.38)	0.999***	(6.67)
48	Jan-86	Dec-11	Bond credit rating anomaly	0.646***	(3.68)	0.573**	(2.41)
49	Feb-86	Dec-11	Bond credit rating changes anomaly	0.701***	(2.82)	0.985***	(3.09)
			11. Skewness anomalies				
50	Jan-27	Dec-11	Lottery-type stocks anomaly	0.463***	(6.71)	0.529***	(6.52)
51	Jul-26	Dec-11	Maximum daily return anomaly	1.318***	(12.33)	0.959***	(6.63)
52	Aug-36	Dec-11	Expected skewness anomaly	0.510***	(4.40)	0.474***	(3.73)
			12. Anomalies related to differences of opinion				
53	Feb-76	Dec-11	Analyst forecast dispersion anomaly	1.338***	(9.31)	1.173***	(5.98)
54	Jul-26	Dec-11	Turnover anomaly	0.741***	(6.52)	0.503***	(3.86)
55	Jul-29	Dec-11	Idiosyncratic risk anomaly (low frequency 1)	0.623***	(5.66)	0.488***	(3.21)
56	Jul-64	Dec-11	Idiosyncratic risk anomaly (low frequency 2)	0.990***	(6.41)	0.960***	(5.45)
57	Jul-64	Dec-11	Idiosyncratic risk anomaly (high frequency)	1.020***	(7.54)	0.998***	(6.48)
			13. Anomalies related to industry effects				
58	Jul-62	Dec-11	Procyclical stocks anomaly	0.312***	(2.83)	0.523***	(3.03)
59	Jan-65	Dec-11	Sin stocks anomaly (industry-based measure)	0.156	(1.29)	0.377**	(2.37)
60	Feb-92	Dec-10	Sin stocks anomaly (rating-based measure)	0.197*	(1.81)	0.0707	(0.49)
			14. Fundamental analysis anomalies				
61	Jul-75	Dec-11	F-Score anomaly	1.062***	(4.73)	1.071***	(3.66)
62	Jul-75	Dec-11	Firms strength anomaly	0.260**	(2.37)	0.432***	(2.63)
63	Nov-75	Dec-11	Sales - inventories anomaly	0.869***	(9.24)	0.805***	(4.84)
64	May-72	Dec-11	Gross margin -s ales anomaly	0.497***	(5.77)	0.196	(1.46)
65	May-72	Dec-11	Administrative expenses - sales anomaly	0.342***	(3.32)	0.082	(0.47)
66	May-74	Dec-11	Change in leverage anomaly	0.373***	(4.38)	0.551***	(3.68)
67	Feb-72	Dec-11	Change in gross profit margin anomaly	0.445***	(5.33)	0.134	(1.04)
68	Mar-72	Dec-11	Return on assets anomaly	1.266***	(7.04)	0.993***	(4.95)
69	Jul-51	Dec-11	Gross profitability anomaly	0.631***	(5.63)	0.922***	(7.43)
			15. Net stock and financing anomalies				
70	Jul-31	Dec-11	Composite equity issuance anomaly	0.646***	(7.84)	0.588***	(5.93)
71	Jul-52	Dec-11	Annual issuance anomaly	0.671***	(9.29)	0.574***	(5.80)
72	Jul-63	Dec-11	Net external financing anomaly (1)	0.734***	(7.26)	0.609***	(4.51)
73	Jul-72	Dec-11	Net external financing anomaly (2)	0.798***	(7.90)	0.650***	(4.05)
			16. Capital investment and growth anomalies				
74	Jul-65	Dec-11	Net operating assets (change) anomaly	0.571***	(4.74)	0.533***	(3.13)
75	Jul-63	Dec-11	Net operating assets (levels) anomaly	0.704***	(5.59)	0.495***	(3.50)
76	Jul-52	Dec-11	Capital investments anomaly	0.571***	(6.68)	0.342***	(3.07)
77	Jul-53	Dec-11	Capital expenditures anomaly	0.294***	(3.63)	0.327***	(2.82)
78	Jul-52	Dec-11	Asset growth anomaly	0.356***	(3.22)	0.145	(1.17)
79	Jul-74	Dec-11	Advertising anomaly	0.345***	(3.09)	0.200	(0.95)
			17. Anomalies related to innovation				
80	Jul-60	Dec-11	R&D to market equity anomaly	0.339**	(2.43)	0.282**	(2.16)
81	Jul-75	Dec-11	R&D growth anomaly	0.436***	(2.89)	0.411***	(3.05)
82	Jul-80	Dec-11	Patent citation anomaly	0.377*	(1.94)	0.327	(1.35)
83	Jul-82	Dec-11	Innovative efficiency anomaly	0.163**	(1.98)	0.267**	(2.01)
84	Jul-80	Jun-10	Innovation predictability anomaly	0.648**	(2.04)	0.824*	(1.77)
			18. Accruals anomalies				
85	Jul-65	Dec-11	Classical accruals anomaly	0.514***	(4.50)	0.547***	(3.48)
86	Jul-52	Dec-11	Accruals (broadly defined) anomaly	0.365***	(4.27)	0.202	(1.63)
87	Jul-72	Dec-11	Abnormal accruals anomaly	0.535***	(6.20)	0.494***	(2.97)
88	Jul-71	Dec-11	Industry-enhanced accruals anomaly	0.574***	(3.46)	0.395	(1.50)
89	Jul-52	Dec-11	Inventory change anomaly	0.514***	(6.19)	0.360***	(3.15)
90	Jul-52	Dec-11	Inventory growth anomaly	0.482***	(5.64)	0.262**	(2.24)
			19. Dividend anomalies				
91	Jul-26	Dec-11	Dividend initiation anomaly	0.263***	(3.23)	0.126	(1.27)
92	Feb-45	Dec-11	Dividend resumption anomaly	0.332**	(2.30)	0.078	(0.46)
93	Jan-65	Dec-11	Change in dividend (absolute level) anomaly	0.256**	(2.24)	0.463**	(2.25)
94	May-72	Dec-11	Change in dividend yield anomaly	0.493**	(2.43)	0.494*	(1.74)
			20. Anomalies related to earnings surprises				
95	Nov-73	Dec-11	PEAD (computation scheme 1)	1.303***	(10.19)	0.803***	(5.01)
96	Nov-72	Dec-11	PEAD (computation scheme 2)	1.319***	(9.41)	1.005***	(5.42)
97	Jul-84	Dec-11	PEAD (computation scheme 3)	0.999***	(8.33)	0.686***	(3.42)
98	Nov-71	Dec-11	PEAD (computation scheme 4)	1.246***	(11.78)	1.030***	(6.10)
99	Nov-84	Dec-11	Streaks in earnings surprises anomaly	0.773***	(7.62)	0.707***	(4.84)
100	Feb-72	Dec-11	Profit/loss anomaly	1.204***	(6.46)	1.108***	(5.12)

Table 2: Return characteristics of meta anomalies

This table provides an overview over the 20 meta anomalies relied on in this paper. *ID* is a running number to identify meta-anomalies in the text, *Meta anomaly* offers a corresponding description. Meta anomalies correspond to the equally weighted average of the constituent anomaly returns. *N* denotes the number of individual anomalies (see table 1) which enter the meta anomaly. *Start* and *End* characterize the sample period over which the anomaly is computed. The sample period is determined by the availability of at least two individual anomalies which enter the meta anomaly under consideration. Where applicable, the *raw return* displays the equally weighed average monthly return (in %) of the long-short meta anomaly. Similarly, the *3f alpha* reports the intercept (in %) obtained from a Fama and French (1993) model. The table also displays the 10th and the 90th percentile of the resulting return distribution, both for the case of raw returns (*raw p10*, *raw p90*) and Fama and French (1993) abnormal returns (*3f p10*, *3f p90*). T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

ID	Meta anomaly	N	Start	End	raw return	t-stat	raw p10	raw p90	3f alpha	t-stat	3f p10	3f p90
1	Violations of the law of one price	4	Jan-87	Feb-11								
2	Momentum anomalies	17	Aug-26	Dec-11	0.871***	(6.50)	-2.83	4.66	1.125***	(9.57)	-2.78	5.04
3	Technical analysis anomalies	6	Oct-26	Dec-11	0.198	(1.19)	-4.92	4.93	0.513***	(3.43)	-4.39	5.36
4	Short-term reversal anomalies	2	Aug-28	Dec-11	1.573***	(11.24)	-2.45	5.56	1.436***	(11.04)	-2.401	5.29
5	Long-term reversal anomalies	2	Mar-31	Dec-11	0.614***	(4.85)	-3.23	4.58	0.338***	(3.57)	-2.84	3.85
6	Calendar-based anomalies	3	Jan-65	Dec-11	0.548***	(8.93)	-0.96	2.09	0.568***	(10.26)	-0.88	2.07
7	Lead-lag anomalies	2	Jan-81	Dec-05	1.062***	(5.01)	-3.00	5.39	1.158***	(5.39)	-2.68	5.30
8	Pairs trading anomaly	4	Jan-62	Dec-08	1.152***	(15.58)	-0.70	3.46	1.114***	(14.30)	-0.78	3.23
9	Beta anomalies	4	Jul-27	Dec-11	0.167	(0.73)	-7.58	8.52	0.859***	(7.57)	-2.95	4.68
10	Distress risk anomalies	5	Nov-71	Dec-11	0.584***	(3.65)	-3.41	4.74	0.988***	(8.21)	-1.75	3.72
11	Skewness anomalies	3	Jan-27	Dec-11	0.355**	(2.40)	-4.18	5.30	0.796***	(10.30)	-1.68	3.12
12	Differences of opinion	5	Jul-29	Dec-11	0.378**	(2.14)	-5.69	7.06	0.834***	(8.94)	-2.71	4.17
13	Industry effects	3	Jan-65	Dec-11	0.233***	(2.64)	-2.30	2.61	0.248***	(3.15)	-2.12	2.55
14	Fundamental analysis anomalies	9	Feb-72	Dec-11	0.575***	(9.28)	-1.02	2.13	0.633***	(10.78)	-0.96	2.20
15	Net stock and financing	4	Jul-52	Dec-11	0.649***	(6.36)	-2.08	3.53	0.672***	(10.69)	-1.30	2.70
16	Capital investment and growth	6	Jul-52	Dec-11	0.475***	(6.60)	-1.72	2.80	0.455***	(6.87)	-1.51	2.50
17	Anomalies related to innovation	5	Jul-75	Dec-11	0.281*	(1.65)	-3.36	3.87	0.337***	(2.92)	-2.58	3.10
18	Accruals anomalies	6	Jul-52	Dec-11	0.498***	(7.14)	-1.64	2.90	0.474***	(6.90)	-1.40	2.61
19	Dividend anomalies	4	Feb-45	Dec-11	0.283***	(4.35)	-1.64	2.42	0.309***	(4.59)	-1.72	2.50
20	Earnings surprises	6	Feb-72	Dec-11	1.095***	(11.23)	-1.46	3.58	1.218***	(13.18)	-1.19	3.67

Table 3: The impact of proxies for lagged market-level arbitrage constraints (binary measure) on raw meta anomaly returns (part 1)

This table displays coefficients from univariate predictive regressions of raw long-short anomaly returns in month t on binary measures of arbitrage constraints in month t-1. The latter are expressed as a dummy variable which takes on a value of 1 (0) if a given arbitrage proxy was above (below) its overall sample median in month t-1 (see figure 1 for a graphical representation). *Baseline* is the intercept of the regression and thus denotes the average monthly anomaly return in periods deemed to be characterized by low limits to arbitrage. *High* represents the coefficient obtained for the measure of arbitrage constraints, and thus denotes the average monthly return difference in periods of high limits to arbitrage when benchmarked against the baseline. *Composite: equally weighted* (*Composite: pooled*) refers to the equally weighted average of all available meta anomalies excluding violations of the law of one price (a pooled regression with meta-anomaly random effects). T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Vix				Idiosyncratic Volatility				Ted Spread			
Meta anomaly	High		Baseline		High		Baseline		High		Baseline	
Violations of the law of one price	0.288***	(5.20)	-0.306***	(-8.96)	0.325***	(5.09)	-0.409***	(-7.41)	0.110*	(1.90)	-0.214***	(-5.61)
Momentum anomalies	-0.154	(-0.29)	0.991***	(4.96)	-0.045	(-0.17)	0.882***	(8.15)	0.159	(0.30)	0.835***	(2.74)
Technical analysis anomalies	-0.797	(-1.17)	1.172***	(4.17)	-0.517	(-1.56)	0.451***	(3.39)	0.013	(0.02)	0.769*	(1.68)
Short-term reversal anomalies	0.917*	(1.71)	0.168	(0.88)	0.933***	(3.34)	1.109***	(10.00)	0.527	(0.98)	0.364	(1.01)
Long-term reversal anomalies	-0.195	(-0.57)	0.487**	(2.55)	0.303	(1.17)	0.468***	(3.91)	-0.419	(-1.22)	0.598**	(2.36)
Calendar-based anomalies	0.085	(0.46)	0.583***	(6.05)	0.102	(0.88)	0.484***	(6.42)	0.070	(0.37)	0.591***	(4.60)
Lead-lag anomalies	-0.257	(-0.52)	1.063***	(4.40)	0.083	(0.19)	0.999***	(2.85)	-0.348	(-0.73)	1.117***	(3.62)
Pairs trading anomaly	0.453**	(2.43)	0.375***	(3.60)	0.247*	(1.75)	1.002***	(10.65)	0.263	(1.46)	0.449***	(4.33)
Beta anomalies	-1.128	(-1.24)	0.860**	(2.39)	-0.101	(-0.22)	0.218	(0.98)	-0.936	(-1.03)	0.761	(1.20)
Distress risk anomalies	-0.005	(-0.01)	0.643***	(3.70)	0.253	(0.87)	0.417**	(2.23)	0.724*	(1.76)	0.282	(1.18)
Skewness anomalies	-0.378	(-0.62)	0.790***	(3.90)	0.147	(0.50)	0.281**	(2.22)	0.189	(0.31)	0.508	(1.23)
Differences of opinion	-0.701	(-1.00)	0.983***	(3.49)	0.171	(0.48)	0.283	(1.53)	0.098	(0.14)	0.585	(1.22)
Industry effects	-0.045	(-0.20)	0.290**	(2.45)	-0.080	(-0.46)	0.284**	(2.27)	-0.077	(-0.34)	0.306**	(2.06)
Fundamental analysis anomalies	-0.008	(-0.05)	0.533***	(6.37)	0.095	(0.83)	0.513***	(6.76)	0.072	(0.44)	0.493***	(4.11)
Net stock and financing	0.053	(0.13)	0.766***	(4.14)	0.286	(1.41)	0.505***	(5.86)	0.015	(0.04)	0.785***	(2.77)
Capital investment and growth	0.249	(1.08)	0.397***	(3.15)	0.333**	(2.33)	0.307***	(3.88)	0.095	(0.41)	0.474***	(3.06)
Anomalies related to innovation	1.012**	(2.34)	-0.119	(-0.65)	0.656**	(2.14)	-0.143	(-0.76)	0.488	(1.13)	0.144	(0.45)
Accruals anomalies	0.097	(0.44)	0.392***	(3.41)	0.276**	(1.98)	0.360***	(4.32)	0.141	(0.64)	0.370**	(2.50)
Dividend anomalies	-0.136	(-0.56)	0.324***	(2.93)	0.084	(0.62)	0.245***	(3.35)	-0.218	(-0.90)	0.364**	(2.24)
Earnings surprises	-0.087	(-0.37)	0.993***	(7.72)	0.334*	(1.85)	0.875***	(7.22)	0.504**	(2.17)	0.700***	(4.96)
Composite: equally weighted	-0.066	(-0.34)	0.607***	(8.40)	0.206	(1.45)	0.455***	(8.42)	0.074	(0.38)	0.537***	(4.04)
Composite: pooled	-0.056	(-0.29)	0.611***	(8.43)	0.174	(1.53)	0.506***	(4.82)	0.077	(0.40)	0.546***	(4.05)

Table 4: The impact of proxies for lagged market-level arbitrage constraints (binary measure) on raw meta anomaly returns (part 2)

This table displays coefficients from univariate predictive regressions of raw long-short anomaly returns in month t on binary measures of arbitrage constraints in month t-1. The latter are expressed as a dummy variable which takes on a value of 1 (0) if a given arbitrage proxy was above (below) its overall sample median in month t-1 (see figure 1 for a graphical representation). *Baseline* is the intercept of the regression and thus denotes the average monthly anomaly return in periods deemed to be characterized by low limits to arbitrage. *High* represents the coefficient obtained for the measure of arbitrage constraints, and thus denotes the average monthly return difference in periods of high limits to arbitrage when benchmarked against the baseline. *Composite: equally weighted* (*Composite: pooled*) refers to the equally weighted average of all available meta anomalies excluding violations of the law of one price (a pooled regression with meta-anomaly random effects). T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Moody's Credit Spread				Bid-Ask Spread				Illiquidity			
Meta anomaly	High		Constant		High		Constant		High		Constant	
Violations of the law of one price	-0.028	(-0.47)	-0.148***	(-4.37)	0.366***	(6.78)	-0.385***	(-9.61)	0.139**	(2.39)	-0.225***	(-6.26)
Momentum anomalies	-0.348	(-1.30)	1.045***	(6.95)	-0.159	(-0.59)	0.950***	(7.95)	-0.540	(-1.60)	1.272***	(5.91)
Technical analysis anomalies	-1.141***	(-3.46)	0.767***	(3.83)	-0.672**	(-2.03)	0.533***	(3.54)	-0.256	(-0.59)	0.748***	(2.86)
Short-term reversal anomalies	1.084***	(3.89)	1.035***	(6.25)	1.119***	(3.97)	1.026***	(8.87)	0.371	(1.10)	0.887***	(4.52)
Long-term reversal anomalies	0.073	(0.28)	0.579***	(4.69)	0.256	(0.98)	0.493***	(4.00)	0.322	(1.29)	0.504***	(3.26)
Calendar-based anomalies	-0.117	(-0.94)	0.610***	(6.01)	0.307**	(2.50)	0.397***	(5.75)	-0.066	(-0.54)	0.582***	(7.30)
Lead-lag anomalies	0.002	(0.00)	1.061***	(3.19)	0.361	(0.87)	0.862***	(3.23)	0.434	(0.98)	0.873***	(3.51)
Pairs trading anomaly	0.317**	(2.16)	1.001***	(9.44)	0.125	(0.84)	1.093***	(10.91)	0.524***	(3.56)	0.891***	(8.78)
Beta anomalies	-0.381	(-0.83)	0.356	(1.28)	-0.535	(-1.16)	0.432*	(1.95)	0.109	(0.19)	0.238	(0.69)
Distress risk anomalies	-0.604*	(-1.88)	0.936***	(3.86)	-0.086	(-0.28)	0.633***	(3.30)	-0.027	(-0.09)	0.597***	(3.20)
Skewness anomalies	-0.174	(-0.59)	0.441**	(2.37)	-0.122	(-0.41)	0.415***	(3.12)	0.148	(0.38)	0.390*	(1.67)
Differences of opinion	-0.211	(-0.60)	0.483**	(2.04)	-0.276	(-0.78)	0.515***	(2.66)	0.024	(0.05)	0.555*	(1.95)
Industry effects	-0.159	(-0.90)	0.318**	(2.40)	0.023	(0.13)	0.222**	(2.04)	0.077	(0.44)	0.194*	(1.73)
Fundamental analysis anomalies	0.008	(0.07)	0.570***	(5.67)	-0.001	(-0.01)	0.576***	(7.32)	-0.069	(-0.56)	0.610***	(8.12)
Net stock and financing	-0.128	(-0.63)	0.704***	(5.02)	0.131	(0.56)	0.598***	(5.98)	0.167	(0.69)	0.629***	(4.33)
Capital investment and growth	-0.006	(-0.04)	0.477***	(5.26)	0.181	(1.18)	0.404***	(4.74)	0.194	(1.17)	0.420***	(3.92)
Anomalies related to innovation	-0.266	(-0.72)	0.438	(1.37)	0.655**	(2.05)	-0.094	(-0.52)	-0.008	(-0.02)	0.285	(1.40)
Accruals anomalies	0.026	(0.18)	0.487***	(5.23)	0.004	(0.03)	0.497***	(5.91)	0.179	(1.14)	0.436***	(3.95)
Dividend anomalies	0.119	(0.88)	0.238***	(2.94)	0.044	(0.30)	0.267***	(3.64)	0.302*	(1.91)	0.197**	(2.00)
Earnings surprises	-0.152	(-0.79)	1.183***	(8.47)	0.195	(1.03)	0.982***	(7.87)	-0.030	(-0.15)	1.110***	(9.22)
Composite: equally weighted	-0.014	(-0.10)	0.575***	(8.79)	0.069	(0.48)	0.534***	(9.61)	0.077	(0.60)	0.591***	(8.15)
Composite: pooled	-0.113	(-0.97)	0.661***	(4.67)	0.040	(0.34)	0.585***	(4.89)	0.092	(0.70)	0.598***	(5.25)

Table 5: The impact of proxies for contemporaneous market-level arbitrage constraints (continuous measure) on raw meta anomaly returns

This table displays coefficients from univariate contemporaneous regressions of raw long-short meta anomaly returns in month t on continuous measures of arbitrage constraints in month t (e.g. the raw level of the Vix). *Composite: equally weighted* (*Composite: pooled*) refers to the equally weighted average of all available meta anomalies excluding violations of the law of one price (a pooled regression with meta-anomaly random effects). T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Vix		Idiosyncratic Volatility		Ted Spread		Moody's Credit Spread		Bid-Ask Spread		Illiquidity	
Violations of the law of one price	0.026***	(7.08)	46.19***	(10.89)	0.133	(1.48)	0.407***	(5.53)	82.13***	(7.75)	0.728	(1.55)
Momentum anomalies	-0.034	(-1.10)	-40.59	(-0.78)	-0.355	(-0.65)	-0.622	(-1.49)	-26.12	(-0.94)	-1.124	(-0.30)
Technical analysis anomalies	0.016	(0.36)	-96.96*	(-1.73)	0.610	(0.83)	-1.582***	(-3.30)	-92.97***	(-3.19)	-0.980	(-0.24)
Short-term reversal anomalies	-0.032	(-0.84)	86.72*	(1.83)	-0.991	(-1.61)	1.631***	(4.60)	100.4***	(4.38)	0.841	(0.23)
Long-term reversal anomalies	-0.023	(-1.11)	36.03	(0.98)	-0.164	(-0.31)	-0.014	(-0.04)	-6.23	(-0.31)	3.441	(1.49)
Calendar-based anomalies	0.034**	(2.59)	53.79**	(2.01)	0.184	(0.77)	-0.212	(-1.47)	54.08***	(2.59)	3.119**	(2.37)
Lead-lag anomalies	0.023	(0.62)	47.36	(0.85)	0.191	(0.32)	0.782	(1.50)	100.80	(1.04)	1.245	(0.36)
Pairs trading anomaly	0.024	(1.60)	16.06	(0.93)	0.281	(1.20)	0.835***	(4.51)	59.38**	(2.32)	5.295***	(3.76)
Beta anomalies	0.168***	(2.96)	11.15	(0.17)	1.109	(1.09)	-0.193	(-0.35)	4.12	(0.12)	18.70***	(3.12)
Distress risk anomalies	0.081***	(2.68)	73.70	(1.63)	0.931	(1.63)	-0.460	(-0.86)	32.80	(0.57)	6.888**	(2.18)
Skewness anomalies	0.103***	(2.97)	24.11	(0.49)	0.598	(0.98)	0.032	(0.10)	17.39	(0.88)	10.10**	(2.39)
Differences of opinion	0.149***	(3.42)	33.13	(0.73)	1.533**	(2.06)	-0.166	(-0.48)	-3.42	(-0.17)	16.15***	(3.41)
Industry effects	0.011	(0.85)	22.67	(0.83)	-0.076	(-0.35)	0.127	(0.51)	37.11	(1.29)	2.645	(1.58)
Fundamental analysis anomalies	0.0190*	(1.88)	8.43	(0.41)	0.013	(0.05)	0.153	(1.04)	16.17	(0.68)	1.249	(1.08)
Net stock and financing	0.084***	(3.52)	67.04*	(1.70)	0.514	(1.22)	0.123	(0.54)	66.69**	(2.27)	5.935**	(2.50)
Capital investment and growth	0.028**	(2.06)	50.89***	(2.64)	0.252	(0.85)	-0.054	(-0.27)	43.69**	(2.17)	2.900**	(2.04)
Anomalies related to innovation	0.001	(0.02)	89.65	(1.42)	-0.290	(-0.69)	-0.222	(-0.64)	9.02	(0.16)	-2.637	(-0.67)
Accruals anomalies	0.013	(1.09)	26.20	(1.31)	0.054	(0.24)	-0.146	(-1.00)	16.02	(0.77)	2.457*	(1.69)
Dividend anomalies	0.033**	(2.03)	12.86	(0.59)	-0.048	(-0.18)	0.356*	(1.95)	38.57*	(1.89)	1.685	(1.05)
Earnings surprises	0.013	(0.80)	18.66	(0.74)	0.188	(0.57)	-0.220	(-0.72)	59.79	(1.56)	1.727	(0.98)
Composite: equally weighted	0.037***	(2.83)	12.83	(0.46)	0.244	(1.22)	-0.064	(-0.26)	0.65	(0.04)	4.461***	(3.67)
Composite: pooled	0.038***	(2.95)	19.91	(0.96)	0.238	(1.19)	-0.075	(-0.39)	2.13	(0.14)	4.396***	(3.58)

Table 6: The impact of proxies for contemporaneous market-level arbitrage constraints (continuous measure) on benchmark-adjusted meta anomaly returns

This table shows the main insights from a two-stage time-series regression approach. In the first (and unreported) stage, benchmark-adjusted abnormal monthly returns are defined as the sum of $\widehat{\alpha}_i$ and the fitted value of $\epsilon_{i,t}$, obtained from regressing the time-series of raw monthly long-short returns of meta anomaly i on a Fama and French (1993) model. In the second (and reported) stage, a univariate contemporaneous regression of these benchmark-adjusted monthly long-short meta anomaly returns on a continuous measure of arbitrage constraints is performed. Displayed are the coefficients obtained for the respective measure of limits to arbitrage (e.g. the raw level of the Vix). *Composite: equally weighted* (*Composite: pooled*) refers the equally weighted average of all available meta anomalies excluding violations of the law of one price (a pooled regression with meta-anomaly random effects). T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Vix		Idiosyncratic Volatility		Ted Spread		Moody's Credit Spread		Bid-Ask Spread		Illiquidity	
Violations of the law of one price	0.024***	(6.46)	44.87***	(10.86)	0.105	(1.22)	0.389***	(5.40)	79.07***	(7.58)	0.573	(1.23)
Momentum anomalies	-0.072**	(-2.42)	-38.420	(-1.03)	-0.873	(-1.64)	-0.568**	(-2.02)	-25.500	(-1.45)	-3.360	(-0.91)
Technical analysis anomalies	-0.086**	(-2.27)	-107.7***	(-2.61)	-0.569	(-0.88)	-1.528***	(-5.04)	-96.11***	(-5.42)	-8.009**	(-2.07)
Short-term reversal anomalies	0.046	(1.36)	102.1**	(2.10)	-0.107	(-0.19)	1.631***	(4.83)	104.8***	(4.63)	7.100**	(2.16)
Long-term reversal anomalies	-0.017	(-0.85)	-4.990	(-0.18)	0.126	(0.30)	-0.271	(-1.05)	-18.560	(-1.12)	2.727	(1.34)
Calendar-based anomalies	0.018	(1.59)	45.28***	(2.69)	0.024	(0.11)	-0.106	(-0.84)	42.35**	(2.30)	1.154	(1.13)
Lead-lag anomalies	-0.004	(-0.11)	39.660	(0.72)	-0.045	(-0.08)	0.812	(1.56)	81.150	(0.85)	-0.888	(-0.26)
Pairs trading anomaly	0.035**	(2.34)	19.180	(1.10)	0.408*	(1.67)	0.819***	(4.64)	62.56**	(2.50)	5.975***	(4.26)
Beta anomalies	-0.045	(-1.22)	-31.380	(-0.95)	-1.106*	(-1.86)	0.130	(0.49)	-8.363	(-0.53)	-5.945*	(-1.95)
Distress risk anomalies	-0.020	(-1.01)	28.750	(0.73)	-0.482	(-1.30)	-0.170	(-0.51)	-23.050	(-0.69)	-0.460	(-0.20)
Skewness anomalies	-0.001	(-0.05)	23.180	(0.99)	-0.566	(-1.07)	0.384**	(2.29)	16.820	(1.63)	-3.753	(-1.61)
Differences of opinion	-0.012	(-0.45)	-0.963	(-0.03)	-0.248	(-0.55)	0.089	(0.36)	-13.480	(-0.86)	-3.240	(-1.30)
Industry effects	0.010	(0.83)	11.690	(0.59)	0.025	(0.11)	0.256	(1.06)	20.060	(0.71)	-0.186	(-0.13)
Fundamental analysis anomalies	0.000	(0.00)	1.980	(0.12)	-0.236	(-0.98)	0.227*	(1.73)	12.700	(0.61)	0.283	(0.27)
Net stock and financing	0.023	(1.57)	43.82***	(2.64)	-0.050	(-0.19)	0.437***	(3.00)	29.72*	(1.85)	-2.115*	(-1.74)
Capital investment and growth	0.011	(0.91)	40.68*	(1.89)	0.130	(0.54)	0.014	(0.08)	25.110	(1.40)	-0.049	(-0.04)
Anomalies related to innovation	0.0354**	(2.22)	110.2***	(3.99)	-0.113	(-0.39)	-0.481**	(-2.10)	50.800	(1.40)	2.505	(1.07)
Accruals anomalies	0.006	(0.55)	19.510	(0.85)	0.019	(0.09)	-0.095	(-0.71)	3.798	(0.19)	0.447	(0.30)
Dividend anomalies	0.000	(0.00)	9.772	(0.50)	-0.428*	(-1.91)	0.409**	(2.32)	33.05*	(1.66)	-0.009	(-0.01)
Earnings surprises	-0.016	(-1.11)	8.654	(0.35)	-0.225	(-0.75)	-0.158	(-0.61)	53.67*	(1.66)	0.521	(0.30)
Composite: equally weighted	-0.006	(-0.65)	2.387	(0.18)	-0.237	(-1.61)	0.040	(0.31)	-1.478	(-0.18)	-0.536	(-0.69)
Composite: pooled	-0.005	(-0.56)	6.576	(0.58)	-0.235	(-1.59)	0.031	(0.29)	-3.056	(-0.40)	-0.444	(-0.55)

Table 7: The impact of proxies for contemporaneous market-level arbitrage constraints (continuous measure) on benchmark-adjusted individual anomaly returns

This table shows the main insights from a two-stage time-series regression approach, similar as in table 6. However, we now rely on individual anomalies (see table 1 and the online appendix), instead of meta anomalies. In the first (and unreported) stage, benchmark-adjusted abnormal monthly returns for each of the 100 individual anomalies are defined as the sum of $\widehat{\alpha}_i$ and the fitted value of $\epsilon_{i,t}$, obtained from regressing raw returns of individual anomaly i on a Fama and French (1993) model. In the second (and reported) stage, a univariate contemporaneous regression of these returns on a continuous measure of arbitrage constraints is performed. *% pos* (*% sig. pos*) denotes the fraction of positive coefficients on the respective proxy for arbitrage constraints (the fraction of coefficients which are statistically significant at least at the 10% level), aggregated within meta anomalies. N denotes the number of individual anomalies within a given meta anomaly. To give an example of how to interpret the table: five out of nine (56%) anomalies based on fundamental analysis load positively on aggregate idiosyncratic volatility, but only one (11%) of these anomalies does so in a statistically significant matter.

Meta anomaly	N	Vix		Idiosyncratic Volatility		Ted Spread		Moody's Credit Spread		Bid-Ask Spread		Illiquidity	
		% pos	% sig. pos	% pos	% sig. pos	% pos	% sig. pos	% pos	% sig. pos	% pos	% sig. pos	% pos	% sig. pos
Violations of the law of one price	4	100%	75%	100%	75%	50%	50%	75%	50%	75%	75%	100%	25%
Momentum anomalies	17	0%	0%	12%	0%	0%	0%	6%	0%	12%	0%	18%	0%
Technical analysis anomalies	6	0%	0%	0%	0%	17%	0%	0%	0%	0%	0%	0%	0%
Short-term reversal anomalies	2	100%	0%	100%	50%	0%	0%	100%	100%	100%	100%	100%	100%
Long-term reversal anomalies	2	0%	0%	50%	0%	100%	0%	0%	0%	0%	0%	100%	0%
Calendar-based anomalies	3	100%	0%	100%	33%	67%	0%	33%	33%	100%	0%	100%	0%
Lead-lag anomalies	2	0%	0%	100%	0%	50%	50%	100%	0%	100%	0%	50%	0%
Pairs trading anomaly	4	100%	75%	75%	50%	100%	25%	100%	100%	100%	100%	100%	100%
Beta anomalies	4	0%	0%	0%	0%	0%	0%	75%	0%	50%	0%	0%	0%
Distress risk anomalies	5	40%	20%	80%	40%	25%	25%	40%	0%	60%	20%	60%	0%
Skewness anomalies	3	33%	0%	100%	0%	0%	0%	100%	33%	100%	0%	0%	0%
Differences of opinion	5	20%	0%	40%	0%	20%	0%	80%	40%	40%	0%	0%	0%
Industry effects	3	67%	0%	67%	0%	33%	0%	67%	0%	67%	0%	0%	0%
Fundamental analysis anomalies	9	56%	0%	56%	11%	33%	11%	78%	22%	78%	0%	56%	22%
Net stock and financing	4	100%	0%	100%	75%	50%	0%	100%	50%	100%	25%	0%	0%
Capital investment and growth	6	83%	17%	83%	50%	67%	0%	33%	0%	67%	0%	50%	0%
Anomalies related to innovation	5	100%	40%	100%	80%	40%	0%	40%	0%	100%	40%	100%	20%
Accruals anomalies	6	67%	0%	83%	17%	33%	0%	33%	0%	33%	0%	50%	0%
Dividend anomalies	4	50%	0%	75%	0%	25%	0%	75%	25%	75%	25%	25%	0%
Earnings surprises	6	17%	0%	50%	0%	33%	0%	0%	0%	100%	0%	67%	0%
Average	5	52%	11%	69%	24%	37%	8%	57%	23%	68%	19%	49%	13%

Table 8: The impact of proxies for contemporaneous market-level arbitrage constraints (continuous measure) on meta anomaly-level arbitrage activity

This table displays coefficients from univariate regressions of measures of meta anomaly-level activity in month t on continuous measures of arbitrage constraints in month t (e.g. the raw level of the Vix). Meta anomaly-level activity measures are either the monthly change in the average short interest rank (long portfolio-short portfolio, left-hand side) or the monthly change in the average turnover rank (0.5*long portfolio + 0.5*short portfolio, right-hand side) of all individual anomalies belonging to a given meta-anomaly. *Composite: equally weighted* (*Composite: pooled*) refers the equally weighted average of all available meta anomalies excluding violations of the law of one price (a pooled regression with meta-anomaly random effects). T-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Changes in short interest						Changes in turnover					
	Vix		TED spread		Bid-Ask spread		Vix		TED spread		Bid-Ask spread	
Momentum anomalies	-0.014	(-0.35)	0.102	(0.15)	38.700	(0.48)	-0.0103	(-1.08)	-0.071	(-0.34)	-2.083	(-0.31)
Technical analysis anomalies	-0.027	(-0.76)	-0.736	(-1.28)	-1.229	(-0.02)	-0.0159	(-1.15)	-0.186	(-0.58)	0.255	(0.04)
Short-term reversal anomalies	-0.014	(-0.20)	0.835	(0.60)	-50.250	(-0.25)	-0.0137	(-0.82)	-0.484	(-1.26)	-4.353	(-0.35)
Long-term reversal anomalies	0.019	(0.71)	0.403	(0.62)	70.610	(0.98)	-0.00736	(-0.60)	-0.002	(-0.01)	0.782	(0.08)
Calendar-based anomalies	-0.028	(-0.87)	-0.180	(-0.27)	-44.040	(-0.47)	0.00551	(0.46)	0.268	(1.05)	-2.264	(-0.21)
Lead-lag anomalies	0.021	(0.23)	0.349	(0.21)	53.330	(0.22)	-0.00534	(-0.21)	-0.167	(-0.36)	4.124	(0.05)
Pairs trading anomaly	0.009	(0.63)	0.361	(1.25)	-15.950	(-0.32)	0.0522**	(2.36)	0.465	(1.07)	47.230	(1.60)
Beta anomalies	-0.017	(-0.88)	-0.444	(-1.26)	-2.493	(-0.05)	0.00193	(0.34)	0.119	(1.20)	-1.625	(-0.51)
Distress risk anomalies	-0.0277*	(-1.74)	-0.709**	(-2.19)	-52.920	(-1.17)	0.0113*	(1.91)	0.220*	(1.72)	1.587	(0.10)
Skewness anomalies	-0.022	(-0.81)	-0.428	(-0.84)	-45.930	(-0.74)	-0.00565	(-0.64)	-0.292	(-1.65)	-3.493	(-0.63)
Differences of opinion	-0.025	(-1.38)	-0.359	(-0.93)	-55.790	(-1.30)	0.00662	(1.41)	0.076	(0.82)	-0.699	(-0.22)
Industry effects	0.005	(0.54)	0.215	(1.10)	5.157	(0.09)	0.00649	(0.99)	-0.117	(-0.89)	13.740	(1.03)
Fundamental analysis anomalies	-0.010	(-0.83)	-0.383	(-1.48)	-20.670	(-0.36)	-0.00401	(-0.91)	-0.030	(-0.35)	-8.112	(-0.58)
Net stock and financing	0.001	(0.07)	-0.321	(-1.34)	7.432	(0.23)	0.00507	(1.07)	0.058	(0.75)	-2.193	(-0.40)
Capital investment and growth	-0.003	(-0.33)	-0.124	(-0.54)	7.353	(0.17)	0.00283	(0.53)	-0.017	(-0.15)	-4.027	(-0.36)
Anomalies related to innovation	-0.005	(-0.14)	-0.401	(-0.42)	-34.630	(-0.52)	0.00381	(0.46)	-0.053	(-0.29)	3.510	(0.16)
Accruals anomalies	-0.010	(-0.71)	0.303	(1.07)	15.310	(0.36)	-0.00718	(-1.18)	-0.189	(-1.38)	-14.020	(-1.04)
Dividend anomalies	-0.004	(-0.07)	-0.630	(-0.57)	-3.797	(-0.03)	0.00519	(0.25)	-0.225	(-0.62)	-12.060	(-1.11)
Earnings surprises	-0.021	(-1.38)	-0.290	(-1.00)	-52.600	(-0.84)	0.00105	(0.15)	-0.015	(-0.08)	0.549	(0.03)
Composite: equally weighted	-0.000	(-1.05)	-0.001	(-0.67)	-0.101	(-0.52)	0.00001	(0.40)	-0.000	(-0.63)	-0.016	(-0.53)
Composite: pooled	-0.009	(-1.09)	-0.130	(-0.69)	-10.730	(-0.56)	0.00128	(0.42)	-0.036	(-0.63)	-2.490	(-0.89)

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