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# What explains the dynamics of 100 anomalies?

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ABSTRACT

Are anomalies strongest when investor sentiment or limits of arbitrage are considered to be greatest? We empirically explore these theoretically deducted predictions. We first identify, categorize, and replicate 100 long-short anomalies in the cross-section of expected equity returns. We then comprehensively study their interaction with popular proxies for time-varying market-level sentiment and arbitrage conditions. We find a powerful (relatively weak) role of the variation in proxies for sentiment (arbitrage constraints). In this context, the predictive power of sentiment is mostly restricted to the short leg of strategy returns. Our insights collectively suggest that the dynamics of sentiment combined with the base level (and not primarily the variations) of limits to arbitrage provide at least a partial explanation for inefficiencies.



## 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 many investors behave irrationally or where arbitrageurs are less capable of aggressively betting against mispricings (see e.g. the discussions in Baker and Wurgler, 2007; Brav et al., 2010; or Hanson and Sunderan, 2014). Empirical tests of this fundamental relationship 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, the empirical 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 and based on the same stock universe and the same methodology, which type of phenomena yields the highest seemingly abnormal returns in which situations? Judging from the "big picture", to what extent can variations in market-wide sentiment on the one hand and variations in market-wide limits to arbitrage on the other hand be deemed to be good explanations for the dynamics of anomaly returns?

We start by synthesizing 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 and 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 the resulting data set of more than 65,500 anomaly months covers a reasonably representative universe of anomalies discussed in the literature.

Of course, the 100 anomalies are not fully independent. For instance, our data set contains many "enhanced" momentum strategies proposed in the literature, which are different from, but still closely related to the approach in the seminal study of Jegadeesh and Titman (1993). Nevertheless, the average correlation of the Fama and French (1993) model adjusted equally weighted

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100 anomaly returns is only .12, suggesting that we are able to capture a diverse set of return phenomena. This insight is consistent with Green et al. (2014) who uncover that the cross-section of expected returns is surprisingly multidimensional. Their findings are derived from 100 return predictive signals as well, which however only partly overlap with our anomaly data base.

Forming a common basis for all anomalies 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 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. Our large-scale analysis is motivated by the lack of comparability, consensus, or even existence of previous work regarding the impact of investor sentiment and particularly of limits to arbitrage on individual anomalies, as we outline in the literature review below.

For instance, a critical issue 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, small stocks have been argued to obstruct the view on the economic importance of arbitrage constraints (e.g. Brav et al., 2010). In light of these concerns, our baseline analysis applies 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 represents the economically meaningful fraction of the market. In sum, our approach helps to assess to what extent prior results dealing with specific anomalies can be generalized.

Our main insights can be summarized as follows. First, 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 on firm size are often stricter. Moreover, our sample period is on average about 20 years longer (due to an often earlier start date and typically more recent data), and thus partly out-of-sample. This suggests that most anomalous returns uncovered in the literature are unlikely to be primarily driven by statistical biases (for further discussions see Green et al., 2013; Green et al., 2014; Harvey et al., 2015; McLean and Pontiff, 2015).

Second, market-level investor sentiment is a strong predictor of anomaly returns. This finding complements the insights of Stambaugh et al. (2012) who uncover that the eleven anomalies they consider tend to be more pronounced following high levels of sentiment. In a follow-up study and based on the same set of anomalies, Stambaugh et al. (2014) run simulations to mitigate concerns regarding a spurious-regression bias. Again, they find strong support for the predictive power of sentiment, and argue that "the key is consistency across anomalies" (p. 1). Our approach of substantially increasing the set of anomalies (as well as sentiment proxies) represents a natural extension of their study. Instead of relying on simulations for a limited set of anomalies, we test for generalizability by providing out-of-sample evidence for many anomalies not covered in their papers.

For more than 80% of the anomalies, the role of sentiment goes in the predicted direction, even though findings are only significant for about 40%. Eliminating noise by focusing on the "big picture" nevertheless reveals a powerful role of sentiment: for the average anomaly, we find that the long-short spread is roughly 50% larger following months with above median (Baker and Wurgler, 2006) sentiment than it is following months with below median sentiment. This is particularly noteworthy as we focus on relatively large and liquid firms for which sentiment is expected to be less relevant (see e.g. Lemmon and Portniaguina, 2006). In line with Stambaugh et al. (2012) and prominent theories, these results are strongest among return phenomena often attributed to investor overreaction, and they are mainly driven by the short leg of the portfolio. With respect to an aggregate anomaly, a one standard deviation increase in lagged sentiment leads to an insignificant return increase of less than 3 bp in the long leg, but to an highly significant return decrease of close to 18 bp in the short leg.[1]

Third, and in contrast to our findings for investor sentiment, we find little evidence that the time variation in proxies for market-wide limits to arbitrage has predictive power for the dynamics of anomaly returns. Building on a literature review, our baseline analysis considers the Vix, average idiosyncratic volatility, the Ted spread, the Moody's credit spread, average bid-ask spreads, and market illiquidity. These variables have a solid theoretical foundation, capture different aspects of limits to arbitrage (e.g. funding liquidity, transaction costs, holdings costs), and are widely employed in the literature. An eyeball test also suggests that the proxies tend to capture periods that one would intuitively classify as phases of relatively high limits to arbitrage (such as the great depression in the 1930ies or the recent financial crisis). In general, these variables turn out to have a low correlation (.0-.2) with the Baker and Wurgler (2006) sentiment measure, and thus make quite distinct predictions.

We run regressions analogously to the ones for investor sentiment. We indeed find that the few relatively unambiguous deviations from the law of one price exhibit a strong positive link to proxies for time-varying limits of arbitrage. To a lesser extent, these insights also hold for short-term reversal, pairs trading, and net stock and financing anomalies. However, the proxies 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 predicted direction. A notable exception is the role of idiosyncratic risk in some specifications. This time-series evidence is consistent with the view that idiosyncratic volatility may be the most important deterrent for arbitrage activity in the cross-section (e.g. Pontiff, 2006; Stambaugh et al., 2014).

The overall relatively low predictive power of most proxies for the magnitude of most anomalies is persistent. Among others, we run predictive and contemporaneous regressions, use the raw level of the proxies or a more reduced form, use changes instead of levels, use additional controls, focus on the long or short leg of the anomaly portfolios, consider quarterly instead of monthly returns, rely on alternative proxies for arbitrage constraints, consider composite anomalies, include or even focus on small firms,

[1] Taken together, these findings are consistent with the overpricing argument formally developed in Miller (1977). Many investors are reluctant or simply unable to go short (e.g. Almazan et al., 2004). In conjunction with such permanent short-sale constraints, mispricing in the sense of overpricing (induced by high investor sentiment) should be more prevalent than mispricing in the sense of underpricing (induced by low investor sentiment). This asymmetric effect suggests that anomalies, to the extent they reflect mispricing, should be more pronounced following positive than following negative sentiment, and that the short leg should be more sensitive to sentiment than the long leg (see also e.g. Stambaugh et al., 2015 and the references therein).

and control for outliers. Inferences do not change. Nevertheless, individually, the proxies might be too noisy. Among others, we thus use principal component analysis to capture as much of the joint variation across the different proxies as possible. This approach mirrors the construction of the Baker and Wurgler (2006) index, which is based on the principal component of six market-wide sentiment proxies such as aggregate turnover or the number of IPOs. Again, inferences do not change: all else equal, time-variation in aggregate sentiment (limits to arbitrage) goes along with or predicts a large (only small) fraction of the variation in anomaly returns.

Fourth, in an attempt to understand the low predictive power better, we uncover that aggregate market-level arbitrage conditions lack explanatory power for time-varying anomaly-level arbitrage popularity. In deriving this finding, we draw on recent studies which argue 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.

These findings do not imply that market-wide limits to arbitrage do not matter. The economically large unconditional return of the diverse set of anomalies analyzed in this study as well as the strong predictive power of investor sentiment for the short leg of anomaly portfolios is highly suggestive of a certain level of ever-present limits to arbitrage, particularly in the sense of permanent short-selling constraints. This is also the line of reasoning behind Stambaugh et al. (2012), as sketched above. What our findings do suggest is that the dynamics around persistent constraints to arbitrage appear to often have a rather weak impact, at least for some forms of market-wide limits to arbitrage. In other words, the ever-present level of aggregate arbitrage constraints (particularly with respect to shorting) might in many settings play a more important role in explaining potential inefficiencies than its fluctuations over time. The apparently weak link between market-level conditions and anomaly-level popularity lends further support for this line of reasoning.

In contrast, the dynamics of investor sentiment appear to be quite important relative to its mean level. Alternatively, given the many facets of limits to arbitrage, measures of investor sentiment themselves might represent some form of limits to arbitrage in that they could proxy for noise trader risk (e.g. Shleifer and Vishny, 1997; Barberis and Thaler, 2003) or other risk factors (Sibley at al., 2013).

Our analysis contributes to the ongoing debate about the real-life relevance of limits to arbitrage. As we describe in the following, not all of these studies arrive at the same conclusion, leaving a blurry picture. Our study provides a partial explanation for these sometimes contrasting findings. It appears that the time variation in limits to arbitrage (as measured in this paper) has a meaningful impact on specific anomalies and in specific settings, but also that these insights do not necessarily can be generalized to all anomalies or all proxies.

Most previous work takes a cross-sectional perspective. Many papers argue that abnormal returns related to a specific anomaly are most pronounced for firms that are most difficult to arbitrage, proxied for by e.g. firm size or idiosyncratic risk. 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). In contrast, Brav et al. (2010) argue that more conservative tests often "fail to support the limits of arbitrage argument" (p. 157) (see also e.g. Lam and Wei, 2011 and Watanabe et al., 2012). Similarly, in a more specialized setting, Ljungqvist and Qian (2014) conclude that "limits to arbitrage may not always be as constraining as sometimes assumed" (p. 1).

Concerning the time-series perspective, most studies (including ours) find a strong impact of market-wide limits to arbitrage for short-term reversal (e.g. Nagel, 2012) or deviations of the law of one price (e.g. Pontiff, 1996). Concerning other anomalies, there appears to be little consensus. Some studies report a strong role of time variation in arbitrage conditions (e.g. Sadka, 2006), many others report a rather mixed role (e.g. Frazzini and Pedersen, 2014; Akbas et al., 2013; Hanson and Sunderan, 2014; Asness et al., 2013)[2], and some find a rather weak role (e.g. Green et al., 2011).

Finally, there is also little consensus on to what extent the growth of the arbitrage industry has affected anomaly returns. For instance, with regard to momentum and value, Hanson and Sunderan (2014) 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 (2013) conclude that there is "little evidence that size, value, and momentum returns are significantly affected by changes in trading costs or institutional and hedge fund ownership over time" (p. 275). Similarly, Chordia et al. (2013) show that abnormal returns for twelve anomalies are much lower in their second subperiod, whereas Haugen and Baker (1996) do not find a pronounced trend. Somewhere in the middle are the intriguing findings of McLean and Pontiff (2015) who analyze 97 anomalies and report a 26% out-of-sample decline as well as a 58% post-publication decline in anomalous returns. Controlling for time or publication effects does not affect our insights.

## 2. Empirical analysis

### 2.1. Anomalies

Our approach involves identifying, categorizing, and replicating stock market anomalies.[3] 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 three-factor model or comparable benchmarks, and 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

[2] With regard to the low beta anomaly, Frazzini and Pedersen (2014) 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 high tightness of investors' funding constraints" (p. 3). Similarly, in their analysis of capital flows to five quantitative trading strategies, Hanson and Sunderan (2014) conclude that the Ted spread does not play an important role. With regard to a composite actively managed trading strategy based on six anomalies, Table 7 of Akbas et al. (2013) shows that lagged proxies for market-wide funding constraints (including a credit spread and aggregate idiosyncratic volatility) have little explanatory power for future returns. While the authors do find that shocks in the flow of capital to the trading strategy can predict the strategy's return, market-level "constraints do not appear to impede market efficiency beyond the effect that operates through the fund flow measure" (p. 22). Asness et al. (2013) state that "while liquidity risk may partly explain the positive risk premium associated with momentum, because value loads negatively on liquidity risk, the positive premium associated with value becomes an even deeper puzzle" (p. 931).

[3] 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.

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 Table A2 in 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* A number of papers focus on 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. Arguably among the best documented cases are price parity deviations of dual-listed companies (“Siamese Twins”, (1), see e.g. Rosenthal and Young, 1990; Froot and Dabora, 1999; Scruggs, 2007; Jong et al., 2009; Baker et al., 2012). Recent evidence also comes from cross-listed stocks ((2), e.g. Gagnon and Karolyi, 2010; Seasholes and Liu, 2011) and dual-class shares ((3), e.g. Schultz and Shive, 2010). A well documented setting is further the relationship of the prices of closed-end fund shares and the per share market value of the assets held by the funds ((4), e.g. Lee et al., 1991; Pontiff, 1996; Chay and Trzcinka, 1999; Cherkes et al., 2009).

*Group 2: momentum* Many studies have argued that the traditional momentum effect ((5), Jegadeesh and Titman, 1993) 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., 2015), (19) change in mutual fund breadth of ownership (Chen et al., 2002), (20) continuous information arrival (Da et al., 2014a), 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 ones (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 ((26), (27), e.g. Brock et al., 1992).

*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. (2014b) 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; Jacobs and Weber, 2015) 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, 2014; and Hong and Sraer, 2014). We follow Frazzini and Pedersen (2014) 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 ((60), e.g. Statman and Glushkov, 2009).

*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) shows 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 predict 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 (2014) 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 ((81), Eberhardt et al., 2004). Gu (2005) shows that changes in patent citations predict stock price behavior (82). Finally, innovative efficiency (Hirshleifer et al., 2013, (83)) and the r&d track record ((84), Cohen et al., 2013) 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 ((86), Richardson et al., 2005), relying on abnormal accruals ((87), Xie, 2001), or focusing on industries in which accruals are likely to be more important ((88), Chan and Jegadeesh, 2006). Thomas and Zhang (2002) argue that inventory changes scaled by total assets drive the accruals anomaly (89), whereas 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 ((94), e.g. Abarbanell and Bushee, 1998).

*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 ((95), e.g. Chordia and Shivakumar, 2006), or by the stock price ((96), e.g. Livnat and Mendenhall, 2006). 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 ((98), e.g. Chan et al., 1996). 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).

### *2.2. Abnormal returns and the role of sentiment*

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 information on the construction and on reference papers (including original sample periods) is provided in Tables A1 and A2 of the online appendix. All phenomena yield statistically significant abnormal returns, even though the point estimates are partly smaller than in the original studies. 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.

Throughout the paper, standard errors are based on the heteroskedasticity-consistent standard errors of White (1980) (as in e.g. Stambaugh et al., 2012), but using Newey and West (1987) standard errors yields very similar findings.

Table 1 also provides some first insights into the predictive power of investor sentiment for the time variation in anomaly returns. Our approach closely follows Stambaugh et al. (2012). We rely on the Baker and Wurgler (2006) market-level investor sentiment index orthogonalized with respect to six macroeconomic variables. We consider the whole time period for which the index is available (July 1965 to December 2010). As in Stambaugh et al. (2012), we rely on a dummy variable which takes on a value of 1 (0) if sentiment was above (below) its median value in the previous month.

We then implement a two-stage regression approach. As in the first columns of Table 1, we regress the monthly time-series of raw equally or value weighted 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*).

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

**Table 1**
Individual anomalies: Sample periods, abnormal returns, and the role of lagged investor sentiment.

| ID | Start | End | Anomaly name | 3 factor alpha (ew) | *T*-stat | 3 factor alpha (vw) | *T*-stat | Sentiment dummy (ew) | *T*-stat | Sentiment dummy (vw) | *T*-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *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 are standardized so that their mean is zero and their standard deviation is one (see Section 2.2) | | | | | | | |
| 2 | Jan-90 | Dec-08 | Cross-listed shares anomaly | | | | | | | | |
| 3 | Jan-87 | Dec-11 | Dual-class shares anomaly | | | | | | | | |
| 4 | Jul-65 | Feb-11 | Closed-end fund anomaly | | | | | | | | |
| *2. Momentum anomalies* | | | | | | | | | | | |
| 5 | Aug-26 | Dec-11 | Standard momentum | 1.014*** | (8.08) | 0.915*** | (6.64) | 0.440 | (1.22) | 0.127 | (0.33) |
| 6 | Sep-26 | Dec-11 | Age-enhanced momentum | 1.232*** | (9.52) | 1.305*** | (8.90) | 0.631 | (1.60) | 0.712 | (1.64) |
| 7 | Aug-26 | Dec-11 | Turnover-enhanced momentum | 1.179*** | (9.10) | 1.207*** | (8.38) | 0.139 | (0.36) | −0.178 | (-0.44) |
| 8 | Jan-72 | Dec-11 | Market-to-book ratio-enhanced momentum | 1.457*** | (6.75) | 1.301*** | (5.44) | 0.513 | (1.23) | 0.155 | (0.33) |
| 9 | Feb-86 | Dec-11 | Credit rating-enhanced momentum | 1.520*** | (4.22) | 1.292*** | (3.40) | 1.266* | (1.79) | 0.706 | (0.97) |
| 10 | Sep-26 | Dec-11 | Size-enhanced Momentum | 0.714*** | (4.61) | 0.768*** | (4.80) | 0.570* | (1.90) | 0.522* | (1.66) |
| 11 | Jan-80 | Dec-11 | (Residual) analyst coverage-enhanced momentum | 1.002*** | (4.46) | 0.790*** | (2.87) | 0.767* | (1.67) | 0.337 | (0.64) |
| 12 | Jan-80 | Dec-11 | Forecast dispersion-enhanced momentum | 1.071*** | (4.14) | 0.983*** | (3.51) | 0.447 | (0.87) | 0.524 | (0.96) |
| 13 | Mar-29 | Dec-11 | $R^2$-enhanced momentum | 0.926*** | (7.17) | 0.973*** | (6.01) | 0.312 | (0.92) | 0.200 | (0.49) |
| 14 | Aug-26 | Dec-11 | Return consistency-enhanced momentum | 1.520*** | (8.82) | 1.444*** | (8.23) | 0.468 | (1.08) | 0.193 | (0.43) |
| 15 | Jul-28 | Dec-11 | (Idiosyncratic) volatility-enhanced momentum | 1.034*** | (8.31) | 1.154*** | (7.37) | 0.447 | (1.23) | 0.569 | (1.39) |
| 16 | Aug-26 | Dec-11 | 52 week high-enhanced momentum | 1.442*** | (9.70) | 1.349*** | (8.45) | 0.762* | (1.72) | 0.445 | (0.96) |
| 17 | Aug-26 | Dec-11 | Formation period return-enhanced momentum | 1.334*** | (8.73) | 1.327*** | (7.87) | 0.559 | (1.25) | 0.176 | (0.37) |
| 18 | Oct-26 | Dec-11 | Signed volume-enhanced momentum | 0.732*** | (7.70) | 0.544*** | (5.33) | 0.404 | (1.36) | 0.023 | (0.07) |
| 19 | Apr-80 | Dec-11 | Change in breadth of ownership-enhanced momentum | 1.010*** | (4.03) | 0.924*** | (3.61) | 0.299 | (0.62) | 0.249 | (0.49) |
| 20 | Aug-26 | Dec-11 | Continuous information-enhanced momentum | 1.455*** | (9.10) | 1.304*** | (7.95) | 0.805* | (1.80) | 0.309 | (0.68) |
| 21 | Jan-27 | Dec-11 | Intermediate momentum | 0.714*** | (6.28) | 0.863*** | (6.23) | 0.029 | (0.09) | −0.459 | (−1.17) |
| *3. Technical analysis anomalies* | | | | | | | | | | | |
| 22 | Oct-26 | Dec-11 | 250 day moving average anomaly (deciles) | 0.602*** | (2.99) | 0.606*** | (2.75) | 0.686 | (1.18) | 0.369 | (0.58) |
| 23 | Oct-26 | Dec-11 | 200 day moving average anomaly (deciles) | 0.388** | (1.99) | 0.392* | (1.84) | 0.554 | (0.98) | 0.352 | (0.56) |
| 24 | Oct-26 | Dec-11 | 250 day moving average anomaly (dummy) | 0.357*** | (3.55) | 0.205** | (2.04) | 0.365 | (1.35) | 0.039 | (0.14) |
| 25 | Oct-26 | Dec-11 | 200 day moving average anomaly (dummy) | 0.238** | (2.42) | 0.113 | (1.18) | 0.368 | (1.40) | 0.181 | (0.69) |
| 26 | Feb-69 | Dec-11 | 250 day moving average anomaly (25% band) | 1.464*** | (5.23) | 1.299*** | (4.09) | 0.232 | (0.42) | 0.0161 | (0.03) |
| 27 | Feb-69 | Dec-11 | 200 day moving average anomaly (25% band) | 1.350*** | (4.52) | 1.274*** | (3.69) | 0.598 | (1.03) | 0.853 | (1.25) |
| *4. Short-term reversal anomalies* | | | | | | | | | | | |
| 28 | Jul-26 | Dec-11 | Short-term reversal | 1.116*** | (7.35) | 0.541*** | (3.08) | −0.110 | (−0.26) | 0.125 | (0.25) |
| 29 | Aug-28 | Dec-11 | Industry residual return-enhanced short-term reversal | 1.715*** | (15.08) | 1.282*** | (9.34) | −0.067 | (−0.25) | 0.088 | (0.27) |
| *5. Long-term reversal anomalies* | | | | | | | | | | | |
| 30 | Mar-31 | Dec-11 | Long-term reversal | 0.177* | (1.82) | 0.002 | (0.02) | −0.168 | (−0.73) | 0.208 | (0.71) |
| 31 | Mar-31 | Dec-11 | Idiosyncratic volatility enhanced-long term reversal | 0.499*** | (4.57) | 0.481*** | (3.40) | −0.160 | (−0.61) | 0.0682 | (0.20) |
| *6. Calendar-based anomalies* | | | | | | | | | | | |
| 32 | Jan-31 | Dec-11 | Seasonality momentum | 0.700*** | (7.47) | 0.705*** | (5.50) | −0.261 | (−1.20) | −0.358 | (−1.08) |
| 33 | Sep-72 | Dec-11 | Earnings announcement premium | 0.555*** | (6.54) | 0.663*** | (4.79) | 0.163 | (1.04) | 0.129 | (0.50) |
| 34 | Jan-65 | Dec-11 | Dividend month anomaly | 0.563*** | (7.33) | 0.438*** | (4.17) | 0.276* | (1.94) | 0.269 | (1.36) |
| *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) | −0.362 | (−0.73) | −0.296 | (−0.40) |
| 36 | Jan-77 | Dec-11 | Complicated firms anomaly | 1.252*** | (5.52) | 0.665*** | (2.77) | 0.296 | (0.70) | 0.216 | (0.46) |
| *8. Pairs trading anomaly* | | | | | | | | | | | |
| 37 | Jan-62 | Dec-08 | Pairs trading (6 months, conservative) | 0.716*** | (9.99) | 0.716*** | (9.99) | 0.204 | (1.41) | 0.204 | (1.41) |
| 38 | Jan-62 | Dec-08 | Pairs trading (6 months) | 0.874*** | (11.78) | 0.874*** | (11.78) | 0.199 | (1.34) | 0.199 | (1.34) |
| 39 | Jan-62 | Dec-08 | Pairs trading (1 month, conservative) | 1.227*** | (13.65) | 1.227*** | (13.65) | 0.096 | (0.53) | 0.096 | (0.53) |
| 40 | Jan-62 | Dec-08 | Pairs trading (1 month) | 1.542*** | (16.64) | 1.542*** | (16.64) | −0.308 | (−1.37) | −0.308 | (−1.37) |

**Table 1** (*continued*)

| ID | Start | End | Anomaly name | 3 factor alpha (ew) | *T*-stat | 3 factor alpha (vw) | *T*-stat | Sentiment dummy (ew) | *T*-stat | Sentiment dummy (vw) | *T*-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *9. Beta anomalies* | | | | | | | | | | | |
| 41 | Jul-27 | Dec-11 | Low beta anomaly (high frequency) | 0.890*** | (6.81) | 0.814*** | (5.26) | 1.010*** | (3.16) | 0.974** | (2.53) |
| 42 | Aug-29 | Dec-11 | Low beta anomaly (low frequency) | 0.685*** | (5.48) | 0.590*** | (4.13) | 0.937*** | (3.10) | 0.933*** | (2.61) |
| 43 | Dec-26 | Dec-11 | Low volatility anomaly (high frequency) | 0.984*** | (7.54) | 0.827*** | (4.86) | 1.105*** | (3.25) | 1.373*** | (3.38) |
| 44 | Dec-28 | Dec-11 | Low volatility anomaly (low frequency) | 0.819*** | (6.64) | 0.737*** | (4.81) | 1.046*** | (3.56) | 1.296*** | (3.58) |
| *10. Distress risk anomalies* | | | | | | | | | | | |
| 45 | Oct-72 | Dec-11 | Distress risk (Campbell et al., 2008) anomaly | 1.405*** | (7.15) | 1.347*** | (5.10) | 0.996** | (2.54) | 0.982* | (1.89) |
| 46 | Nov-71 | Dec-11 | Distress risk (Ohlson, 1980) anomaly | 0.787*** | (7.31) | 0.678*** | (5.19) | 0.556** | (2.55) | 0.576** | (2.18) |
| 47 | Jul-51 | Dec-11 | Distress risk (Shumway, 2001) anomaly | 1.067*** | (6.38) | 0.999*** | (6.67) | 0.420 | (1.09) | 0.558* | (1.65) |
| 48 | Jan-86 | Dec-11 | Bond credit rating anomaly | 0.646*** | (3.68) | 0.573** | (2.41) | 0.709** | (2.05) | 0.932** | (2.01) |
| 49 | Feb-86 | Dec-11 | Bond credit rating changes anomaly | 0.701*** | (2.82) | 0.985*** | (3.09) | −0.203 | (−0.40) | 0.317 | (0.50) |
| *11. Skewness anomalies* | | | | | | | | | | | |
| 50 | Jan-27 | Dec-11 | Lottery-type stocks anomaly | 0.463*** | (6.71) | 0.529*** | (6.52) | 0.801*** | (4.30) | 0.904*** | (4.05) |
| 51 | Jul-26 | Dec-11 | Maximum daily return anomaly | 1.318*** | (12.33) | 0.959*** | (6.63) | 1.044*** | (3.68) | 1.336*** | (3.76) |
| 52 | Aug-36 | Dec-11 | Expected skewness anomaly | 0.510*** | (4.40) | 0.474*** | (3.73) | 0.306 | (1.02) | 0.400 | (1.09) |
| *12. Anomalies related to differences of opinion* | | | | | | | | | | | |
| 53 | Feb-76 | Dec-11 | Analyst forecast dispersion anomaly | 1.338*** | (9.31) | 1.173*** | (5.98) | 0.794*** | (2.73) | 0.638* | (1.67) |
| 54 | Jul-26 | Dec-11 | Turnover anomaly | 0.741*** | (6.52) | 0.503*** | (3.86) | 0.666** | (2.31) | 0.768** | (2.18) |
| 55 | Jul-29 | Dec-11 | Idiosyncratic risk anomaly (low frequency 1) | 0.623*** | (5.66) | 0.488*** | (3.21) | 0.840*** | (3.10) | 0.895*** | (2.69) |
| 56 | Jul-64 | Dec-11 | Idiosyncratic risk anomaly (low frequency 2) | 0.990*** | (6.41) | 0.960*** | (5.45) | 0.967*** | (3.13) | 1.153*** | (3.28) |
| 57 | Jul-64 | Dec-11 | Idiosyncratic risk anomaly (high frequency) | 1.020*** | (7.54) | 0.998*** | (6.48) | 0.816*** | (3.00) | 0.800** | (2.45) |
| *13. Anomalies related to industry effects* | | | | | | | | | | | |
| 58 | Jul-62 | Dec-11 | Procyclical stocks anomaly | 0.312*** | (2.83) | 0.523*** | (3.03) | 0.339 | (1.45) | 0.537 | (1.52) |
| 59 | Jan-65 | Dec-11 | Sin stocks anomaly (industry-based measure) | 0.156 | (1.29) | 0.377** | (2.37) | 0.323 | (1.27) | 0.279 | (0.87) |
| 60 | Feb-92 | Dec-10 | Sin stocks anomaly (rating-based measure) | 0.197* | (1.81) | 0.0707 | (0.49) | −0.040 | (−0.22) | 0.119 | (0.43) |
| *14. Fundamental analysis anomalies* | | | | | | | | | | | |
| 61 | Jul-75 | Dec-11 | F-Score anomaly | 1.062*** | (4.73) | 1.071*** | (3.66) | 0.660 | (1.48) | 0.941* | (1.70) |
| 62 | Jul-75 | Dec-11 | Firms strength anomaly | 0.260** | (2.37) | 0.432*** | (2.63) | −0.070 | (−0.30) | 0.256 | (0.77) |
| 63 | Nov-75 | Dec-11 | Sales - inventories anomaly | 0.869*** | (9.24) | 0.805*** | (4.84) | 0.196 | (1.07) | 0.012 | (0.05) |
| 64 | May-72 | Dec-11 | Gross margin - sales anomaly | 0.497*** | (5.77) | 0.196 | (1.46) | −0.174 | (−1.06) | 0.196 | (0.76) |
| 65 | May-72 | Dec-11 | Administrative expenses - sales anomaly | 0.342*** | (3.32) | 0.082 | (0.47) | 0.111 | (0.56) | −0.276 | (−0.84) |
| 66 | May-74 | Dec-11 | Change in leverage anomaly | 0.373*** | (4.38) | 0.551*** | (3.68) | 0.413** | (2.40) | 0.180 | (0.61) |
| 67 | Feb-72 | Dec-11 | Change in gross profit margin anomaly | 0.445*** | (5.33) | 0.134 | (1.04) | −0.256 | (−1.62) | −0.150 | (−0.59) |
| 68 | Mar-72 | Dec-11 | Return on assets anomaly | 1.266*** | (7.04) | 0.993*** | (4.95) | 0.792** | (2.22) | 0.707* | (1.79) |
| 69 | Jul-51 | Dec-11 | Gross profitability anomaly | 0.631*** | (5.63) | 0.922*** | (7.43) | 0.503* | (1.85) | 0.388 | (1.34) |
| *15. Net stock and financing anomalies* | | | | | | | | | | | |
| 70 | Jul-31 | Dec-11 | Composite equity issuance anomaly | 0.646*** | (7.84) | 0.588*** | (5.93) | 0.253 | (1.38) | 0.505** | (2.03) |
| 71 | Jul-52 | Dec-11 | Annual issuance anomaly | 0.671*** | (9.29) | 0.574*** | (5.80) | 0.516*** | (3.16) | 0.842*** | (4.07) |
| 72 | Jul-63 | Dec-11 | Net external financing anomaly (1) | 0.734*** | (7.26) | 0.609*** | (4.51) | 0.774*** | (3.69) | 0.867*** | (3.05) |
| 73 | Jul-72 | Dec-11 | Net external financing anomaly (2) | 0.798*** | (7.90) | 0.650*** | (4.05) | 0.755*** | (3.79) | 0.746** | (2.36) |
| *16. Capital investment and growth anomalies* | | | | | | | | | | | |
| 74 | Jul-65 | Dec-11 | Net operating assets (change) anomaly | 0.571*** | (4.74) | 0.533*** | (3.13) | 0.288 | (1.18) | 0.166 | (0.49) |
| 75 | Jul-63 | Dec-11 | Net operating assets (levels) anomaly | 0.704*** | (5.59) | 0.495*** | (3.50) | 0.426* | (1.67) | 0.462* | (1.70) |
| 76 | Jul-52 | Dec-11 | Capital investments anomaly | 0.571*** | (6.68) | 0.342*** | (3.07) | 0.306 | (1.55) | 0.541** | (2.21) |
| 77 | Jul-53 | Dec-11 | Capital expenditures anomaly | 0.294*** | (3.63) | 0.327*** | (2.82) | −0.062 | (−0.34) | 0.260 | (1.05) |
| 78 | Jul-52 | Dec-11 | Asset growth anomaly | 0.356*** | (3.22) | 0.145 | (1.17) | 0.317 | (1.24) | 0.373 | (1.33) |
| 79 | Jul-74 | Dec-11 | Advertising anomaly | 0.345*** | (3.09) | 0.200 | (0.95) | −0.077 | (−0.34) | −0.075 | (−0.18) |

(*continued on next page*)

**Table 1** (*continued*)

| ID | Start | End | Anomaly name | 3 factor alpha (ew) | *T*-stat | 3 factor alpha (vw) | *T*-stat | Sentiment dummy (ew) | *T*-stat | Sentiment dummy (vw) | *T*-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *17. Anomalies related to innovation* | | | | | | | | | | | |
| 80 | Jul-60 | Dec-11 | R&D to market equity anomaly | 0.339** | (2.43) | 0.282** | (2.16) | −0.170 | (−0.59) | −0.127 | (−0.46) |
| 81 | Jul-75 | Dec-11 | R&D growth anomaly | 0.436*** | (2.89) | 0.411*** | (3.05) | 0.047 | (0.16) | −0.158 | (−0.57) |
| 82 | Jul-80 | Dec-11 | Patent citation anomaly | 0.377* | (1.94) | 0.327 | (1.35) | −0.165 | (−0.46) | −0.861* | (−1.87) |
| 83 | Jul-82 | Dec-11 | Innovative efficiency anomaly | 0.163** | (1.98) | 0.267** | (2.01) | 0.123 | (0.77) | −0.097 | (−0.37) |
| 84 | Jul-80 | Jun-10 | Innovation predictability anomaly | 0.648** | (2.04) | 0.824* | (1.77) | 0.072 | (0.11) | −1.104 | (−1.20) |
| *18. Accruals anomalies* | | | | | | | | | | | |
| 85 | Jul-65 | Dec-11 | Classical accruals anomaly | 0.514*** | (4.50) | 0.547*** | (3.48) | −0.206 | (−0.90) | −0.354 | (−1.14) |
| 86 | Jul-52 | Dec-11 | Accruals (broadly defined) anomaly | 0.365*** | (4.27) | 0.202 | (1.63) | 0.079 | (0.41) | 0.196 | (0.71) |
| 87 | Jul-72 | Dec-11 | Abnormal accruals anomaly | 0.535*** | (6.20) | 0.494*** | (2.97) | −0.073 | (−0.44) | 0.002 | (0.07) |
| 88 | Jul-71 | Dec-11 | Industry-enhanced accruals anomaly | 0.574*** | (3.46) | 0.395 | (1.50) | −0.006 | (−0.02) | −0.675 | (−1.30) |
| 89 | Jul-52 | Dec-11 | Inventory change anomaly | 0.514*** | (6.19) | 0.360*** | (3.15) | 0.167 | (0.87) | 0.285 | (1.12) |
| 90 | Jul-52 | Dec-11 | Inventory growth anomaly | 0.482*** | (5.64) | 0.262** | (2.24) | 0.349* | (1.80) | 0.683*** | (2.62) |
| *19. Dividend anomalies* | | | | | | | | | | | |
| 91 | Jul-26 | Dec-11 | Dividend initiation anomaly | 0.263*** | (3.23) | 0.126 | (1.27) | 0.200 | (1.01) | 0.186 | (0.69) |
| 92 | Feb-45 | Dec-11 | Dividend resumption anomaly | 0.332** | (2.30) | 0.078 | (0.46) | −0.554 | (−1.44) | −0.037 | (−0.08) |
| 93 | Jan-65 | Dec-11 | Change in dividend (absolute level) anomaly | 0.256** | (2.24) | 0.463** | (2.25) | 0.555** | (2.47) | 0.848** | (2.21) |
| 94 | May-72 | Dec-11 | Change in dividend yield anomaly | 0.493** | (2.43) | 0.494* | (1.74) | −0.673 | (−1.63) | −0.193 | (−0.35) |
| *20. Anomalies related to earnings surprises* | | | | | | | | | | | |
| 95 | Nov-73 | Dec-11 | PEAD (computation scheme 1) | 1.303*** | (10.19) | 0.803*** | (5.01) | 0.007 | (0.03) | 0.320 | (1.00) |
| 96 | Nov-72 | Dec-11 | PEAD (computation scheme 2) | 1.319*** | (9.41) | 1.005*** | (5.42) | 0.108 | (0.39) | 0.101 | (0.29) |
| 97 | Jul-84 | Dec-11 | PEAD (computation scheme 3) | 0.999*** | (8.33) | 0.686*** | (3.42) | −0.130 | (−0.54) | 0.003 | (0.01) |
| 98 | Nov-71 | Dec-11 | PEAD (computation scheme 4) | 1.246*** | (11.78) | 1.030*** | (6.10) | 0.024 | (0.14) | −0.047 | (−0.14) |
| 99 | Nov-84 | Dec-11 | Streaks in earnings surprises anomaly | 0.773*** | (7.62) | 0.707*** | (4.84) | 0.097 | (0.47) | 0.202 | (0.71) |
| 100 | Feb-72 | Dec-11 | Profit/loss anomaly | 1.204*** | (6.46) | 1.108*** | (5.12) | 0.844** | (2.26) | 0.509 | (1.16) |

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 2.2. *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. The last columns show results obtained from a regression of abnormal returns as implied by the Fama and French (1993) model on a dummy variable which is 1 (0) if the investor sentiment index of Baker and Wurgler (2006) was above (below) its median value in the previous month. The maximum sample period for this test is August 1965 to January 2011. *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 *,**,***, respectively.

Benchmark-adjusted abnormal monthly returns are then defined as the sum of $\widehat{\alpha}_i$ and the fitted value of $\epsilon_{i,t}$. Unless noted otherwise, we rely on these abnormal returns in the remainder of the paper. The resulting time series is then regressed on our lagged measure of above or below median investor sentiment.

For the average equally weighted anomaly, the benchmark-adjusted abnormal return is about 63 bp per month conditional on below median sentiment in the previous month. In contrast, the return is 95 bp (or 50% larger) following months with above median sentiment. The corresponding estimates for value weighted returns are 54 bp and 85 bp.

These findings uncover that the line a reasoning in Stambaugh et al. (2012) and Stambaugh et al. (2014) can largely be transferred to our much broader anomaly universe. For ten of the eleven anomalies considered in Stambaugh et al. (2012), we find a positive coefficient (with accruals being the exception) and almost always a comparable level of statistical significance. These insights are remarkable given that our screens filter out a large number of small and illiquid firms.[4] The online appendix shows that inferences are very similar if we rely on the lagged level of the sentiment index instead of on a dummy variable.

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 in the previous section, 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 for meta anomalies 2 to 20. 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.

However, there is large time-series variation for each anomaly. The difference between the 10th percentile and the 90th percentile of monthly abnormal returns is always several hundred bp. Table 2 uncovers that, in the overall picture, investor sentiment is important in this context. 17 meta anomalies (85%) load positively on a

[4] If we rely on the same firm universe as Stambaugh et al. (2012), also the accruals anomaly loads positively on lagged sentiment.

**Table 2**
Meta anomalies: Sample periods, abnormal returns, and the role of lagged investor sentiment.

| ID | Meta anomaly | N | Start | End | Raw return | T-stat | 3f alpha | t-stat | 3f p10 | 3f p90 | Sent. dummy | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Violations of the law of one price | 4 | Jan-87 | Feb-11 | Constituents are standardized to have zero mean and unit variance | | | | | | 0.292*** | (3.31) |
| 2 | Momentum anomalies | 17 | Aug-26 | Dec-11 | 0.871*** | (6.50) | 1.125*** | (9.57) | −2.78 | 5.04 | 0.452 | (1.28) |
| 3 | Technical analysis anomalies | 6 | Oct-26 | Dec-11 | 0.198 | (1.19) | 0.513*** | (3.43) | −4.39 | 5.36 | 0.465 | (1.06) |
| 4 | Short-term reversal anomalies | 2 | Aug-28 | Dec-11 | 1.573*** | (11.24) | 1.436*** | (11.04) | −2.401 | 5.29 | 0.021 | (0.11) |
| 5 | Long-term reversal anomalies | 2 | Mar-31 | Dec-11 | 0.614*** | (4.85) | 0.338*** | (3.57) | −2.84 | 3.85 | −0.164 | (−0.72) |
| 6 | Calendar-based anomalies | 3 | Jan-65 | Dec-11 | 0.548*** | (8.93) | 0.568*** | (10.26) | −0.88 | 2.07 | 0.046 | (0.42) |
| 7 | Lead-lag anomalies | 2 | Jan-81 | Dec-05 | 1.062*** | (5.01) | 1.158*** | (5.39) | −2.68 | 5.30 | −0.165 | (−0.41) |
| 8 | Pairs trading anomaly | 4 | Jan-62 | Dec-08 | 1.152*** | (15.58) | 1.114*** | (14.30) | −0.78 | 3.23 | 0.088 | (0.56) |
| 9 | Beta anomalies | 4 | Jul-27 | Dec-11 | 0.167 | (0.73) | 0.859*** | (7.57) | −2.95 | 4.68 | 1.025*** | (3.65) |
| 10 | Distress risk anomalies | 5 | Nov-71 | Dec-11 | 0.584*** | (3.65) | 0.988*** | (8.21) | −1.75 | 3.72 | 0.548** | (2.29) |
| 11 | Skewness anomalies | 3 | Jan-27 | Dec-11 | 0.355** | (2.40) | 0.796*** | (10.30) | −1.68 | 3.12 | 0.717*** | (3.48) |
| 12 | Differences of opinion | 5 | Jul-29 | Dec-11 | 0.378** | (2.14) | 0.834*** | (8.94) | −2.71 | 4.17 | 0.839*** | (3.61) |
| 13 | Industry effects | 3 | Jan-65 | Dec-11 | 0.233*** | (2.64) | 0.248*** | (3.15) | −2.12 | 2.55 | 0.285* | (1.72) |
| 14 | Fundamental analysis anomalies | 9 | Feb-72 | Dec-11 | 0.575*** | (9.28) | 0.633*** | (10.78) | −0.96 | 2.20 | 0.256** | (2.20) |
| 15 | Net stock and financing | 4 | Jul-52 | Dec-11 | 0.649*** | (6.36) | 0.672*** | (10.69) | −1.30 | 2.70 | 0.543*** | (3.61) |
| 16 | Capital investment and growth | 6 | Jul-52 | Dec-11 | 0.475*** | (6.60) | 0.455*** | (6.87) | −1.51 | 2.50 | 0.206 | (1.32) |
| 17 | Anomalies related to innovation | 5 | Jul-75 | Dec-11 | 0.281* | (1.65) | 0.337*** | (2.92) | −2.58 | 3.10 | 0.060 | (0.27) |
| 18 | Accruals anomalies | 6 | Jul-52 | Dec-11 | 0.498*** | (7.14) | 0.474*** | (6.90) | −1.40 | 2.61 | 0.082 | (0.52) |
| 19 | Dividend anomalies | 4 | Feb-45 | Dec-11 | 0.283*** | (4.35) | 0.309*** | (4.59) | −1.72 | 2.50 | −0.122 | (−0.76) |
| 20 | Earnings surprises | 6 | Feb-72 | Dec-11 | 1.095*** | (11.23) | 1.218*** | (13.18) | −1.19 | 3.67 | 0.127 | (0.68) |

This table provides an overview over 20 aggregate return phenomena. Meta anomaly returns correspond to the equally weighted average of the *N* constituent individual anomaly returns (see Table 1). *Start* and *End* characterize the sample period for each meta anomaly which is determined by the joint availability of at least two entering individual anomalies. The *Raw return* (*3f alpha*) displays the equally weighted average monthly return (the intercept obtained from a Fama and French, 1993 model) of the long-short meta anomaly, expressed in %. The table also displays the 10th and the 90th percentile of the resulting distribution of abnormal returns (*3f p10*, *3f p90*). The last columns show results obtained from a regression of abnormal returns (orthogonalized with respect to a Fama and French, 1993 model) on a dummy variable which is 1 (0) if the Baker and Wurgler (2006) sentiment index was above (below) its median value in the previous month. The maximum sample period for this test is August 1965 to December 2011. *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 *,**,***, respectively.

lagged sentiment dummy, and these findings are statistically significant for 8 (5) anomalies at the 10% (1%) level. In line with the economic intuition, the impact of sentiment appears to be weakest among anomalies often attributed to investor underreaction (lead-lag effects among economically linked firms, pairs trading, anomalies related to innovation, dividend anomalies, and earnings surprises) and strongest among phenomena often attributed to investor overreaction (such as beta, differences of opinion, net stock and financing anomalies).

In the following, we concentrate on the question whether a similar role can be established for time variation in limits to arbitrage.

### 2.3. Proxies for market-level arbitrage constraints

Our goal is to identify useful measures for the willingness and ability of speculators 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.

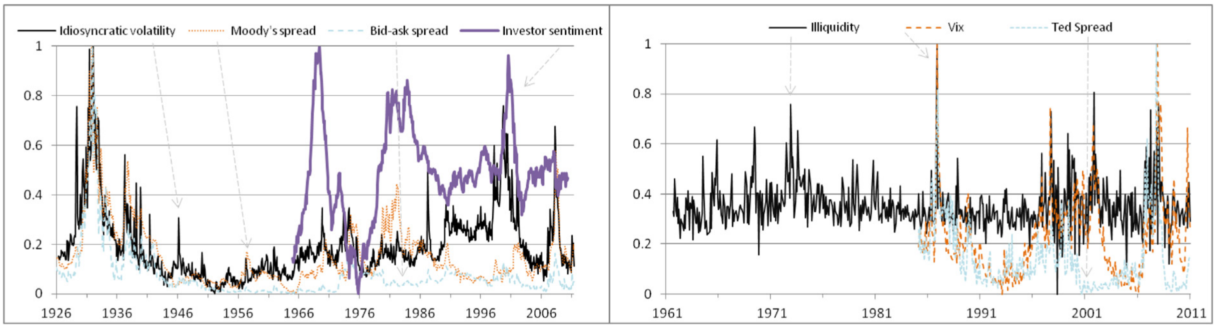
*Overall expected volatility and uncertainty* We consider the Chicago Board Options Exchange Market Volatility Index (Vix), which reflects the implied volatility of S&P index options. Theoretical work suggests that higher expected volatility leads to tighter funding constraints of speculators (e.g. Gromb 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 1920ies. 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., 2013; 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 1920ies 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

The following graphs illustrate the behavior of the six baseline proxies for limits to arbitrage, as characterized in section 2.3. In addition, the investor sentiment proxy of Baker and Wurgler (2006) is displayed. The graphs show the time-series of the level of each 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 and high investor sentiment, respectively.




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

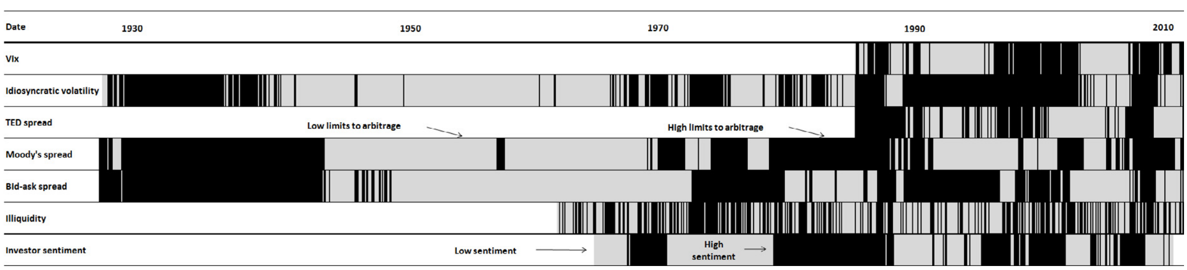



**Fig. 1.** Time-series characteristics of popular proxies for market-wide limits to arbitrage or investor sentiment.

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 Fig. 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 lower half of the figure shows the time-series evolution of dummy variables, which take on a value of 1 (0) if a given arbitrage proxy was above (below) its median value in the previous month. This approach is equivalent to our approach for the investor sentiment proxy whose time-series behavior is also displayed in Fig. 1.

The proxies appear to share a common component. For instance, during the recent financial crisis, they all indicate severe constraints. There are similar clusterings around the stock market crash of 1929 and the subsequent great depression during the 1930ies, around the stock market crash of 1987, and around the collapse of Long Term Capital Management and the "dot.com period" towards the end of the 1990ies. This eyeball test lines up fairly well with intuitive estimates and anecdotal evidence of when arbitrage might have be limited (see e.g. Ben-David et al., 2012; Lamont and Thaler, 2003; Mitchell et al., 2007).

Nevertheless, the average correlation between the proxies is only .42 (.21) in the upper (lower) half of the figure. Thus, each variable also seems to capture different aspects of limits to arbitrage, which justifies the separate consideration of all proxies in the following tests. Notably, the average correlation of the investor sentiment proxy with the proxies for arbitrage constraints is only .1 (.05) in the upper (lower) half of the graph, and not a single correlation coefficient is higher than .25 (with the Vix dummy, see Table A3 in the online appendix for all pairwise correlations). Collectively, proxies for sentiment and limits to arbitrage tend to make quite different predictions about the time variation in anomaly returns.

### *2.4. The impact of market-level arbitrage constraints on anomaly returns*

We start by mirroring our analysis on the impact of investor sentiment (see Table 2). That is, we compute benchmark-adjusted returns (relative to a Fama and French, 1993 model) for each meta anomaly, and then regress the resulting time-series univariately on each of the six proxies for limits to arbitrage. The latter are expressed as a dummy variable which is 1 (0) if the previous month indicates higher (lower) than median limits to arbitrage.

We run 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. Unless noted otherwise and to conserve space, we report equally weighted returns in the following. This is also justified by the small differences in equally weighted and value weighted returns (see Table 1). Tables 3 and 4 show the main results.

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 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

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

| Meta anomaly | Vix | | | | Idiosyncratic Volatility | | | | Ted Spread | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | High | | Baseline | | High | | Baseline | | High | | Baseline | |
| Violations of the law of one price | 0.279*** | (5.06) | −0.295*** | (−8.56) | 0.318*** | (4.96) | −0.396*** | (−7.12) | 0.107* | (1.86) | −0.206*** | (−5.38) |
| Momentum anomalies | −0.370 | (−0.71) | 1.247*** | (6.15) | −0.113 | (−0.46) | 1.170*** | (9.92) | 0.083 | (0.16) | 1.021*** | (3.46) |
| Technical analysis anomalies | −1.026 | (−1.61) | 1.577*** | (5.48) | −0.598** | (−1.99) | 0.806*** | (5.68) | 0.117 | (0.18) | 1.008** | (2.51) |
| Short-term reversal anomalies | 1.017** | (2.02) | −0.089 | (−0.47) | 0.997*** | (3.73) | 0.940*** | (8.83) | 0.426 | (0.84) | 0.206 | (0.63) |
| Long-term reversal anomalies | −0.191 | (−0.61) | 0.402** | (2.32) | 0.116 | (0.58) | 0.281*** | (2.73) | 0.033 | (0.11) | 0.291 | (1.34) |
| Calendar-based anomalies | 0.288** | (2.07) | 0.491*** | (5.95) | 0.144 | (1.42) | 0.477*** | (6.79) | 0.047 | (0.34) | 0.611*** | (6.14) |
| Lead-lag anomalies | −0.298 | (−0.62) | 1.203*** | (5.00) | 0.097 | (0.22) | 1.083*** | (3.11) | −0.321 | (−0.68) | 1.224*** | (4.05) |
| Pairs trading anomaly | 0.463** | (2.50) | 0.345*** | (3.37) | 0.249* | (1.76) | 0.963*** | (10.11) | 0.268 | (1.50) | 0.421*** | (4.14) |
| Beta anomalies | −0.168 | (−0.42) | 0.738*** | (3.87) | −0.017 | (−0.07) | 0.867*** | (7.83) | −0.693* | (−1.77) | 0.997*** | (3.75) |
| Distress risk anomalies | 0.038 | (0.12) | 0.951*** | (6.49) | 0.118 | (0.55) | 0.911*** | (6.44) | 0.236 | (0.76) | 0.853*** | (4.69) |
| Skewness anomalies | 0.389 | (1.31) | 0.569*** | (4.20) | 0.345** | (2.20) | 0.624*** | (9.31) | 0.055 | (0.18) | 0.736*** | (4.16) |
| Differences of opinion | 0.079 | (0.26) | 0.889*** | (5.94) | 0.286 | (1.45) | 0.685*** | (6.35) | 0.042 | (0.14) | 0.908*** | (4.60) |
| Industry effects | 0.134 | (0.68) | 0.148 | (1.24) | −0.036 | (−0.22) | 0.271** | (2.28) | 0.098 | (0.49) | 0.166 | (1.29) |
| Fundamental analysis anomalies | 0.081 | (0.55) | 0.536*** | (6.09) | 0.08 | (0.72) | 0.581*** | (7.44) | −0.013 | (−0.09) | 0.582*** | (5.63) |
| Net stock and financing | 0.536** | (2.46) | 0.581*** | (4.58) | 0.362*** | (2.94) | 0.491*** | (7.09) | 0.156 | (0.71) | 0.770*** | (4.99) |
| Capital investment and growth | 0.256 | (1.17) | 0.414*** | (3.40) | 0.315** | (2.47) | 0.296*** | (4.14) | 0.256 | (1.17) | 0.414*** | (2.86) |
| Anomalies related to innovation | 0.460* | (1.73) | 0.202 | (1.40) | 0.458** | (2.14) | 0.041 | (0.27) | 0.202 | (0.76) | 0.332* | (1.74) |
| Accruals anomalies | 0.083 | (0.38) | 0.405*** | (3.58) | 0.268** | (2.05) | 0.339*** | (4.38) | 0.226 | (1.04) | 0.334** | (2.32) |
| Dividend anomalies | 0.009 | (0.04) | 0.318*** | (2.94) | 0.103 | (0.78) | 0.262*** | (3.50) | −0.260 | (−1.24) | 0.452*** | (3.32) |
| Earnings surprises | −0.05 | (−0.23) | 1.069*** | (8.27) | 0.276 | (1.58) | 1.037*** | (8.51) | 0.317 | (1.47) | 0.888*** | (6.40) |
| Composite: equally weighted | 0.083 | (0.63) | 0.623*** | (10.67) | 0.222*** | (2.62) | 0.637*** | (16.93) | 0.065 | (0.50) | 0.632*** | (7.32) |
| Composite: pooled | 0.093 | (0.71) | 0.628*** | (6.80) | 0.177** | (2.42) | 0.639*** | (6.64) | 0.071 | (0.54) | 0.640*** | (5.08) |

The table displays coefficients from univariate predictive regressions of anomaly returns (orthogonalized with respect to a Fama and French, 1993 model) 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 Fig. 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 *,**,***, respectively.

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

| Meta anomaly | Moody's Credit Spread | | | | Bid-Ask Spread | | | | Liquidity | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | High | | Baseline | | High | | Baseline | | High | | Baseline | |
| Violations of the law of one price | −0.035 | (−0.60) | −0.137*** | (−4.07) | 0.365*** | (6.79) | −0.378*** | (−9.42) | 0.136** | (2.34) | −0.216*** | (−5.99) |
| Momentum anomalies | −0.348 | (−1.43) | 1.299*** | (8.48) | −0.144 | (−0.59) | 1.197*** | (9.94) | −0.487 | (−1.48) | 1.422*** | (6.63) |
| Technical analysis anomalies | −1.089*** | (−3.64) | 1.056*** | (5.26) | −0.652** | (−2.17) | 0.838*** | (5.57) | −0.300 | (−0.73) | 1.030*** | (3.95) |
| Short-term reversal anomalies | 1.038*** | (3.89) | 0.921*** | (5.76) | 1.136*** | (4.20) | 0.881*** | (7.89) | 0.447 | (1.41) | 0.667*** | (3.52) |
| Long-term reversal anomalies | −0.112 | (−0.56) | 0.391*** | (3.53) | 0.044 | (0.22) | 0.317*** | (2.95) | 0.148 | (0.69) | 0.357** | (2.56) |
| Calendar-based anomalies | −0.004 | (−0.04) | 0.570*** | (7.00) | 0.327*** | (3.13) | 0.407*** | (5.86) | −0.141 | (−1.34) | 0.639*** | (9.65) |
| Lead-lag anomalies | −0.002 | (−0.01) | 1.159*** | (3.49) | 0.398 | (0.97) | 0.936*** | (3.51) | 0.378 | (0.87) | 0.993*** | (4.00) |
| Pairs trading anomaly | 0.307** | (2.10) | 0.968*** | (9.14) | 0.121 | (0.82) | 1.057*** | (10.51) | 0.513*** | (3.50) | 0.856*** | (8.48) |
| Beta anomalies | 0.16 | (0.68) | 0.779*** | (5.43) | −0.315 | (−1.34) | 1.014*** | (8.41) | −0.540** | (−2.03) | 0.842*** | (5.43) |
| Distress risk anomalies | −0.287 | (−1.18) | 1.156*** | (5.93) | −0.003 | (−0.01) | 0.990*** | (6.86) | −0.098 | (−0.42) | 1.038*** | (6.94) |
| Skewness anomalies | 0.236 | (1.50) | 0.679*** | (6.63) | 0.105 | (0.67) | 0.744*** | (10.26) | −0.181 | (−0.93) | 0.790*** | (6.56) |
| Differences of opinion | 0.223 | (1.13) | 0.722*** | (5.94) | −0.097 | (−0.49) | 0.881*** | (8.08) | −0.451** | (−2.04) | 1.074*** | (7.78) |
| Industry effects | −0.01 | (−0.06) | 0.254** | (2.29) | 0.046 | (0.29) | 0.225** | (2.20) | −0.026 | (−0.16) | 0.262** | (2.47) |
| Fundamental analysis anomalies | 0.076 | (0.64) | 0.589*** | (6.30) | 0.036 | (0.32) | 0.612*** | (7.94) | −0.071 | (−0.61) | 0.669*** | (9.53) |
| Net stock and financing | 0.218* | (1.72) | 0.579*** | (7.36) | 0.179 | (1.32) | 0.603*** | (8.81) | −0.107 | (−0.75) | 0.771*** | (8.08) |
| Capital investment and growth | 0.084 | (0.64) | 0.419*** | (5.10) | 0.166 | (1.20) | 0.390*** | (5.26) | 0.075 | (0.51) | 0.444*** | (4.48) |
| Anomalies related to innovation | −0.515** | (−2.27) | 0.642*** | (3.61) | 0.445** | (2.04) | 0.082 | (0.54) | 0.304 | (1.35) | 0.193 | (1.42) |
| Accruals anomalies | 0.09 | (0.68) | 0.435*** | (4.88) | −0.005 | (−0.04) | 0.476*** | (6.26) | 0.093 | (0.62) | 0.447*** | (4.19) |
| Dividend anomalies | 0.175 | (1.31) | 0.242*** | (3.04) | 0.057 | (0.40) | 0.288*** | (3.87) | 0.259* | (1.68) | 0.241** | (2.55) |
| Earnings surprises | −0.102 | (−0.55) | 1.278*** | (8.99) | 0.225 | (1.26) | 1.088*** | (9.08) | 0.009 | (0.05) | 1.214*** | (10.53) |
| Composite: equally weighted | 0.085 | (1.00) | 0.715*** | (16.68) | 0.163* | (1.92) | 0.676*** | (18.27) | −0.026 | (−0.31) | 0.719*** | (13.66) |
| Composite: pooled | 0.024 | (0.31) | 0.727*** | (6.33) | 0.079 | (1.04) | 0.700*** | (7.14) | −0.026 | (−0.30) | 0.738*** | (6.56) |

The table displays coefficients from univariate predictive regressions of anomaly returns (orthogonalized with respect to a Fama and French, 1993 model) 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 Fig. 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 *,**,***, respectively.

volatility is associated with a 2/3 standard deviation increase. Second, some other anomalies related to short-term reversal, pairs trading, net stock and financing, and innovation appear to be related to market-wide dynamics in arbitrage conditions, even though this assessment is not stable across proxies.

It is difficult to identify a common economic or psychological factor behind these anomalies. Violations of the law of on one price are among the most undisputed mispricings. A strong link to limits to arbitrage is therefore expected and in line with previous work. Short-term reversal and net stock anomalies are often attributed to investor overreaction, whereas pairs trading and innovation anomalies tend to be regarded as underreaction anomalies.

Third, among the six measures for market-wide arbitrage constraints, aggregate idiosyncratic volatility has the strongest impact in the overall picture. 75% of the meta anomalies load positively on this factor, and 40% do so in a statistically significant way. As a consequence, the composite anomaly is about a 20 bp more pronounced in months following high idiosyncratic volatility than it is following periods of low idiosyncratic volatility. This finding is statically significant, and also substantial in relative terms: the difference of 20 bp corresponds to about 1/3 of the average anomaly return following times of lower than median idiosyncratic risk.

However, fourth, there appears to be a weak link between the dynamics of the other arbitrage constraints and the magnitude of the remaining meta anomalies. Anomaly returns only sporadically load on arbitrage risk factors in a statistically significant matter in the direction suggested by theory. For instance, anomalies related to earnings surprises appear to yield monthly returns of 89 to 128 bp if one explicitly conditions on environments characterized by low limits to arbitrage. Similar insights are gained from attempts to measure the overall impact of limits to arbitrage on anomaly returns by focusing on the composite meta-anomaly return or the pooled meta anomaly returns.

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 proxies lagged by one month. Table 5 displays the main results.

Our findings for anomalies related to the law of one price, short-term reversal, and pairs trading remain unchanged. For the other anomalies, however, the impact of the proxies tends to become (even) weaker. Most notably, idiosyncratic volatility loses its statistical and economic significance for many anomalies. Using 1960 (or other dates) as starting point in order to exclude the impact of the 1930ies in which available proxies indicate very large limits to arbitrage does not change any insights.

### 2.5. Robustness checks

The overall weak role of popular proxies for arbitrage constraints does not materially change after a number of sensitivity checks which we briefly describe in the following. For means of brevity, results are only selectively tabulated or reported in the online appendix.

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

*Value-weighted anomaly returns* In sum, findings become slightly weaker.

**Table 5**
The impact of proxies for lagged market-level arbitrage constraints (continuous measure) on meta anomaly returns.

| | Vix | | Idiosyncratic Volatility | | Ted Spread | | Moody's Credit Spread | | Bid-Ask Spread | | Liquidity | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Violations of the law of one price | 0.0249*** | (6.11) | 44.78*** | (9.67) | 0.166* | (1.81) | 0.0112 | (1.36) | 79.73*** | (7.65) | 0.658 | (1.38) |
| Momentum anomalies | −0.0770** | (−2.09) | −30.89 | (−0.86) | −0.223 | (−0.36) | −0.0184 | (−0.51) | −32.07 | (−1.50) | −3.121 | (−0.78) |
| Technical analysis anomalies | −0.109*** | (−2.83) | −123.2*** | (−2.89) | −0.0394 | (−0.06) | −0.0302 | (−0.66) | −92.62*** | (−5.49) | −1.597 | (−0.36) |
| Short-term reversal anomalies | 0.0665* | (1.93) | 138.7*** | (3.15) | 0.459 | (0.67) | 0.103** | (2.55) | 86.72*** | (3.08) | 3.815 | (1.20) |
| Long-term reversal anomalies | −0.0246 | (−1.20) | −16.35 | (−0.61) | 0.0854 | (0.23) | 0.0117 | (0.39) | −17.22 | (−0.94) | −1.827 | (−0.97) |
| Calendar-based anomalies | 0.0195** | (2.00) | 31.82** | (2.03) | 0.121 | (0.53) | 0.0202 | (1.27) | 36.11** | (2.11) | −0.912 | (−0.99) |
| Lead-lag anomalies | −0.0272 | (−0.80) | −24.94 | (−0.38) | −0.439 | (−0.62) | −0.0562 | (−0.94) | 14.47 | (0.14) | 5.922 | (1.47) |
| Pairs trading anomaly | 0.0384*** | (2.81) | 13.05 | (0.75) | 0.381 | (1.54) | 0.0484** | (2.19) | 60.17** | (2.31) | 4.799*** | (3.80) |
| Beta anomalies | −0.0306 | (−1.13) | −0.907 | (−0.03) | −1.063** | (−2.01) | −0.0253 | (−0.72) | 4.019 | (0.21) | −3.239 | (−1.12) |
| Distress risk anomalies | −0.0218 | (−1.06) | 24.71 | (0.59) | 0.0093 | (0.03) | −0.0256 | (−0.75) | −15.76 | (−0.43) | 0.406 | (0.17) |
| Skewness anomalies | 0.0160 | (0.79) | 50.86** | (2.16) | −0.287 | (−0.57) | −0.0064 | (−0.27) | 20.48* | (1.79) | 1.703 | (0.70) |
| Differences of opinion | 0.0007 | (0.03) | 0.894 | (0.03) | −0.114 | (−0.27) | −0.0065 | (−0.21) | 2.707 | (0.13) | −2.102 | (−0.86) |
| Industry effects | 0.0113 | (0.78) | 37.90* | (1.85) | 0.0443 | (0.20) | 0.0123 | (0.52) | 28.62 | (0.96) | 0.319 | (0.23) |
| Fundamental analysis anomalies | 0.0034 | (0.39) | 8.418 | (0.51) | −0.0085 | (−0.05) | −0.0120 | (−0.70) | 17.17 | (0.87) | 0.558 | (0.61) |
| Net stock and financing | 0.0229** | (2.04) | 41.65** | (2.49) | −0.0310 | (−0.12) | 0.0094 | (0.57) | 29.01* | (1.81) | 0.0990 | (0.08) |
| Capital investment and growth | 0.0023 | (0.17) | 24.97 | (1.19) | 0.0598 | (0.25) | −0.0018 | (−0.09) | 16.11 | (0.91) | −0.0755 | (−0.07) |
| Anomalies related to innovation | 0.0300* | (1.80) | 95.08*** | (3.27) | 0.0144 | (0.06) | −0.0440 | (−1.25) | 47.50 | (1.26) | 3.725* | (1.92) |
| Accruals anomalies | −0.0050 | (−0.44) | 2.334 | (0.10) | 0.0642 | (0.29) | −0.0124 | (−0.61) | −13.41 | (−0.68) | 0.0236 | (0.02) |
| Dividend anomalies | 0.0081 | (0.52) | 8.032 | (0.41) | −0.247 | (−0.94) | 0.0054 | (0.27) | 37.82* | (1.78) | 3.776** | (2.14) |
| Earnings surprises | −0.0161 | (−1.10) | 14.16 | (0.60) | −0.0476 | (−0.18) | −0.0070 | (−0.26) | 46.34 | (1.36) | 2.834 | (1.42) |
| Composite: equally weighted | −0.0058 | (−0.58) | 2.015 | (0.11) | −0.0671 | (−0.47) | 0.0032 | (0.25) | −7.035 | (−0.55) | 0.604 | (0.68) |
| Composite: pooled | −0.0048 | (−0.52) | 10.89 | (0.91) | −0.0599 | (−0.43) | 0.0011 | (0.10) | −1.684 | (−0.18) | 0.577 | (0.63) |

The table displays coefficients from univariate predictive regressions of anomaly returns (orthogonalized with respect to a Fama and French, 1993 model) in month $t$ on a continuous measure of arbitrage constraints measured in month $t-1$. 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 *,**,***, respectively.

*Return measurement* If we use raw long-short returns, the impact of the proxies for arbitrage constraints is mixed.[5] If we orthogonalize anomaly returns only with respect to the market factor, results are similar to our baseline findings for the three factor model.

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

*Timing and lags* It might be the case that the impact of limits to arbitrage matters at low frequencies only. However, most proxies exhibit substantial autocorrelation (see Fig. 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. We have also measured the arbitrage proxies contemporaneously (see e.g. Tables A12 and A13 in the online appendix.) Our findings remain similar.

*Changes vs. levels* We decompose the contemporaneous level of a given arbitrage proxy into its value in month $t-1$ and its change from $t-1$ to t. Alternatively, we only rely on the change of the proxies, and either on the level or the change of anomaly returns.

*Time trends and publication effects* Even though there does not seem to be consensus on this issue (see the introduction), 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. We also include a dummy variable which characterizes the (average) post-publication period for meta-anomalies (see McLean and Pontiff, 2015 and the online appendix). The qualitative nature of our insights does not change.

*Other proxies for market-level arbitrage constraints* We have relied on the Amihud (2002) illiquidity ratio, average changes in short interest, and the market-wide illiquidity measure proposed in Hu et al. (2013). As a conceptually different proxy, we have also used meta anomaly 1, i.e. the level of deviations of the law of one price, as a proxy for limits to arbitrage (see Table A9 in the online appendix). Finally, we have also experimented with a number of proxies deemed to measure the role of institutions likely to act as arbitrageurs and with the role of interest-related variables.[6] In all cases, inferences are similar to the ones obtained for the baseline analysis.

*Further controls* Inspired by Baker and Wurgler (2006) and Stambaugh et al. (2012), we have added macroeconomic variables to the regression (e.g. growth in industrial production, growth in durable consumption, growth in nondurable consumption, growth in services consumption, growth in employment, NBER recession dummy, consumption-wealth ratio, see Table A9 in the online appendix for some of the results).

*Combined proxies* As one might be concerned that individual proxies are noisy, we have experimented with different approaches

[5] More precisely, the Vix and the illiquidity measure tend to become more significant if we use their raw level in the previous month. They remain insignificant if we rely on the dummy approach distinguishing between high and low periods of limits to arbitrage. The impact of idiosyncratic volatility becomes weaker than in the baseline analysis. The role of the Baker and Wurgler (2006) index becomes even slightly stronger. These results notwithstanding, one of course might have doubts that raw anomaly returns unadjusted for even the market factor can be regarded as truly "anomalous".

[6] 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 and the term spread.

**Table 6**
The impact of aggregate proxies for lagged market-level arbitrage constraints on meta anomaly returns.

| Measure of limits to arbitrage | Panel A Principal component based on 3 arbitrage proxies | | Panel B Principal component based on 6 arbitrage proxies | | Panel C Aggregate measure based on 3 arbitrage proxies | | Panel D Aggregate measure based on 6 arbitrage proxies | | Panel E Financial crisis dummy | |
|---|---|---|---|---|---|---|---|---|---|---|
| Sample period | 1926–2011 | | 1986–2011 | | 1926–2011 | | 1986–2011 | | 2005–2011 | |
| Violations of the law of one price | 0.614*** | (12.45) | 0.244*** | (7.82) | 0.572*** | (12.52) | 0.247*** | (8.18) | 0.283* | (1.79) |
| Momentum anomalies | −0.404 | (−1.61) | −0.743** | (−2.12) | −0.396 | (−1.59) | −0.745** | (−2.10) | −1.971** | (−2.07) |
| Technical analysis anomalies | −1.163*** | (−5.21) | −0.789** | (−2.04) | −1.149*** | (−5.09) | −0.794** | (−2.03) | −0.604 | (−0.54) |
| Short-term reversal anomalies | 1.141*** | (3.45) | 0.457 | (1.33) | 1.137*** | (3.49) | 0.462 | (1.33) | −0.999 | (−1.30) |
| Long-term reversal anomalies | −0.187 | (−0.86) | −0.214 | (−1.14) | −0.181 | (−0.84) | −0.208 | (−1.10) | −0.735 | (−1.16) |
| Calendar-based anomalies | 0.197 | (1.21) | 0.133 | (1.35) | 0.191 | (1.24) | 0.133 | (1.35) | −0.176 | (−0.66) |
| Lead-lag anomalies | 0.155 | (0.16) | −0.049 | (−0.12) | 0.096 | (0.11) | −0.057 | (−0.13) | | |
| Pairs trading anomaly | 0.610*** | (3.00) | 0.425*** | (2.89) | 0.549*** | (2.86) | 0.431*** | (2.90) | | |
| Beta anomalies | −0.018 | (−0.08) | −0.286 | (−1.04) | 0.077 | (0.34) | −0.284 | (−1.03) | −1.602*** | (−2.69) |
| Distress risk anomalies | 0.093 | (0.21) | −0.079 | (−0.39) | 0.112 | (0.26) | −0.077 | (−0.37) | −0.459 | (−0.78) |
| Skewness anomalies | 0.329** | (2.40) | 0.296 | (1.23) | 0.335** | (2.46) | 0.300 | (1.24) | −0.507 | (−1.10) |
| Differences of opinion | 0.085 | (0.35) | 0.050 | (0.25) | 0.086 | (0.36) | 0.050 | (0.25) | −0.645 | (−1.42) |
| Industry effects | 0.466* | (1.86) | 0.179 | (1.35) | 0.448* | (1.91) | 0.185 | (1.39) | 0.253 | (0.64) |
| Fundamental analysis anomalies | 0.232 | (1.31) | 0.044 | (0.57) | 0.211 | (1.26) | 0.045 | (0.58) | −0.129 | (−0.49) |
| Net stock and financing | 0.474*** | (3.11) | 0.198* | (1.79) | 0.457*** | (3.12) | 0.200* | (1.80) | −0.466 | (−1.12) |
| Capital investment and growth | 0.174 | (0.96) | −0.013 | (−0.10) | 0.172 | (0.98) | −0.014 | (−0.10) | −0.351 | (−0.74) |
| Anomalies related to innovation | 0.578* | (1.91) | 0.321** | (2.26) | 0.593** | (2.06) | 0.323** | (2.26) | 0.119 | (0.28) |
| Accruals anomalies | −0.043 | (−0.24) | −0.114 | (−1.20) | −0.033 | (−0.20) | −0.117 | (−1.21) | −0.486* | (−1.90) |
| Dividend anomalies | 0.290 | (1.58) | 0.146 | (0.98) | 0.260 | (1.49) | 0.145 | (0.97) | −0.267 | (−0.72) |
| Earnings surprises | 0.102 | (0.33) | −0.046 | (−0.32) | 0.088 | (0.30) | −0.042 | (−0.29) | −0.281 | (−0.66) |
| Composite: equally weighted | 0.033 | (0.28) | −0.016 | (−0.17) | 0.037 | (0.32) | −0.015 | (−0.16) | −0.517** | (−2.40) |
| Composite: value weighted | −0.049 | (−0.33) | −0.009 | (−0.09) | −0.043 | (−0.29) | −0.007 | (−0.06) | −0.147 | (−0.54) |

The table displays coefficients from univariate predictive regressions of anomaly returns (orthogonalized with respect to a Fama and French, 1993 model) in month $t$ on a continuous measure of arbitrage constraints. In panel A (B), arbitrage constraints are represented by the first principal component of average idiosyncratic volatility, the Moody's credit spread and average bid-ask spread (additionally the Vix, the Ted spread, and the aggregate liquidity level), all of which are measured in month $t-1$. In panel C (D), we use the same individual limits to arbitrage proxies as in panel A (B), standardize them to range from 0 to 1, and then define an aggregate monthly proxy as the sum of these values divided by the number of available individual proxies. In panels A to D, the resulting aggregate proxy is standardized to have zero mean and unit variance. In Panel E, we rely on a financial crisis dummy, which is one for the years 2007–2009 and zero for the years 2005/2006 and 2010/2011. *Composite: equally weighted* (*Composite: value weighted*) refers to the equally weighted (value weighted) average of all available meta anomalies excluding violations of the law of one price. *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 *,**,***, respectively.

to assess the overall impact of market-level arbitrage proxies. Table 6 shows some of the findings.

In panel A and B, we perform a principal component analysis of the three (six) baseline proxies which are available from 1926 (1986) onwards. The first principal component explains 80% (47%) of the sample variance of the 3 (6) proxies.

In panel C (D), we use the same individual limits to arbitrage proxies as in panel A (B), standardize them to range from 0 to 1, and then define an aggregate monthly proxy as the sum of these values divided by the number of available individual proxies in a given month.

Finally, in panel E, we rely on a financial crisis dummy, which is one for the years 2007–2009 and zero for the years 2005/2006 and 2010/2011. This test is motivated by the fact that all proxies signal high limits to arbitrage during the financial crisis. Table 6 reveals that the insights from our baseline analysis largely carry over, irrespective of how exactly we construct aggregate proxies for time-varying limits to arbitrage.

*Combined anomalies* In order to isolate the common component of abnormal return patterns, we perform a principal component analysis also for the meta anomalies. In the overall picture, and in contrast to investor sentiment, individual and composite proxies for time-varying limits to arbitrage cannot reliably explain or predict the common component of anomaly returns.

*Small firms* Our baseline analysis excludes firm months attributable to small and illiquid stocks. The impact of arbitrage constraints becomes only slightly stronger if we include or explicitly focus on these stocks when constructing anomaly returns. For instance, replicating Tables 3 and 4 with small stocks increases the average coefficient on the arbitrage constraints measures in the context of the equally weighted (value weighted) composite anomaly by about 3 (10) bp. The resulting estimates are still economically small and statistically typically not significant. The same applies to the combined proxies for arbitrage constraints, as outlined above.

### 2.6. Combined analysis of investor sentiment and limits to arbitrage

Table 7 shows our main insights from a joint test of the impact of aggregate investor sentiment and aggregate arbitrage constraints. In order to consider the maximum joint sample period (August 1965-January 2011), we measure lagged arbitrage constraints as in panel C and D of Table 6. A principal component analysis (with either a subset of the six proxies or a subset of the sample period) yields very similar findings. To ease interpretation, both the Baker and Wurgler (2006) investor sentiment proxy and the aggregate arbitrage constraints measure are standardized to have zero mean and unit variance.

Panel A focuses on arbitrage constraints only. Again, findings tend to be weak. A notable exception is again the deviation from the law of one price for which the $R^2$ is 27%. Panel B focuses on investor sentiment only. Findings are strong with positive coefficients for 85% of anomalies and $t$-statistics of about 3.50 to 4.00 for an equally weighted or value weighted composite anomaly. Results are also economically large: a one standard deviation change in investor sentiment predicts a 17 bp change in the equally weighted composite anomaly.

Panel C considers both sentiment and arbitrage constraints jointly. Coefficients are very similar as in the univariate tests. A few anomalies such as long-term reversal or lead-lag effects show no reliable relation to either arbitrage constraints or sentiment. For most remaining anomalies, variation in sentiment is clearly more

**Table 7**
The impact of lagged investor sentiment and lagged arbitrage constraints on meta anomaly returns.

| Sample period 8/1965–1/2011 | $N$ | Panel A: Limits to arbitrage | | | Panel B: Baker/Wurgler sentiment | | | Panel C: Combined analysis | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Coefficient | $t$-stat | $R^2$ | Coefficient | $t$-stat | $R^2$ | Limits to arbitrage | | Baker/Wurgler sentiment | | Constant | | $R^2$ |
| Violations of the law of one price | 289 | 0.238*** | (8.11) | 0.269 | 0.191*** | (4.09) | 0.040 | 0.229*** | (7.49) | 0.0986** | (2.39) | −0.153*** | (−5.95) | 0.279 |
| Momentum anomalies | 546 | −0.502** | (−2.17) | 0.015 | 0.216 | (1.12) | 0.003 | −0.498** | (−2.15) | 0.207 | (1.07) | 1.192*** | (6.81) | 0.017 |
| Technical analysis anomalies | 546 | −0.739*** | (−2.67) | 0.021 | 0.304 | (1.29) | 0.004 | −0.733*** | (−2.66) | 0.290 | (1.24) | 0.894*** | (4.11) | 0.024 |
| Short-term reversal anomalies | 546 | 0.640*** | (2.74) | 0.026 | −0.074 | (−0.41) | 0.000 | 0.639*** | (2.73) | −0.062 | (−0.35) | 0.918*** | (5.49) | 0.027 |
| Long-term reversal anomalies | 546 | −0.198 | (−1.43) | 0.005 | 0.004 | (0.03) | 0.000 | −0.198 | (−1.43) | 0.005 | (0.02) | 0.448*** | (3.93) | 0.006 |
| Calendar-based anomalies | 546 | 0.075 | (1.09) | 0.004 | −0.010 | (−0.16) | 0.000 | 0.074 | (1.09) | −0.008 | (−0.13) | 0.572*** | (10.65) | 0.004 |
| Lead-lag anomalies | 300 | 0.174 | (0.47) | 0.001 | 0.101 | (0.24) | 0.000 | 0.160 | (0.45) | 0.039 | (0.09) | 1.145*** | (5.21) | 0.001 |
| Pairs trading anomaly | 521 | 0.476*** | (4.38) | 0.066 | 0.055 | (0.67) | 0.001 | 0.477*** | (4.36) | 0.061 | (0.76) | 1.138*** | (15.07) | 0.067 |
| Beta anomalies | 546 | −0.040 | (−0.20) | 0.000 | 0.520*** | (3.44) | 0.025 | −0.030 | (−0.15) | 0.520*** | (3.43) | 0.538*** | (3.83) | 0.025 |
| Distress risk anomalies | 471 | −0.014 | (−0.09) | 0.000 | 0.407*** | (2.65) | 0.020 | 0.007 | (0.05) | 0.407*** | (2.60) | 1.012*** | (8.95) | 0.020 |
| Skewness anomalies | 546 | 0.249 | (1.62) | 0.011 | 0.409*** | (3.72) | 0.028 | 0.257* | (1.68) | 0.413*** | (3.77) | 0.703*** | (6.88) | 0.039 |
| Differences of opinion | 546 | 0.112 | (0.70) | 0.002 | 0.501*** | (4.12) | 0.033 | 0.121 | (0.78) | 0.503*** | (4.15) | 0.842*** | (7.27) | 0.035 |
| Industry effects | 546 | 0.131 | (1.17) | 0.005 | 0.226** | (2.53) | 0.014 | 0.135 | (1.21) | 0.229** | (2.58) | 0.246*** | (3.00) | 0.019 |
| Fundamental analysis anomalies | 468 | 0.107 | (1.58) | 0.007 | 0.175*** | (2.65) | 0.016 | 0.117* | (1.71) | 0.182*** | (2.80) | 0.620*** | (11.02) | 0.024 |
| Net stock and financing | 546 | 0.111 | (1.43) | 0.004 | 0.223*** | (3.08) | 0.016 | 0.115 | (1.51) | 0.225*** | (3.10) | 0.746*** | (9.89) | 0.020 |
| Capital investment and growth | 546 | 0.017 | (0.20) | 0.000 | 0.115 | (1.56) | 0.004 | 0.019 | (0.22) | 0.116 | (1.56) | 0.525*** | (6.70) | 0.004 |
| Anomalies related to innovation | 427 | 0.166 | (1.42) | 0.005 | 0.211* | (1.71) | 0.005 | 0.156 | (1.34) | 0.193 | (1.59) | 0.316*** | (3.01) | 0.009 |
| Accruals anomalies | 546 | −0.044 | (−0.53) | 0.001 | 0.040 | (0.44) | 0.000 | −0.044 | (−0.52) | 0.033 | (0.42) | 0.507*** | (6.41) | 0.001 |
| Dividend anomalies | 546 | 0.194* | (1.85) | 0.011 | −0.095 | (−1.10) | 0.003 | 0.193* | (1.84) | −0.091 | (−1.06) | 0.377*** | (4.69) | 0.013 |
| Earnings surprises | 468 | 0.120 | (0.95) | 0.004 | 0.076 | (0.70) | 0.001 | 0.125 | (0.98) | 0.084 | (0.78) | 1.223*** | (13.86) | 0.005 |
| Composite: equally weighted | 546 | 0.044 | (0.73) | 0.002 | 0.173*** | (3.50) | 0.028 | 0.047 | (0.79) | 0.174*** | (3.52) | 0.720*** | (16.37) | 0.030 |
| Composite: value weighted | 546 | 0.004 | (0.07) | 0.000 | 0.203*** | (3.95) | 0.033 | 0.008 | (0.13) | 0.203*** | (3.94) | 0.605*** | (12.78) | 0.033 |

The table displays coefficients from predictive regressions of anomaly returns (orthogonalized with respect to a Fama and French, 1993 model) in month $t$ on an aggregate measure of arbitrage constraints measured in month $t-1$ (in panel A), on the Baker and Wurgler (2006) sentiment index measured in month $t-1$ (in panel B), or on both (in panel C). The arbitrage constraints measure is based on all six individual measures (Vix, average idiosyncratic volatility, Moody's credit spread, Ted spread, average bid-ask spread, aggregate liquidity level) available in a given month. We standardize each of the individual measures to range from 0 to 1, and then define the aggregate arbitrage constraints measure as the sum of these values divided by the number of available individual proxies. Both the Baker and Wurgler (2006) investor sentiment proxy and the aggregate arbitrage constraints measure are standardized to have zero mean and unit variance. In all panels, the sample period is August 1965 to January 2011 ($N$ = 546 months) or a shorter period of time as limited by the availability of meta anomaly returns (see e.g. Table 2). *Composite: equally weighted* (*Composite: value weighted*) refers to the equally weighted (value weighted) average of all available meta anomalies excluding violations of the law of one price. $T$-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 *,**,***, respectively.

important than variation in limits to arbitrage. This is also reflected in the behavior of the equally weighted or value weighted composite anomaly. A one standard deviation in previous month's sentiment is estimated to generate a 17 to 20 bp increase in anomaly returns in this month ($t$-stat 3.50–3.90). For limits to arbitrage, the corresponding estimates are 1 to 5 bp ($t$-stat 0.1–0.8).

In Table 8, we perform the analysis of panel B in Table 7 with three alternative proxies for sentiment (see e.g. Fisher and Statman, 2003 or Lemmon and Portniaguina, 2006). More precisely, we rely on the Index of Consumer Expectations as published by the Michigan Survey Research Center, on the Conference Board Consumer Confidence Index, and on the Sentiment Survey of the American Association of Individual Investors. On a monthly basis, the indices become available from the middle of the 70ies or 80ies onwards. To isolate the sentiment component, we first regress all indices on the same macroeconomic factors as used in Baker and Wurgler (2006). We find that a one standard deviation change in any of the lagged orthogonalized indices goes along with an about 15 to 17 bp change in the equally weighted composite anomaly ($t$-stats 1.73 to 3.00). Thus, our findings are not restricted to the Baker and Wurgler (2006) sentiment measure.

### 2.7. Long vs. short leg

In the following, we test whether the overall strong predictive power of investor sentiment for anomaly returns is disproportionately driven by the long leg or the short leg. As this analysis is motivated by Stambaugh et al. (2012), we closely follow their methodological approach (see their Tables 4 and 5).[7]

[7] As deviations of the law of one price are conceptually different from all other anomalies as we have limited data on the long and short leg, meta anomaly 1 is excluded from the following analysis.

**Table 8**
The impact of alternative measures of lagged investor sentiment on meta anomaly returns.

| | Michigan Index of Consumer Expectations | | | Conference Board Consumer Confidence Index | | | AAII Sentiment Survey | | |
|---|---|---|---|---|---|---|---|---|---|
| | *N* | Coefficient | *t*-stat | *N* | Coefficient | *t*-stat | *N* | Coefficient | *t*-stat |
| Violations of the law of one price | 288 | 0.0135 | (0.41) | 288 | −0.0718** | (−2.20) | 280 | 0.0264 | (0.81) |
| Momentum anomalies | 395 | 0.661*** | (2.72) | 402 | 0.883*** | (2.99) | 280 | 0.976*** | (3.54) |
| Technical analysis anomalies | 395 | 0.797** | (2.23) | 402 | 0.930*** | (2.60) | 280 | 1.148*** | (3.19) |
| Short-term reversal anomalies | 395 | −0.077 | (−0.24) | 402 | −0.006 | (−0.02) | 280 | −0.538** | (−1.97) |
| Long-term reversal anomalies | 395 | 0.011 | (0.06) | 402 | 0.045 | (0.30) | 280 | 0.280* | (1.94) |
| Calendar-based anomalies | 395 | 0.063 | (0.86) | 402 | 0.114 | (1.60) | 280 | −0.028 | (−0.35) |
| Lead-lag anomalies | 300 | −0.105 | (−0.41) | 300 | −0.254 | (−1.02) | 220 | −0.147 | (−0.61) |
| Pairs trading anomaly | 371 | −0.227** | (−2.32) | 378 | −0.267** | (−2.51) | 256 | −0.158* | (−1.72) |
| Beta anomalies | 395 | 0.293 | (1.61) | 402 | 0.013 | (0.06) | 280 | 0.334 | (1.52) |
| Distress risk anomalies | 395 | 0.374** | (2.57) | 402 | 0.307* | (1.73) | 280 | 0.270 | (1.58) |
| Skewness anomalies | 395 | 0.153 | (0.92) | 402 | −0.040 | (−0.23) | 280 | 0.070 | (0.41) |
| Differences of opinion | 395 | 0.070 | (0.44) | 402 | −0.139 | (−0.81) | 280 | 0.018 | (0.11) |
| Industry effects | 395 | −0.084 | (−0.87) | 402 | −0.053 | (−0.48) | 280 | 0.002 | (0.04) |
| Fundamental analysis anomalies | 395 | 0.0210 | (0.28) | 402 | 0.006 | (0.08) | 280 | 0.003 | (0.12) |
| Net stock and financing | 395 | 0.221** | (2.09) | 402 | 0.0490 | (0.44) | 280 | 0.018 | (0.14) |
| Capital investment and growth | 395 | 0.300*** | (2.63) | 402 | 0.213* | (1.75) | 280 | 0.267** | (2.15) |
| Anomalies related to innovation | 395 | 0.321** | (2.21) | 402 | 0.330** | (2.37) | 280 | 0.189 | (1.06) |
| Accruals anomalies | 395 | 0.270** | (2.30) | 402 | 0.268** | (2.37) | 280 | 0.298** | (2.35) |
| Dividend anomalies | 395 | −0.181 | (−1.61) | 402 | −0.128 | (−1.14) | 280 | −0.148 | (−1.29) |
| Earnings surprises | 395 | 0.106 | (0.99) | 402 | 0.188 | (1.56) | 280 | 0.197* | (1.68) |
| Composite: equally weighted | 395 | 0.167*** | (3.00) | 402 | 0.151** | (2.03) | 280 | 0.171** | (2.37) |
| Composite: value weighted | 395 | 0.172** | (2.57) | 402 | 0.150* | (1.89) | 280 | 0.134* | (1.73) |

The table displays coefficients from predictive regressions of anomaly returns (orthogonalized with respect to a Fama and French, 1993 model) in month $t$ on an aggregate measure of investor sentiment measured in month $t-1$. More precisely, we rely on the lagged Index of Consumer Expectations as published by the Michigan Survey Research Center (sample period 2/1978–12/2010), on the Conference Board Consumer Confidence Index (sample period 7/1977–12/2010), or on the Sentiment Survey of the American Association of Individual Investors (sample period 9/1987–12/2010). All investor sentiment proxies are orthogonalized with respect to the same macroeconomic variables that Baker and Wurgler (2006) use. Moreover, all orthogonalized investor sentiment proxies are standardized to have zero mean and unit variance. *Composite: equally weighted* (*Composite: value weighted*) refers to the equally weighted (value weighted) average of all available meta anomalies excluding violations of the law of one price. *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 *,**,***, respectively.

**Table 9**
Long leg vs short leg: contribution to long-short meta anomaly returns.

| Sample period 8/1965–1/2011 | | Panel A: Long leg | | Panel B: Short leg | |
|---|---|---|---|---|---|
| Value weighted meta anomaly | *N* | Coefficient | *t*-stat | Coefficient | *t*-stat |
| Momentum anomalies | 546 | 0.474*** | (4.71) | −0.673*** | (−6.56) |
| Technical analysis anomalies | 546 | 0.305*** | (2.65) | −0.368** | (−2.55) |
| Short-term reversal anomalies | 546 | −0.000 | (−0.00) | −0.338*** | (−3.05) |
| Long-term reversal anomalies | 546 | 0.231** | (2.41) | −0.016 | (−0.16) |
| Calendar-based anomalies | 546 | 0.459*** | (7.60) | −0.135*** | (−3.53) |
| Lead-lag anomalies | 300 | 0.238 | (1.40) | −0.707*** | (−4.01) |
| Pairs trading anomaly | 521 | 0.623*** | (6.84) | −0.514*** | (−6.29) |
| Beta anomalies | 546 | 0.0226 | (0.36) | −0.455*** | (−3.57) |
| Distress risk anomalies | 471 | 0.232*** | (3.87) | −0.722*** | (−7.10) |
| Skewness anomalies | 546 | 0.138*** | (3.12) | −0.475*** | (−5.66) |
| Differences of opinion | 546 | 0.147*** | (2.76) | −0.580*** | (−5.76) |
| Industry effects | 546 | 0.287*** | (3.64) | −0.117** | (−2.25) |
| Fundamental analysis anomalies | 468 | 0.216*** | (4.51) | −0.340*** | (−5.64) |
| Net stock and financing | 546 | 0.140*** | (2.86) | −0.455*** | (−6.79) |
| Capital investment and growth | 546 | 0.140*** | (2.70) | −0.238*** | (−3.66) |
| Anomalies related to innovation | 427 | 0.349*** | (2.98) | −0.039 | (−0.78) |
| Accruals anomalies | 546 | 0.163** | (2.10) | −0.239*** | (−3.31) |
| Dividend anomalies | 546 | 0.178* | (1.88) | −0.129** | (−2.01) |
| Earnings surprises | 468 | 0.378*** | (6.91) | −0.590*** | (−6.79) |
| Composite | 546 | 0.245*** | (10.06) | −0.364*** | (−8.81) |

The table displays value-weighted meta anomaly returns (orthogonalized with respect to a Fama and French, 1993 model) separately for the long leg and the short leg. The sample period is August 1965 to January 2011 ($N = 546$ months) or a shorter period of time as limited by the availability of meta anomaly returns (see e.g. Table 2). *Composite* refers to the average of all available meta anomalies excluding violations of the law of one price. *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 *,**,***, respectively.

Table 9 shows the long and short leg of meta anomaly separately. We condition on the time period for which the Baker and Wurgler (2006) sentiment proxy is available. For the long and short portfolio of each individual anomaly, we compute value-weighted returns in excess of the risk free rate, and aggregate them into meta anomalies as before. Separately for the long and short leg, we finally orthogonalize the returns with respect to the Fama and French (1993) factors.

Table 9 demonstrates that most meta anomaly returns are effectively driven by the short leg. For instance, in the case of distress risk anomalies, the long leg contributes a monthly alpha of 23 bp (*t*-stat 3.87), whereas the short leg contributes 72 bp (*t*-stat

7.10). Averaged across all meta anomalies, these numbers are 24.5 bp and 36.4 bp. Only a few anomalies (long-term reversal, calendar-based, pairs trading, innovation, industry, dividends) are stronger on the long leg.

In sum, this asymmetry in the returns of long-short anomalies is consistent with the idea that permanent short-selling constraints lead to overpricing being a more important source of mispricing than underpricing (see e.g. Miller, 1977; Hirshleifer et al., 2011; Stambaugh et al., 2015).

Overpricing should be magnified in times of high sentiment which implies low expected returns for stocks in the short leg of anomalies. Following Stambaugh et al. (2012), we consequently hypothesize that the predictive power of investor sentiment for long-short anomalies mainly stems from the short leg. Note that this argument necessarily rests on limits to arbitrage, but only in the sense that there are permanent constraints which are more binding for the short leg than for the long leg (e.g. due to short-selling constraints). The argument does not require that there are time-varying limits to arbitrage. In fact, our analysis so far shows that the dynamics of market-wide limits to arbitrage have little predictive power for long-short anomaly returns, so that the time-varying (but not the time-invariant) part is likely to affect the long and short leg similarly.

We test these predictions in Table 10 where we run predictive regressions of meta anomaly returns on the Baker and Wurgler (2006) sentiment proxy and on an aggregate proxy for limits to arbitrage as in panels C and D of Table 6.

A clear pattern emerges. Sentiment can hardly predict the returns in the long leg of the portfolio, but it has substantial power to predict the short leg. For instance, for the composite anomaly which takes into account information from all meta anomalies, a one standard deviation increase in sentiment leads to an return increase of less than 3 bp in the long leg ($t$-stat 1.14), but to an return decrease of 17.7 bp in the short leg ($t$-stat 3.96).

In contrast, time variation of limits to arbitrage again does not have predictive power and (consistent with the analysis from the long-short returns) affects the long and short leg to a similar extent. A one standard deviation increase in the proxy leads to a 3 bp (2 bp) return increase in the long (short) leg of the composite anomaly. Both values are far from statistically significant.

The strong asymmetric affect of sentiment and the weak role of limits to arbitrage are robust to a large number of methodological changes. For instance, the last two rows of Table 10 show that they are also existent when simply using raw returns in excess of the risk free rate instead of abnormal returns. The online appendix (Tables A10 and A11) shows similar findings when analysing the role of sentiment and limits to arbitrage separately instead of jointly. It also shows that the impact of sentiment is similar in times characterized by low and high periods of limits to arbitrage. In general, running the analysis at the individual anomaly level instead of at the meta anomaly level does not change the main insights.

In sum, our findings provide strong independent support for Stambaugh et al. (2012) who document the asymmetric role of sentiment. Results are also consistent with the idea that, in the context of most long-short anomalies, market wide limits to arbitrage are primarily important due to their permanent existence, not due to the variations around their average level.

**Table 10**
Long leg vs. short leg: Impact of lagged investor sentiment and lagged arbitrage constraints.

| Sample period 8/1965–1/2011 | | Panel A: Long leg | | | | Panel B: Short leg | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Baker/Wurgler Sentiment | | Limits to arbitrage | | Baker/Wurgler Sentiment | | Limits to arbitrage | |
| Anomaly | N | Coefficient | $t$-stat | Coefficient | $t$-stat | Coefficient | $t$-stat | Coefficient | $t$-stat |
| Momentum anomalies | 546 | −0.0729 | (−0.75) | −0.339*** | (−2.90) | −0.149 | (−1.45) | 0.115 | (0.94) |
| Technical analysis anomalies | 546 | −0.00149 | (−0.01) | −0.332** | (−2.02) | −0.223 | (−1.57) | 0.464*** | (3.41) |
| Short-term reversal anomalies | 546 | −0.112 | (−0.88) | 0.113 | (0.67) | −0.163 | (−1.60) | −0.0508 | (−0.36) |
| Long-term reversal anomalies | 546 | −0.0472 | (−0.49) | 0.0401 | (0.31) | −0.0593 | (−0.63) | −0.0151 | (−0.13) |
| Calendar-based anomalies | 546 | −0.0589 | (−0.99) | 0.0461 | (0.66) | 0.0112 | (0.28) | 0.0765* | (1.66) |
| Lead-lag anomalies | 300 | −0.0703 | (−0.26) | −0.0151 | (−0.06) | −0.0562 | (−0.18) | 0.00335 | (0.01) |
| Pairs trading anomaly | 521 | 0.141 | (1.59) | 0.442*** | (4.17) | 0.0802 | (1.08) | −0.0353 | (−0.32) |
| Beta anomalies | 546 | 0.0988 | (1.53) | 0.0410 | (0.51) | −0.479*** | (−3.39) | −0.0284 | (−0.18) |
| Distress risk anomalies | 471 | 0.110* | (1.68) | −0.0865 | (−1.42) | −0.433*** | (−3.36) | −0.0810 | (−0.70) |
| Skewness anomalies | 546 | 0.102** | (2.22) | 0.0224 | (0.35) | −0.431*** | (−4.61) | −0.165* | (−1.70) |
| Differences of opinion | 546 | 0.153*** | (2.84) | 0.0713 | (1.05) | −0.375*** | (−3.45) | −0.0333 | (−0.30) |
| Industry effects | 546 | 0.235*** | (3.12) | 0.0605 | (0.69) | −0.0978* | (−1.79) | 0.0702 | (1.24) |
| Fundamental analysis anomalies | 468 | 0.00177 | (0.04) | 0.00363 | (0.06) | −0.252*** | (−3.50) | −0.0149 | (−0.22) |
| Net stock and financing | 546 | 0.101** | (2.13) | 0.132** | (2.25) | −0.230*** | (−3.69) | 0.113* | (1.75) |
| Capital investment and growth | 546 | −0.0329 | (−0.63) | 0.136** | (1.97) | −0.179*** | (−2.75) | 0.0655 | (0.96) |
| Anomalies related to innovation | 427 | 0.0896 | (0.70) | 0.177 | (1.43) | 0.00348 | (0.06) | 0.0673 | (0.86) |
| Accruals anomalies | 546 | −0.132* | (−1.94) | −0.0536 | (−0.65) | −0.216*** | (−2.89) | 0.0467 | (0.69) |
| Dividend anomalies | 546 | 0.0570 | (0.57) | 0.0730 | (0.61) | 0.0626 | (0.95) | −0.176* | (−1.86) |
| Earnings surprises | 468 | −0.00595 | (−0.10) | 0.134** | (2.16) | −0.0558 | (−0.56) | −0.0385 | (−0.34) |
| Composite: Abnormal returns Coeff. | 546 | 0.0264 | (1.14) | 0.0289 | (0.79) | −0.177*** | (−3.96) | 0.0205 | (0.45) |
| Composite: Abnormal returns Constant | | 0.245*** | | (10.06) | | −0.364*** | | (−8.95) | |
| Composite: Excess returns Coeff. | 546 | −0.322 | (−1.52) | 0.005 | (0.02) | −0.654** | (−2.40) | 0.026 | (0.08) |
| Composite: Excess returns Constant | | 0.685*** | | (3.45) | | 0.187 | | (0.76) | |

The table displays coefficients from predictive regressions of the long leg (in panel A) or of the short leg (in panel B) of value weighted anomaly returns (orthogonalized with respect to a Fama and French, 1993 model) in month $t$ on an aggregate measure of arbitrage constraints measured in month $t-1$ and on the Baker and Wurgler (2006) sentiment index measured in month $t-1$. The arbitrage constraints measure is based on all six individual measures (Vix, average idiosyncratic volatility, Moody's credit spread, Ted spread, average bid-ask spread, aggregate liquidity level) available in a given month. We standardize each of the individual measures to range from 0 to 1, and then define the aggregate arbitrage constraints measure as the sum of these values divided by the number of available individual proxies. Both the Baker and Wurgler (2006) investor sentiment proxy and the aggregate arbitrage constraints measure are standardized to have zero mean and unit variance. In all panels, the sample period is August 1965 to January 2011 ($N$ = 546 months) or a shorter period of time as limited by the availability of meta anomaly returns (see e.g. Table 2). *Composite: Abnormal returns* (*Composite: Excess returns*) refers to the average of the abnormal return (excess return) of all available meta anomalies excluding violations of the law of one price. $T$-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 *,**,***, respectively.

**Table 11**
The impact of proxies for market-level arbitrage constraints on meta anomaly-level arbitrage activity.

| | 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) |

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 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 *,**,***, respectively.

### *2.8. 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? 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 which 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, may signal changes in arbitrage activity (e.g. Hanson and Sunderan, 2014; Hwang and Liu, 2014). 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, 2014), we focus on relative measures (e.g. McLean and Pontiff, 2015).

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, 2015). 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.

In our regression framework, 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.[8] The major insight from Table 11 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. The analysis thus appears to confirm the insights from the baseline analysis.

## 3. Conclusion

The idea that investor sentiment and limits to arbitrage offer a convincing rationale for the survival of alleged mispricings has gained much interest in recent years. Our analysis of 100 cross-sectional phenomena sheds some new light on the ongoing debate. The dynamics of popular proxies for market-level investor sentiment (limits to arbitrage) turn out to be a powerful (relatively weak) predictor for most anomaly returns, in particular on the short side of the portfolios. These stylized facts are suggestive of

[8] 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 as well as with changes of the proxies for arbitrage constraints. 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.

the idea that market-wide variations in sentiment combined with the base level (and not primarily the variations) of different forms of limits to arbitrage provide at least a partial explanations for the potential inefficiencies observable in the data.

Our insights suggest different directions for future research. For instance, our findings indicate a need for the identification of (further) drivers of fluctuations in anomaly returns. Given the apparently weak link between market-wide arbitrage constraints and anomaly-level arbitrage popularity measures, a fruitful starting point in this respect could be the exploration of anomaly-level (as opposed to market-level) sentiment and arbitrage constraints. Moreover, due to the aggregate nature of our study, we are limited in our ability to consider the economic or psychological forces behind all anomalies in detail. We hope that our novel insights on the "big picture" might serve as a fruitful starting point for future research exploring specific contexts and interpretations in more depth.

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## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jbankfin.2015.03.006.

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