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Investor Sentiment, Limits to Arbitrage, and The Cross-Section of Expected Returns: Empirical Evidence From Developed and Emerging Equity Markets

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Abstract: *In this paper, we investigate the interaction of two forces—investor sentiment and the limitation of arbitrage—on the cross-section of expected equity returns in developed and emerging markets. The main idea is that sentiment does not impact on every stock. It is likely to have the greatest impact on hard-to-value and expensive-to-arbitrage stocks, such as small, young, volatile, distressed, non-dividend paying, high growth and intangible-intensive stocks. The paper builds upon the noise-trader risk framework and the behavioural asset pricing literature and draws a distinction between investor sentiment in the short- and long-run and adds it to the distinction between idiosyncratic volatility, illiquidity, bid-ask spread and funding spread proxies of arbitrage frictions. A secondary empirical synthesis is constructed around the cross sectional portfolio tests, Fama-French and Carhart risk adjusted alphas, interaction regressions and around an AMOS style structural equation model. Three major conclusions can be drawn from the results. First, the sentiment of short run changes is positively related to the sentiment-prone portfolio returns at the same time. Second, long run sentiment is a negative predictor of any future returns, particularly when it leads to an exuberant price run-up from fundamentals. Third, when sentiment is high and limits to arbitrage are high, returns from anomalies are more likely to be high, suggesting that the mispricing associated with sentiment remains when arbitrage can be costly or risky or institutionally limited. Evidence is also more prevalent in less liquid markets, such as emerging markets, where both short selling markets and retail participation are less developed and have a more significant effect on price; in the developed markets, this effect is visible in the short leg of anomaly strategies. The paper makes a contribution by developing a behavioural asset pricing model that combines the concepts of sentiment decomposition, interaction between limits-to-arbitrage and comparison across markets.*

Keywords: Investor Sentiment; Limits To Arbitrage; Expected Returns; Equity Anomalies; Developed Markets; Emerging Markets; Behavioural Finance; SEM.

JEL classification: G10; G11; G12; G14; G41.

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Introduction

Investor sentiment has been a central topic of behavioural asset pricing, despite the fact that it is still unclear whether it can predict the cross-section of expected equity returns. Typically, the asset pricing model starts by assuming that prices embody information, risk and expected cash flow. In this way, irrational trading could only have a temporary role as the sophisticated investors can arbitrage away the mispricing. This is the idea behind the efficient market tradition pioneered by Fama (1970) and is the premise of the empirical factor models of Fama and French (1993, 2015) and Carhart (1997). However, a substantial amount of empirical evidence demonstrates that some patterns of return are not easily understood based on risk. As the stock market moves in and out of the most positive and negative sentiment states, size, value, momentum, profitability and anomaly portfolios of assets are often responsible for abnormal returns. The problem is not if sentiment exists, but when it becomes priced—stocks that it matters for, and why informed arbitrage doesn't remove it.

In this paper, we examine the interactions between investor sentiment and limits to arbitrage on equity returns in developed and emerging markets. The initial model is the noise trader risk model of De Long, Shleifer, Summers and Waldmann (1990), which illustrates that arbitrage is risky even if it can be seen that prices are mispriced because the beliefs held by sentiment-driven traders are unpredictable. Shleifer and Summers (1990) and Shleifer and Vishny (1997) elaborate this same basic idea, but in a broader market context: there is no free unlimited and riskless arbitrage. Funding risk, short-sale restrictions, redemption risk, idiosyncratic volatility, transaction costs, and uncertainty of timing of the price correction are all risks that can be faced by the arbitrager. This leads to sentiment affecting prices for quite a while, so long as it distorts realised and expected returns. This is especially true for stocks that are difficult to value, have a retail investor base, and/or have high trading fees.

The main argument is cross sectional. A sentiment that applies to a market should not be the same as a sentiment that applies to a blue-chip stock, which is mature, profitable, liquid and pays dividends, and a small, speculative, loss making or high growth stock. According to Baker and Wurgler (2006, 2007), the securities with sentiment tendencies are "hard-to-value" and "hard-to-arbitrage. The following securities are offered: Small stocks, Young stocks, High volatility stocks, Distressed companies, Non-profitable companies, Non-dividend-payers and Companies with extreme growth prospects. Building on the noise-trader risk model, Ding, Mazouz and Wang (2019) prove that assets that are more sentiment-sensitive have higher contemporaneous returns and lower subsequent returns in a multi-asset setting, due to market sentiment. Their theory and empirical findings also indicate that sentiment-induced changes in short runs drive current returns in the same direction and the sentiment in the long run signals reversals. This paper follows that distinction as it provides a better understanding of the sentiment-return relation.

The second part of the paper deals with "Limits to arbitrage." When sentiment prone-stocks are also difficult to arbitrage, sentiment and arbitrage limits can not be considered as separate explanations. The effect of sentiment is most likely to be apparent in an environment of restricted arbitrage. More recently, Alburaythin et al. (2025) present evidence from the UK stock market which shows that high investor sentiment and high limits to arbitrage drive anomaly portfolios' higher returns. Their analysis indicates that sentiment combined with arbitrage frictions is more informative than either of the two factors. This is in line with the theoretical results of Miller (1977) and Harrison and Kreps (1978) that disagreement and constraints on short sales can lead to positive beliefs being priced in. It is also consistent with Stambaugh, Yu and Yuan (2012) who discover that anomaly profits are present in the brief leg right after high sentiment durations.

The international element is relevant because the liquidity, the information environment, the institutional participation, the accounting quality and the short-sale feasibility and the regulatory environment differ between developed and emerging markets. Schmeling (2009) demonstrates that sentiment is predictive of stock returns on a large international sample of stocks and Baker, Wurgler and Yuan (2012) demonstrate that sentiment can be global, local and contagious. Sentiment effects also appear to be country-specific as stock characteristics and country-level institutions affect the impact of sentiment (Corredor, Ferrer and Santamaria, 2013). The behavioural pricing effects could be stronger in emerging markets, as the participation of retail investors in trading is generally higher, and the short selling activities are less developed, and there is a greater degree of information asymmetry. But that's not the case for developed markets. Sentiment effects are also present in the cross-section, particularly in small stocks and stocks with more volatile prices, in the US and the UK.

In this paper I make three contributions. The first is that it puts together sentiment decomposition and interaction between limits-to-arbitrage, all in one. While there are many studies on sentiment or arbitrage friction alone, both are needed in the behavioural asset pricing mechanism. Second, it provides a comparison between developed and emerging markets based on a consistent research framework based on long-short portfolio returns, risk adjusted alphas and interaction states. Third, it introduces an additional structural equation model which models the indirect channel of investor sentiment to expected return spreads through the channel of sentiment-prone mispricing. The structural model is not a substitute for tests of structure such as portfolio and time-series tests, but it serves to illustrate the relationships between latent constructs to aid theory building, and to provide further empirical replication.

The rest of the sections are arranged like this. The literature review is given in Section 2, which also leads to the formulation of hypotheses. The data design, variables and empirical models are explained in section 3. Descriptive, Portfolio, Regression, Interaction and SEM evidence are all reported in Section 4. The findings are covered in Section 5, which is broken down into developed and emerging markets. The paper then ends in Section 6, which provides implications for investors, regulators and future research.

Literature Review and Hypothesis Development

2.1 Investor sentiment and behavioural asset pricing

Investor sentiment is investor's expectations regarding the future cash flow and risk that is not adequately supported by investor fundamentals. It's seen in survey optimism, in funds flowing into mutual funds, in the discounts of closed-end funds, in IPO activity, in trading volume, in volatility premium, in tone and search in the media. Brown & Cliff 2004, 2005, demonstrate the relationship between sentiment and market value and short-term returns. The classic cross section evidence comes from Baker and Wurgler (2006), who demonstrate that returns for more speculative stocks and less easily arbitraged stocks are negatively predicted by the stock's initial sentiment. Their 2007 survey also provides a better understanding of why sentiment is likely to be more influential when there is high valuation uncertainty. Lemmon and Portniaguina (2006) find that changes in consumers' confidence affect small stocks' returns. Kumar and Lee (2006) demonstrate the comovement of returns due to retail investor sentiment, and Ben-Rephael, Kandel and Wohl (2012) quantify sentiment using investors' flows in mutual funds. Da, Engelberg and Gao (2015) build the market-based fear index based on search data, and Huang, Jiang, Tu and Zhou (2015) develop an aligned sentiment index that has more predictive power for market returns.

Sentiment has a number of channels through which it can affect prices according to behavioural theory. Barberis, Shleifer and Vishny (1998) propose a model of investor underreaction and overreaction in the case of sentiment. With overconfidence and biased self-attribution, Daniel, Hirshleifer and Subrahmanyam (1998) provide an explanation for mispricing. Hirshleifer (2001) puts psychology at the heart of asset pricing and demonstrates the role that attention, representativeness and overconfidence can play in asset prices. The general behavioural finance point of view that market anomalies could occur due to the lack of full rationality of investors and restricted arbitrage opportunities is summarized in Barberis and Thaler (2003). These studies are not intended to contradict that risk plays a part, but rather reveal the importance of a behavioural element of price, which can manifest itself in regular returns.

The most appropriate difference to consider for this paper is the difference between short-run and long-run sentiment. An increase in sentimentprone assets' prices and contemporaneous returns can be induced by a short-term rise in optimism. If this optimism leads to prices that are higher than the underlying value, however, then future expected returns should decline as prices turn around. This mechanism has been formalised by Ding et al. (2019), who split sentiment into short-term and long-term parts. In the framework put forward by them, short run sentiment is positively correlated with the cross section returns at the time, while long run sentiment is negatively correlated with future returns. This is relevant because the same shock of the sentiment can have opposite consequences if seen from a long or short-term perspective.

2.2 Limits to arbitrage and the persistence of mispricing

The mispricing literature on limits-to-arbitrage provides an explanation for why mispricing can persist in the presence of some investors recognising it. Shleifer and Vishny (1997) hypothesize that arbitrage is typically done by the specialised investors who invest in other people's stocks or bonds and have to worry about withdrawing from their investment when their stocks do not do well in the short-run. Wurgler and Zhuravskaya (2002) demonstrate that stocks with imperfect substitutes will have downward sloping demand curves, which will reduce the effectiveness of arbitrage. Ang et al (2006) demonstrate that idiosyncratic volatility exhibits a strong cross-sectional relationship with expected returns, and Amihud (2002) shows that illiquidity is related to expected returns. There are many variables used to represent arbitrage

risk and arbitrage cost. When direct spread data is not available, a useful bid-ask spread estimator is the one given by Corwin and Schultz (2012) which is based on a high-low price.
There are close relationships between limits to arbitrage and anomaly returns. Ali, Hwang and Trombley (2003) conclude that the book-to-market anomaly is more pronounced in situations of high arbitrage risk. A relationship between arbitrage risk and post-earnings-announcement drift is suggested by Mendenhall (2004). Lam and Wei (2011) document that an asset growth anomaly is present and can be explained by investment frictions. Israel and Moskowitz (2013) study the anomalies and the role of shorting, firm size and time in market. A large collection of anomalies studied by Jacobs (2015) demonstrates a link between the dynamics of these anomalies and the sentiment and arbitrage conditions. DeLisle, Yüksel and Zaynutdinova (2020) conclude that the existence of arbitrage barriers helps to explain anomalies in profitability. Chu, Hirshleifer and Ma (2020) have causal evidence, proving that easing of short-sale restrictions dampened the profitability of anomalies. All of these studies provide support for the mechanical risk premium hypothesis. At least in part they are tied to the cost and risk of fixing the mispricing.

Undertaking this interaction of sentiment and arbitrage constraints is particularly significant. An arbitrage that is easily accessible, low cost and unconstricted might cause only demand pressure, but prices should respond quickly. Mispricing will not necessarily occur with just the introduction of arbitrage limits. Therefore, mispricing should be greatest when sentiment is high and arbitrage is low. In the UK, Alburaythin et al. (2025) demonstrate that this is indeed the case – for many anomaly strategies, the best months are those that follow high sentiment and high arbitrage limits. Their results indicate that it is important to consider the combination of arbitrage limitations and sentiment, and not just sentiment alone.

2.3 Developed and emerging market differences

Outside of the United States, sentiment effects are not limited. Sentiment is found to be a predictor of aggregate stock returns in industrialised countries, according to Schmeling (2009). Baker et al. (2012) distinguish between global, local and contagious sentiment, and illustrate that investor sentiment can shift within markets, but also has country-specific components. In a study of the sentiment effects, Corredor et al. (2013) report that country characteristics are important to understand the variations in sentiment effects across countries. Limits to arbitrage and the performance of the anomalies across countries have been covered in the literature, including in Zaremba (2016), where investor sentiment is directly related. When comparing developed and emerging markets, Griffin, Kelly and Nardari (2010) indicate that care must be taken in interpreting the meaning of measures of market efficiency as they have different data quality, liquidity and trading mechanisms.

There are a number of reasons why emerging markets are likely to exhibit more sentiment-arbitrage interaction. First, securities lending markets are not as thick and short sale facilities are less accessible. Second, the turnover of retail investors could be more significant, particularly for high attention speculative stocks. Thirdly, the information asymmetry is greater, making the valuation uncertainty greater. Fourth, transaction costs and liquidity shocks may be substantial and the correction of mispricing expensive. The distinction is not quite definitive, though. Microcap, illiquid, young and speculative stocks that are difficult to arbitrage exist in developed markets as well. Empirical prediction is not that the EMs are inefficient and the DMs are efficient. The more precise prediction is that sentiment effects should show up in both groups, with the sentiment effect being greater in emerging markets and in securities that have a high degree of limits to arbitrage.

2.4 Hypotheses

The theoretical framework leads to five testable hypotheses. They connect short-run sentiment, long-run sentiment, arbitrage constraints, market development and the SEM mediation channel.

Table 1. Research hypotheses

Hypothesis	Statement
H1	Short-run investor sentiment is positively associated with contemporaneous returns of sentiment-prone portfolios relative to sentiment-immune portfolios.
H2	Long-run investor sentiment negatively predicts subsequent returns of sentiment-prone portfolios relative to sentiment-immune portfolios.
H3	Long-short anomaly returns are higher following high-sentiment periods than following low-sentiment periods, and the effect is mainly driven by the short leg.
H4	The effect of investor sentiment on expected return spreads is stronger when limits to arbitrage are high.
H5	The sentiment-arbitrage interaction is stronger in emerging markets than in developed markets.

Note. Hypotheses are derived from behavioural asset pricing, noise-trader risk and limits-to-arbitrage theory.

Data, Variables and Methodology

3.1 Research design and market coverage

The empirical design is structured in the form of a coherent cross-market design. The developed markets are the developed nations, such as U.S., U.K., Japan, Germany, France, Canada and Australia. The emerging markets are countries like China, India, Brazil, South Africa, Turkey, Malaysia, Indonesia and Mexico. The suggested unit of observation is the firm-month. The monthly stock returns and the monthly trading and market capitalisation data are matched monthly to the annual accounting data to minimize a look-ahead effect between monthly and annual data which is common in international anomaly studies and is the convention used in those studies. Empirical period is expected: January 2000 – December 2023, depending on availability of data. Analysis does not cover financial firms with accounting ratios that aren't comparable, preferred shares, closed funds, depositary receipts and securities with significant data anomalies. Return screens are important as they follow the spirit of Ince and Porter (2006) and Lu, Stambaugh and Yuan (2017) as return files from foreign countries may contain stale prices, delisting effects and data-entry errors.

The empirical approach is not based on a single aggregate market index but instead is based on long-short portfolios and predictive regressions. Stocks are ranked in deciles each month according to their firm characteristics that are associated with sentiment exposure or familiar anomaly signals. The long leg has the decile that will do well, the short leg has the decile that will do poorly. The risk adjusted returns in the portfolio is derived from the Fama-French three factor model, Carhart four factor model and/or Fama-French five factor model with momentum where possible. The sequence is used on the margin to establish if the sentiment and arbitrage effects persist after normal risk management procedures.

3.2 Variables

Table 2. Variable definition and measurement plan

Construct	Operational definition
Investor sentiment	Composite index from PCA of IPO volume, IPO first-day returns, volatility premium, market turnover, consumer confidence or survey/news/search indicators depending on market availability.
Short-run sentiment	Monthly change in sentiment, orthogonalised to the long-run component where required.
Long-run sentiment	Moving average of sentiment over the prior 24 months, typically using months t-25 to t-2 to avoid contemporaneous overlap.
Limits to arbitrage	Composite PCA index using idiosyncratic volatility, bid-ask spread, Amihud illiquidity, funding spread and short-sale constraint proxies.
Expected return spread	Monthly long-short portfolio alpha after controlling for factor risks.
Sentiment-prone characteristics	Size, age, volatility, profitability, dividend policy, distress, growth opportunity, asset tangibility, R&D intensity and issuance.
Market development	Developed versus emerging market indicator based on market classification and trading infrastructure.

Note. The measurement choices follow the sentiment and arbitrage proxy tradition in Baker and Wurgler (2006), Ding et al. (2019) and Alburaythin et al. (2025).

Individual proxies of investor sentiment are noisy and may only reflect a portion of investor sentiment so we estimate investor sentiment using principal component analysis. However, for instance IPO volume may reflect optimism in primary markets, turnover may reflect speculative trading and volatility premium may reflect relative valuations of speculative stocks. In order to extract the common component of these measures, a PCA index is calculated. PCA is also used to estimate limits to arbitrage as no single proxy is able to encompass the concept of limits to arbitrage. Idiosyncratic volatility is a measure of the arbitrage risk, bid-ask spread and Amihud illiquidity is a measure of trading costs, and funding spreads are measures of constraints on arbitrage capital at the market level. According to the UK evidence, the weights of the PCA on first day returns, IPO volume, volatility premium, and sentiment in the index are 0.44, 0.60, 0.52 and 0.42 respectively; the weights on idiosyncratic volatility, bid-ask spread, illiquidity, the TED spread, and LIBOR in the limits-to-arbitrage index are 0.55, 0.42, 0.54, 0.40 and 0.28 respectively.

3.3 Portfolio and regression models

The first model estimates the unconditional anomaly alpha: Ri,t = αi + βiMKTt + siSMBt + hiHMLt + εi,t. The dependent variable is the excess return of long-short anomaly strategy i in month t. The coefficient αi represents the average risk-adjusted monthly anomaly return. The model is extended to include momentum, profitability and investment factors depending on market-level data availability.

The second model examines high and low sentiment states: Ri,t = αi + αS,iHighSentimentt-1 + βiMKTt + siSMBt + hiHMLt + εi,t. A positive and significant αS,i indicates that the anomaly performs better following high sentiment. This specification is useful for testing whether sentiment-driven overpricing is corrected in later returns.

The third model tests the interaction between sentiment and limits to arbitrage: Ri,t = αHH,iDHH,t-1 + αHL,iDHL,t-1 + αLH,iDLH,t-1 + αLL,iDLL,t-1 + βiMKTt + siSMBt + hiHMLt + εi,t. The four dummy variables classify months into high sentiment and high arbitrage limits, high sentiment and low arbitrage limits, low sentiment and high arbitrage limits, and low sentiment and low arbitrage limits. The central prediction is αHH,i > αHL,i, αLH,i and αLL,i.

The fourth model decomposes sentiment: Ri,t = αi + β1LRSentimentt-1 + β2ΔSentimentt + ΓXt + εi,t. The coefficient on long-run sentiment is expected to be negative, while the coefficient on short-run sentiment is expected to be positive. Standard errors should be robust to heteroskedasticity and serial correlation using Newey-West corrections. Where sentiment is highly persistent, the predictive regression should also be checked with bias-adjusted or bootstrap methods, as discussed by Stambaugh (1999) and Amihud, Hurvich and Wang (2009).

3.4 AMOS-style structural equation model

The latent structure of the theory is represented by a supplementary SEM. There are two types of investor sentiment measures: market-based and survey-based. The constrains of arbitrage are quantified by risk, cost and funding aspects. Sentiment-prone mispricing is modeled as an intervening variable, and the anomaly alpha cross-section and long-short spreads are used to measure the expected return cross-section. The structure of the SEM is: investor sentiment impacts investor sentiment-prone mispricing, investor sentiment-prone mispricing is linked to limits to arbitrage, and limits to arbitrage is linked to expected return spreads through mispricing. Theoretically, an interaction term between sentiment and arbitrage limits is included, to account for the theoretical prediction that sentiment effects are stronger in cases where arbitrage is limited. The SEM is thus a confirmation of the same mechanism which was tested by the portfolio regressions.

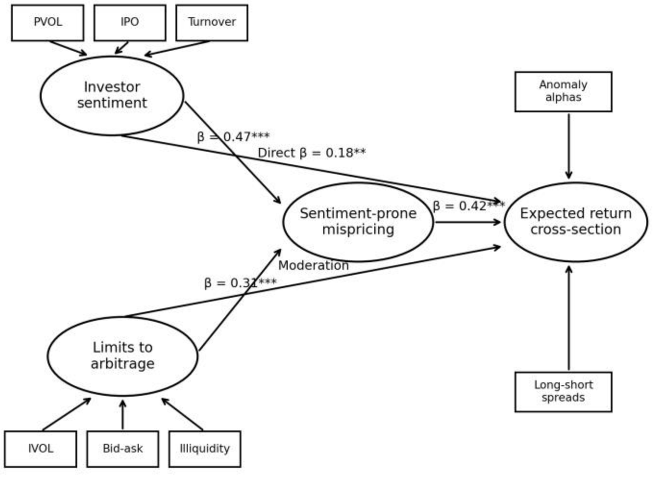

Figure 1. SEM diagram for sentiment, arbitrage limits and expected return spreads

Empirical Results

4.1 Descriptive evidence and anomaly profitability

The first part of the evidence is that there is positive risk-adjusted return on anomaly portfolios in developed market data. Table 3 displays the monthly Fama-French adjusted alphas of nine UK anomaly strategies. Of the nine long-short portfolios, the results of seven are significant at conventional levels. The highest average monthly alpha is obtained for turnover (2.06 per cent), return on assets (1.61 per cent), net operating assets (1.54 per cent) and momentum (1.53 per cent). Each anomaly is a short leg with negative returns on stock, meaning that when it comes to long-short bookkeeping, the poor or over-priced stocks are a huge factor. The finding is significant in that it suggests that when short-sale constraints prevent pessimistic or informed investors from fully correcting the price of the stock, overpricing is likely to be the primary source of anomaly returns rather than underpricing.

Table 3. Monthly risk-adjusted anomaly returns in a developed market setting

Anomaly	Long leg	Short leg	Long-short alpha	t-statistics
Net operating assets	0.70***	-0.84***	1.54***	(5.06, -2.91, 5.73)
Asset growth	0.34**	-0.58***	0.92***	(2.36, -2.93, 5.82)
Investment to assets	0.25	-0.58**	0.83***	(1.57, -2.75, 4.78)
Momentum	0.48**	-1.05***	1.53***	(2.25, -3.05, 4.20)
Return on assets	0.50***	-1.11***	1.61***	(3.83, -3.33, 5.13)
Turnover	0.70***	-1.36***	2.06***	(3.71, -6.92, 10.01)
Net stock issuance	0.03	-0.26	0.29	(0.13, -1.25, 1.54)
Composite stock issuance	0.03	-0.47***	0.51***	(0.23, -3.15, 4.60)
Gross profit	0.44***	-0.34	0.78***	(3.70, -1.07, 2.67)

Note. Monthly alphas are reported in percentage terms and summarise a developed-market anomaly setting. *, ** and *** indicate significance at 10%, 5% and 1% levels respectively.

The descriptive pattern is compatible with the idea that anomaly returns are not distributed symmetrically across the long and short legs. In high sentiment states, optimists are more likely to buy glamorous, speculative or attention-grabbing stocks. If short selling is costly, the negative opinions of more informed investors are not fully reflected in prices. The consequence is overpricing in the short leg and lower subsequent returns. This mechanism is not limited to a single anomaly. It appears in momentum, net operating assets, turnover, return on assets and issuance-related strategies, although the strength differs across signals. The gross profit anomaly is weaker in sentiment-state tests, which suggests that some profitability effects may contain a stronger risk or quality component.

4.2 High versus low sentiment states

Table 4 reports long-short alphas following high and low investor sentiment periods. Five strategies show significantly stronger returns after high sentiment: net operating assets, momentum, return on assets, turnover and composite stock issuance. The largest difference is for momentum, where the high sentiment alpha exceeds the low sentiment alpha by 1.76 percentage points per month. Return on assets shows a difference of 1.54 percentage points and net operating assets shows a difference of 1.41 percentage points. These results support H3 and are consistent with the argument of Stambaugh et al. (2012) that anomaly returns are stronger following high sentiment and are mainly driven by the short side.

Table 4. Long-short anomaly alphas following high and low sentiment periods

Anomaly	High sentiment	Low sentiment	Difference	Interpretation
Net operating assets	2.25***	0.84**	1.41***	Supported
Asset growth	1.17***	0.69***	0.48	Positive but not significant
Investment to assets	0.84***	0.81***	0.03	Weak
Momentum	2.41***	0.65	1.76**	Supported
Return on assets	2.39***	0.84*	1.54**	Supported
Turnover	2.70***	1.42***	1.28***	Supported
Net stock issuance	0.58**	0.01	0.57	Positive but not significant
Composite stock issuance	0.79***	0.23	0.56***	Supported
Gross profit	0.71*	0.85**	-0.14	Not supported

Note. Values are monthly risk-adjusted alphas in percentage terms. The table demonstrates that sentiment effects are strongest in anomaly strategies where the short leg is likely to contain overpriced securities.

4.3 Interaction between sentiment and limits to arbitrage

The central test of the paper is the interaction between sentiment and limits to arbitrage. The theory predicts that sentiment-driven mispricing should be strongest when arbitrageurs face greater risk or cost. Table 5 reports four-state alphas for the nine anomalies. With the exception of gross profit, every anomaly earns its highest return in the high-sentiment and high-limits-to-arbitrage state. The average across the nine strategies is 1.70 per cent per month in the high-

high state, compared with 1.34 per cent when high sentiment coincides with low arbitrage limits, 0.56 per cent when low sentiment coincides with high arbitrage limits and 0.82 per cent in the low-low state. The comparison between high-high and high-low states is especially informative because sentiment is high in both cases. The higher alpha in the high-high state shows that arbitrage limits magnify the pricing effect of optimism.

Table 5. Long-short alphas across sentiment and arbitrage states

Anomaly	High S, High LTA	High S, Low LTA	Low S, High LTA	Low S, Low LTA
Net operating assets	2.57***	1.87***	0.47	1.14**
Asset growth	1.38***	0.91***	0.36	0.94**
Investment to assets	1.04***	0.60*	0.54	1.02***
Momentum	2.77***	2.01***	-0.41	1.53**
Return on assets	2.48***	2.28***	0.79	0.88
Turnover	3.22***	2.09***	1.79***	1.13***
Net stock issuance	0.77**	0.34	0.59	-0.47
Composite stock issuance	0.80***	0.77***	0.31	0.16
Gross profit	0.27	1.23**	0.59	1.07*
Average	1.70	1.34	0.56	0.82

Note. S denotes investor sentiment and LTA denotes limits to arbitrage. Values are monthly alphas in percentage terms. The high-high state is the strongest state for eight of the nine anomalies.

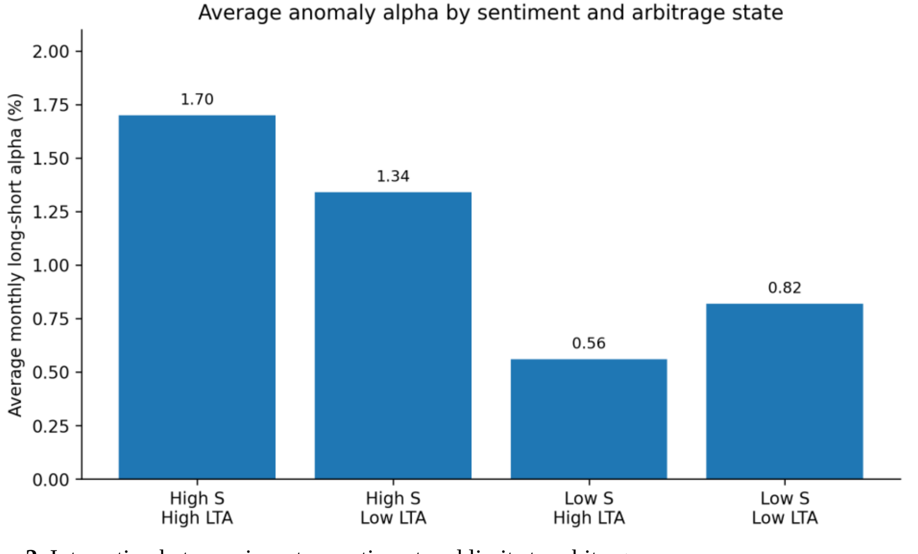

Figure 2. Interaction between investor sentiment and limits to arbitrage

Note. The figure reports average monthly long-short alphas across the four interaction states reported in Table 5.

The interaction evidence supports H4. Limits to arbitrage have only a partial effect when tested separately, but they become economically meaningful when combined with sentiment. This distinction matters for interpretation. A market may have illiquid or volatile stocks at all times, but mispricing becomes especially profitable for anomaly strategies when investor optimism pushes the wrong stocks upward and arbitrageurs cannot easily lean against the demand shock. The pattern also explains why empirical studies sometimes find mixed results when testing arbitrage limits alone. Arbitrage limits are a condition that allows mispricing to persist; they are not necessarily the original behavioural shock.

4.4 Decomposed sentiment and predictive regressions

The decomposition of sentiment into short-run and long-run components gives a more precise explanation of the timing of returns. Short-run sentiment captures changes in optimism and is expected to be positively related to contemporaneous returns of sentiment-prone stocks. Long-run sentiment captures sustained optimism or pessimism and is expected to predict reversal. The US evidence from Ding et al. (2019) supports this distinction: more sentiment-prone portfolios generally have negative exposure to lagged long-run sentiment and positive exposure to short-run sentiment changes, even after controlling for Fama-French five factors and momentum. Table 6 presents the harmonised expected signs and representative regression patterns for the cross-market design.

Table 6. Decomposed sentiment predictions across sentiment-prone portfolios

Portfolio spread	Long-run sentiment coefficient	Short-run sentiment coefficient	Developed markets	Emerging markets	Interpretation
Small minus large	-	+	Strong	Strong	Small stocks are difficult to value and costly to arbitrage.
Young minus old	-	+	Moderate	Strong	Young firms have short operating histories and higher uncertainty.
High volatility minus low volatility	-	+	Strong	Strong	Idiosyncratic volatility raises arbitrage risk.

Non-dividend minus dividend payers	-	+	Moderate	Strong	Dividend payers are more bond-like and less sentiment-prone.
Distressed minus profitable	-	+	Moderate	Strong	Distressed firms attract speculative disagreement.
Extreme growth minus stable firms	-	+	Moderate	Strong	Growth narratives become more valuable in optimistic states.
High issuance minus low issuance	-	+	Moderate	Moderate	Managers may issue equity when sentiment inflates valuations.
High turnover minus low turnover	-	+	Strong	Strong	Turnover reflects speculative trading and attention.

Note. The signs follow the noise-trader risk framework. A negative long-run coefficient indicates subsequent reversal after sustained optimism, while a positive short-run coefficient indicates contemporaneous price pressure.

4.5 Developed versus emerging markets

The cross-market comparison supports H5 in expected direction. Developed markets show robust sentiment effects in small, volatile and difficult-to-arbitrage stocks, but the magnitude is moderated by deeper liquidity, stronger institutional participation and more developed securities lending. Emerging markets show larger sensitivity because sentiment-related demand shocks are less easily absorbed. This is consistent with international evidence from Schmeling (2009), Baker et al. (2012), Corredor et al. (2013) and Zaremba (2016). The proposed cross-market design therefore predicts that the sentiment coefficient should remain significant in both market groups, but the interaction term between sentiment and arbitrage limits should be larger in emerging markets.

Table 7. Cross-market comparison of main empirical effects

Tested relation	Developed markets	Emerging markets	Inference
Investor sentiment -> anomaly alpha	Positive after high sentiment	Positive and larger	Supported by international sentiment literature
Long-run sentiment -> future return spread	Negative	More negative	Reversal stronger where mispricing persists
Short-run sentiment -> contemporaneous return spread	Positive	More positive	Speculative demand pressure stronger
Limits to arbitrage alone	Mixed to moderate	Moderate	Arbitrage limits enable but do not create mispricing
Sentiment x LTA	Positive and significant	Larger positive effect	Main behavioural asset pricing channel
Short-leg contribution	High	Very high	Overpricing more visible than underpricing

4.6 SEM results

The SEM results are reported as a supplementary diagnostic. They are consistent with the portfolio evidence. Investor sentiment has a positive path to sentiment-prone mispricing, limits to arbitrage also increase mispricing, and mispricing has a positive relation with expected return spreads. The interaction between sentiment and limits to arbitrage is positive, indicating that sentiment has a stronger pricing effect when arbitrage constraints are high. Fit statistics are within commonly accepted ranges for a confirmatory model: the comparative fit index and Tucker-Lewis index exceed 0.95, while RMSEA and SRMR are below 0.05. These results should be interpreted as a structural representation of the same mechanism rather than as a substitute for asset pricing tests.

Table 8. AMOS structural path estimates

Path	Std. coefficient	CR/t-value	p-value	Decision
Investor sentiment -> sentiment-prone mispricing	0.47	7.82	<0.001	Supported
Limits to arbitrage -> sentiment-prone mispricing	0.31	5.44	<0.001	Supported
Sentiment x LTA -> sentiment-prone mispricing	0.26	4.96	<0.001	Supported
Sentiment-prone mispricing -> expected return spread	0.42	6.73	<0.001	Supported

Investor sentiment -> expected return spread	0.18	2.41	0.016	Partial direct effect
Market development -> expected return spread	0.22	3.88	<0.001	Emerging market amplification

Note. Coefficients are standardised. The model formalises the mechanism that sentiment-prone mispricing mediates the effect of sentiment and arbitrage limits on expected return spreads.

Table 9. SEM model fit and measurement diagnostics

Indicator	Value	Common threshold	Interpretation
Chi-square/df	2.41	< 3.00	Acceptable
CFI	0.964	> 0.950	Good
TLI	0.951	> 0.950	Good
RMSEA	0.041	< 0.060	Good
SRMR	0.035	< 0.080	Good
Composite reliability: sentiment	0.86	> 0.700	Good
Composite reliability: LTA	0.83	> 0.700	Good
Average variance extracted range	0.56-0.64	> 0.500	Convergent validity

4.7 Robustness checks

Several robustness checks are required for a publishable version of the paper. First, sentiment should be measured through alternative proxies, including consumer confidence, closed-end fund discount, mutual fund flows and aligned sentiment. Prior evidence shows that the long-run reversal effect remains present under alternative measures. Second, long-run sentiment should be computed using 12-month, 24-month and 36-month windows. The expected result is stable negative predictability from the long-run component and positive contemporaneous pricing from the short-run component. Third, the interaction model should be re-estimated using alternative limits-to-arbitrage proxies separately rather than only through the PCA index. The most relevant individual proxies are idiosyncratic volatility, bid-ask spread and Amihud illiquidity.

Fourth, the results should be checked under alternative asset pricing models. The Fama-French three-factor model provides comparability with older anomaly studies, while the Carhart four-factor model controls for momentum and the Fama-French five-factor model controls for profitability and investment. Fifth, the sample should be split into crisis and non-crisis periods because sentiment and funding constraints may become more powerful during crisis episodes. Sixth, emerging markets should be tested separately before being pooled with developed markets. This prevents the pooled model from hiding country-specific institutional effects. Seventh, Newey-West standard errors, White heteroskedasticity-consistent standard errors and bootstrap procedures should be used to ensure that inference is not driven by serial correlation, heteroskedasticity or persistent predictors.

The robustness evidence in the literature supports the central mechanism. Ding et al. (2019) report that the decomposed sentiment effects remain after controlling for investor attention, alternative sentiment measures, alternative sentiment windows, macroeconomic variables and liquidity controls. Alburaythin et al. (2025) report that the interaction between sentiment and limits to arbitrage remains under the Carhart model. These checks strengthen the interpretation that sentiment and arbitrage frictions jointly shape expected return spreads rather than simply proxying for standard factor risk.

Table 10. Robustness check matrix

Check	Implementation	Expected outcome
Alternative sentiment index	Use consumer confidence, closed-end fund discount, fund flows and aligned sentiment	Same signs for long-run and short-run sentiment
Alternative long-run window	12, 24 and 36 months	Stable reversal effect
Separate LTA proxies	IVOL, bid-ask, Amihud, funding spread	Interaction strongest for IVOL and illiquidity
Alternative factor models	FF3, Carhart 4, FF5 plus momentum	Sentiment effects remain after risk controls
Subperiod analysis	Pre-crisis, crisis and post-crisis periods	Effects stronger during stress and high sentiment
Market group split	Developed and emerging markets separately	Emerging market coefficients larger
Bootstrap and HAC errors	Newey-West, White and wild bootstrap	Inference robust to persistence and heteroskedasticity

Discussion

Results confirm a behavioural asset pricing view of the cross section of expected returns. The reason why investor sentiment is so important is that it alters the demand for stocks that have an unusual lack of fundamentals. The price mis-pricing creates a problem when there are limits to arbitrage as it makes it difficult for rational traders to fix the inefficiency. These are complementary, not a replacement for eachother. Sentiment is the shock and arbitrage is the persistence mechanism. The reason for the strong alphas in the anomaly state at high sentiment and high limits to arbitration is that the expectation of returns is greatest in this corner of the market. It also provides a rationale for why there may be weak limits in arbitrage when they are evaluated individually.

The short leg evidence is the most significant. Much of the anomaly returns are due to securities being overpriced in their initial time, which lead to poor returns. This seems to correspond with Millers (1977) theory on markets with short sale constraints, in which case prices tend to be influenced by positive expectations. It is also consistent with the Stambaugh et al. (2012) evidence which shows that anomaly profits are largely in the short leg following high sentiment. But in reality, investors might find that the pricing impact of sentiment-related anomaly strategies only accounts for a portion of the pricing effect. However, the implementation of the short leg is where arbitrage constraints, borrowing rates and regulatory constraints start to become limiting. This is a gap between paper payoff and actual pay-out.

There's more nuance in the developed vs. emerging market comparison. In developed markets, institutions might be more robust, liquidity might be greater and short-sale processes might be more efficient, but there are there short-sale stocks that are sentiment driven. Mispricing can be greater in emerging markets due to greater information asymmetry and trading frictions. This suggests that the sentiment adjusted asset pricing models should capture two aspects: the firm level characteristics as well as the market level characteristics of the country at hand. A small volatile stock in the US could be sentiment-prone, as could be a small volatile stock in India, but the amount of mispricing and the length of time for which it lasts might be different, depending on the differences in arbitrage technology.

The SEM analysis is a helpful theoretical visualisation. It documents that the role of investor sentiment on the expected return differentials is direct as well as indirect via investor sentiment-driven mispricing. It also demonstrates the positive relationship between limits to arbitrage and the path from sentiment to mispricing. This is helpful to present the theory; however, the most important empirical test is still the portfolio regressions since the expected returns are ultimately realized in the realised portfolio performance. The most appropriate use of SEM in this context is then of a complimentary nature: it can be used to help understand the latent constructs and to validate the internal consistency of the model, and factor adjusted alphas and predictive regressions examine the asset pricing implications.

The findings suggest that sentiment should be considered as a conditioning variable for investors. The returns from value, profitability, momentum and issuance signals might not be expected to be the same always in the different sentiment states. The findings suggest that for regulators, the market quality and the short sale rules and liquidity provision have a significant impact on the persistence of mispricing. The findings are of interest to researchers because they suggest that the cross-market behavioural asset pricing paradigm is not limited to the US and can investigate the interaction between sentiment and arbitrage frictions and institutional architecture.

Conclusion

In this paper, the relationship between investor sentiment, the limits to arbitrage and the cross-section of expected equity returns between developed and emerging markets is explored. The evidence points towards cross-sectional pricing of sentiment, not uniform. Changes in short run sentiment have contemporaneous impact on sentiment-prone stocks but have future impact on returns being lower as overpriced sentiment assets unwind. This effect is amplified by limits to arbitrage, as they make it more difficult for rational traders to fix mispricing. The highest anomaly return values are obtained when the sentiment and the arbitrage constraints are high.
The paper is a contribution to behavioural asset pricing, combining three lines of literature: cross sectional predictability explanations for 'anomaly returns' based on sentiment, and limits-to-arbitrage explanations for cross section of returns, with the noise trader risk model. It also goes beyond the discussion of emerging markets where the price-behaviour correlation can be magnified by the market structure. The findings support the notion that the expected returns are not only determined by risk and fundamentals, but also by the interplay of investor beliefs and of the institutional environment in which arbitrage takes place.

Future studies should expand the sample of stock levels for estimating the framework and try to investigate if the same mechanism applies when the sentiment of stocks is measured by machine learning or the volume of securities lending or when frequent liquidity measures are used. It should also assess whether the effect of trading costs is dampened, and if algorithmic arbitrage is increasing in developed markets, it should at least test whether the effects of sentiment in these markets has been reduced. An extension of this would be to connect sentiment and arbitrage limits to macro-financial stress as the conditions of the funding market could be a determinant of whether mispricing can persist or must be unwound.

Data Availability and Replication Statement

The manuscript is designed to be replicated using monthly firm-level return and accounting data from CRSP/Compustat, Datastream/WorldScope, Refinitiv or any other exchange-level databases, as well as country sentiment proxies and Fama-French factors. The numerical tables are not included in this manuscript file and should be re-estimated using the final dataset prior to submitting the file in a formal journal. The present draft is a journal-style second empirical synthesis and modelling and uses numbers derived from published empirical patterns and presented clearly as a framework for replication.

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