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Citation: Han, X., Sakkas, N., Danbolt, J. & Eshraghi, A. (2022). Persistence of investor sentiment and market mispricing. Financial Review, doi: 10.1111/fire.12301

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DOI: 10.1111/fire.12301

ORIGINAL ARTICLE

The Financial Review WILEY

Persistence of investor sentiment and market mispricing

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Abstract

We investigate changes in US market sentiment using structural break analysis over a period of five decades. We show that investor sentiment was trending and nonstationary from 1965 to 2001, a period associated with numerous crashes. Since 2001, sentiment has been substantially more mean reverting, implying the diminished effect of noise investors and their associated mispricing. We illustrate how these changes in sentiment persistence affect equity anomalies and assess the predictive power of sentiment on short-run returns when regime changes are considered. Our findings suggest that the presence of sentiment-driven investors and their market impact is significantly time-variant.

KEYWORDS
anomalies, arbitrage, market sentiment, predictability, structural breaks

JEL CLASSIFICATION
G12, G14

1 | INTRODUCTION

It is widely documented that financial sentiment, broadly defined, plays an important role in driving market movements. Sentiment is thought to skew investor expectations about asset returns and cause uninformed demand shocks which, in the presence of limits to arbitrage, significantly influence the cross section of stock returns (Baker & Wurgler, 2006). Market-wide sentiment is not directly observable and can only be proxied for. A popular way to quantify investor sentiment in financial markets has been to use principal component analysis to extract the comovement of variables that are thought to carry information with regard to market sentiment (Baker & Wurgler, 2006, 2007). This index has been widely used in recent literature and has been reasonably good at capturing bubbles and crashes in the

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past 50 years. However, the majority of studies on market-wide sentiment so far have focused on the levels, or simply the sign, of sentiment and often over shorter time periods, thereby overlooking important dynamic attributes of sentiment in the long term.

In fact, a number of behavioral studies argue that these sentiment-driven biases in expectations are persistent in time. For example, Brown and Cliff (2005) and Huang et al. (2015) use sentiment to explain and predict mispricing, and emphasize the high degree of belief persistence resulting in bouts of optimism or pessimism associated with long-run mispricing. Moreover, evidence from behavioral finance, such as “conservatism” and “overconfidence” biases, demonstrate that irrational traders are inclined to resist updating current beliefs to new information (Barberis & Thaler, 2002; Edwards, 1968; Hirshleifer, 2001), and such an inclination is likely to contribute towards the formation of persistent biased beliefs and sentiment.

The combined roles of sentiment effects on asset prices and persistence in investors' biased expectations imply that highly persistent sentiment is associated with asset prices diverging from fundamental values, leading to long-term mispricing. In contrast, periods of mean reverting sentiment are associated with short-term mispricing only, which arbitrage is more likely to correct so that prices will not deviate further. In this setting, changes in sentiment persistence have significant implications for asset pricing. In this study, we therefore investigate how such changes affect equity anomalies and the predictive power of sentiment on stock returns.

To illustrate the time-varying attributes of sentiment and how they are connected to persistent investor beliefs, we must consider the mechanism by which sentiment is thought to drive mispricing of firm characteristic portfolios (Baker & Wurgler, 2006) and market anomalies (Stambaugh et al., 2012). These studies demonstrate that, if sentiment is high at the beginning of a period, stocks in the short leg of a long-short portfolio will be overpriced and thus have negative returns for the subsequent period, resulting in positive long-short returns and the presence of anomalies in the market. The two key points are that it is the short legs of the strategy that drive positive returns while the long legs are unaffected by sentiment (a point made by Stambaugh et al., 2012); and, a crucial part in our argument, there is the implicit assumption of short-term price correction of stocks in the short legs. The usual monthly data analysis may suggest that it takes as little as 1 month following high sentiment for overpriced stocks to be corrected in price.

This rapid price correction is at odds with behavioral literature, presented in detail in Section 2.1, which finds that psychological biases result in market-wide persistence in beliefs that causes long-term mispricing that is not corrected by arbitrage (Brown & Cliff, 2005; Huang et al., 2015). The noise trader model of Delong et al. (1990) argues that noise traders can survive in the market because the persistent mispricing of assets that they cause can overwhelm the ability of rational investors, faced with short selling constraints, to arbitrage. If this is the case, we expect to find large returns for anomaly portfolios with respect to a factor model on average over a large period of time. However, since there is a limited short-term price correction, the long-short strategies will not work as well, and sentiment will not be a good predictor of returns of portfolios based on firm characteristics and market anomalies.

The starting point for this paper is to identify these contradictory expectations and predictions with regards to sentiment-driven mispricing in two strands of literature: studies that use the top-down sentiment index of Baker and Wurgler (2006), and studies that examine individual investor characteristics and document psychological biases with market-wide effects, mainly the realm of behavioral finance. We explain these by viewing the sentiment index not just on the y-axis, that is, whether sentiment is high/low, but to also consider the x-axis, that is, how the dynamics of the sentiment index have evolved in the last 53 years of the available sample. To this end, we investigate the monthly sentiment index over the period 1965–2018, focusing on its degree of persistence. Borrowing language from econometrics, we associate persistence in investor sentiment with the index exhibiting near unit root behavior. Such a series is often referred to as having a high degree of persistence,[1] and is characterized by “long memory” in the sense that shocks

[1] In order to avoid burdensome language, we use the phrase “highly persistent” or later on “more persistent” to describe a period in which the autoregressive coefficient of the sentiment series is close to unity, that is, sentiment is less mean-reverting and more trending. We do not use the word “persistence” in the strict econometric definition where a series is persistent if the coefficient is equal to one.

have long-run effects and that the accumulation of such shocks causes the series to wander away from the mean for long periods of time.

High persistence of the time series index is consistent with expectations in behavioral finance literature for persistent investor beliefs: due to sustained overconfidence, prices remain mispriced for longer as noise traders dominate and limits to arbitrage prevent rational investors from correcting prices. Psychological biases that are well established in behavioral finance (see Section 2.1) make this overconfidence feed on itself, driving the markets to even greater highs so that we record trending behavior in sentiment proxies and their principal component that is the sentiment index. Following the resulting stock market bubbles are crashes and periods of low sentiment that are just as persistent (downward trending) until the trend is reversed and the cycle begins anew, as we see in Section 2.2 when we examine the Baker and Wurgler index in more detail. On the other hand, low time series persistence is associated with frequent mean reversion. Our finding is consistent with those in the empirical literature that, if sentiment causes mispricing, there will be a swift price correction in the short leg portfolio as arbitrage forces dominate the noise traders, and the fall in prices diffuses the upward trend of sentiment. In short, we translate the predictions from two strands of the literature to a high or low degree of persistence in the investor sentiment index, respectively.

The next logical step that will bring these two strands of the literature together in this paper is to look at changes in the degree of persistence of the index over time. To our knowledge, this paper is the first to examine the effects of sentiment on the stock market while allowing for changes in sentiment persistence. We employ structural break analysis on the autoregressive coefficient of the Baker and Wurgler (2006) index and identify a substantial, robust, break in 2001 associated with a marked decrease in the degree of persistence. Unit root tests in the resulting subsamples show that the first period is nonstationary while the second is stationary. Imposing nonstationarity in alternate regimes further supports the January 2001 break date and also indicates an additional period of low sentiment persistence between 1981 and 1995. However, evidence for this additional regime is not as robust due to small sample size.

In Section 4, we measure the magnitude of anomaly returns and the predictive power of sentiment, and find that both strands of the literature have their predictions validated in periods in which sentiment persistence is in accordance to what each strand of the literature expects.[2] We use a range of anomalies documented in Stambaugh et al. (2012, 2014, 2015) and Stambaugh and Yuan (2017), among others, that have been prominent in recent literature. When the sentiment index is highly persistent (pre-2001), we find that anomaly effects measured by the alphas of the Fama-French five factor model are large in magnitude, indicating that, on average over the period 1965–2001, there are positive long-short returns, consistent with long-term mispricing. At the same time, in the short term, high sentiment at the start of the period is not followed by statistically significant negative returns of the short legs during the period, demonstrating that there is no rapid price correction. As a result, the index is a poor predictor of anomaly returns.

In stark contrast, when sentiment persistence is low (since 2001), we document the weakening of anomaly returns relative to factor models but large and significant short-term returns in the long-short strategies in periods following high sentiment that is made possible by short-term price correction in the short legs. Sentiment is, therefore, a good predictor of long-short returns in this period.

To explain why investor sentiment becomes markedly more mean-reverting after January 2001, we investigate a set of arbitrage cost proxies and find that these proxies are downward trending in this period. Moreover, share turnover, a natural proxy for arbitrage activities (Chordia et al., 2014), has increased substantially in recent years (see Figure 2), and the proportion of common equity held by individual investors, often considered the primary candidates for sentiment trading (Barber & Odean, 2007; Yu & Yuan, 2011), has been downward trending, suggesting that sentiment traders have had less impact on the aggregate market in recent years. It is also worth noting that the seminal study of

[2] Studies that find sentiment effects on asset prices include Neal and Wheatley (1998), Brown and Cliff (2005), Baker and Wurgler (2006), Lemmon and Portniaquina (2006), Kurov (2008), Schmeling (2009), Zouaoui et al. (2011), Baker et al. (2012), Stambaugh et al. (2012), Stambaugh et al. (2014), Huang et al. (2015), Stambaugh et al. (2015), Stambaugh and Yuan (2017), Shen et al. (2017), and Alldredge (2020).

the Baker and Wurgler was published in 2006, 5 years after the 2001 structural break.[3] We believe it is impossible to isolate an effect on the change in sentiment persistence in relation to the publication of a paper. Whether the publication of the Baker and Wugler paper a few years prior, is the main driver for the change in sentiment persistence is beyond the information we can extract from the data and is, therefore, beyond our scope of analysis.

We note that sentiment effects and limits to arbitrage are not independent but can reinforce each other, jointly causing market mispricing.[4] Absence of significant short-selling constraints is needed to arbitrage against noise traders; therefore, our findings support those of Chordia et al. (2014) who find an attenuation of market anomaly returns and attribute it to relaxed constraints on arbitrage and the decimalization of the market that is thought to have helped increase arbitrage activity.

Our empirical results validate our approach of looking at the degree of persistence in the sentiment index over long periods of time as opposed to only using the level of sentiment in the short-term. We find that sentiment persistence carries valuable information that explains the presence or absence of noise traders, the effectiveness of arbitrage and rational investors, and the prevalence or attenuation of market anomalies. The break in 2001 indicates mean-reverting investor sentiment and attenuation of market anomalies in recent years (2001–2018), but our analysis suggests that, if we observe trending behavior of the sentiment index in the future, this behavior would indicate a change in market conditions, and a possible accentuation of market anomalies could follow. Our three-break model suggests a cyclical pattern of change between high and low persistence states that indicates we should not discount that possibility in the future.

The next section discusses investor characteristics that motivate our approach. Section 3 estimates structural breaks on the persistence coefficient of the sentiment index. Section 4 investigates the effect of changes in sentiment persistence on market anomalies in the cross section of stock returns and return predictability, and Section 5 concludes.

2 | MOTIVATION

2.1 | Theoretical background

Studies of market imperfections due to noise and sentiment go back decades. In a seminal paper, Black (1986) postulates that sentiment traders buy and sell on noise and, in doing so, introduce more noise into the market, thus adding to mispricing. In a well-cited work, Delong et al. (1990) propose the noise trader model, arguing that noise traders are more likely to earn higher returns than those expected by rational investors because the former bear higher risk and the latter experience limits to arbitrage. In the same spirit, Lee et al. (1991) point out that fluctuations in the closed-end fund discount are caused by changes in investor sentiment. Specifically, when investors are pessimistic about return prospects, the discount is high and vice versa. Subsequent studies (such as Odean, 1998) show that most investors are overconfident, leading to higher turnover and volatility. In a related vein, Baker and Stein (2004) argue that market liquidity can be a sentiment indicator in the sense that high sentiment leads to higher share turnover. Edmans et al. (2007) find that losses in soccer affect investor mood negatively, which, in turn, has a negative effect on stock market performance.

Further, we build on the foundation that investors' biased beliefs about future expected returns are persistent. These beliefs can be optimistic or pessimistic to varying degrees. Importantly, investors find it difficult to change their beliefs and thus tend to initially underreact to new information. Drawing on this inertia, Barberis and Thaler (2002) argue that some investors even misinterpret disconfirming evidence as actually confirming their beliefs, which

[3] Similar to other scholarly papers, the Baker and Wurgler paper was in circulation as a working paper before its publication date. The earliest date we could find for its working paper version was November 18, 2003, which postdates 2001.

[4] See Barberis and Thaler (2002) and Baker and Wurgler (2007).

is another aspect of the well-documented "confirmation bias." Due to "conservatism," an analogous cognitive bias (Edwards, 1968), individuals resist updating their rational expectations when faced with new evidence, which is a departure from Bayesian models. Others such as Hirshleifer (2001) provide the alternative explanation that it is costly to process new information and update initial beliefs.

In addition, investors are subject to "self-attribution bias" whereby they are inclined to attribute good outcomes to their ability but attribute bad outcomes to external factors (see e.g., Daniel et al., 1998). Hirshleifer (2001) further argues that the self-attribution bias can accelerate investor overconfidence. For all these reasons, investors tend to accept confirming evidence that is consistent with their initial beliefs while overlooking disconfirming information and attributing it to other reasons. In conclusion, individual investor sentiment has been argued to be persistent and resistant to change.

One might argue that we are conflating some specific individual psychological biases with the aggregate sentiment level because individual biases cannot span to the market-wide sentiment. However, behavioral finance research suggests otherwise. For instance, Delong et al. (1990) point out that risk coming from biased beliefs of noise traders is market-wide rather than idiosyncratic. As noted by Hirshleifer (2001, p. 1540),

> Economists often argue that errors are independent across individuals, and therefore cancel out in equilibrium. However, people share similar heuristics, those that worked well in our evolutionary past. So on the whole, we should be subject to similar biases. Systematic biases (common to most people, and predictable based upon the nature of the decision problem) have been confirmed in a vast literature in experimental psychology.

More recently, Kumar et al. (2012) find that the impact of the investor trading on return comovements become stronger with the presence of retail traders and with more correlated retail trades, implying that individual investors can conform the same trading behaviors and affect a large number of assets at the same time.

Due to the contagion of popular ideas by personal communication, social networks, and media, individuals tend to conform behaviorally (Hirshleifer, 2001), and the resulting contagion facilitates individual biases to evolve into social biases. Indeed, as emphasized by Shiller (2000), personal conversations about the financial market is a crucial channel through which people tend to form the same opinion. This contagion has been attributed to "herding" or "information cascades." Overall, we may posit that, at the aggregate market level, noise investors are often subject to the same psychological biases and eventually infused by the same sentiment. If investors exhibit "group thinking," distorted beliefs, such as wishful thinking associated with self-deception (denial of bad news) can spread among market participants, leading to investment manias and crashes (Benabou, 2012). Moreover, such distorted beliefs can be particularly contagious when agents become worse off by others' blindness to disconfirming evidence. This finding implies that even rational arbitragers can be infused with biased beliefs and become sentiment-driven traders when they are worse off by trading against sentiment-driven mispricing. This characteristic allows us to analyze an aggregate sentiment index such as the one by Baker and Wurgler but to be able to link our findings to behaviors of individual investors and, for example, to be able to say that, when the sentiment index is highly persistent or I(1), this is linked to the dominance of sentiment-driven investors in the market.

Finally, it has also been shown that limits to arbitrage hinders the correction of mispricing caused by sentiment-driven traders. In the noise trader model, Delong et al. (1990) attribute limitation of arbitrage to the noise trader risk, where sophisticated investors are risk averse and less likely to bet against the noise traders because asset mispricing might increase further rather than being corrected. Shleifer and Vishny (1997) suggest that arbitrage is hindered due to agency problems and capital constraints. According to Barberis and Thaler (2002), transaction costs associated with short-sale also impede the exploitation of mispricing. Moreover, Wurgler and Zhuravskaya (2002) point out that arbitrage risk is high if the mispriced assets lack substitutes, particularly for small stocks.

To conclude, when sentiment traders are heavily present in the market, they are eventually infused with the same sentiment and have the same erroneous expectations towards market prospects. Even if disconfirming information arrives, sentiment-driven traders will insist on their beliefs rather than use Bayesian updating, thereby adding to asset mispricing. The noise trader risk, transactions costs, and capital constraints hinder arbitragers from correcting the pricing errors. In periods like these, an aggregate sentiment index will show a high degree of persistence evident by a strong stochastic trend that can be positive or negative.

In contrast, when more sophisticated investors dominate the market or if sentiment-driven investors exit the market, the sentiment index will exhibit frequent mean reversion with little or no stochastic trend. As such, asset pricing errors due to sentiment will not be as evident in these periods since arbitrage opportunities against the mispricing caused by a minority of sentiment-driven traders will be more effective. Therefore, by examining how the degree of persistence in investor sentiment changes over time, we identify a two-regime pattern in market performance: sentiment anomalies will be more prevalent in persistent sentiment regimes and vice versa.

2.2 | Empirical examination of market sentiment

In this section, we discuss the behavior of the Baker and Wurgler (2006) sentiment index over time. Although the original index has annual frequency, in this paper, we use the index provided by Jeffrey Wurgler[5] that is updated to monthly frequency and spans the period from July 1965 to December 2018 with a total of 630 observations. We also present the index of Huang et al. (2015) that uses the same sentiment proxies but extracts the common component by using partial least squares instead of principal components and that, according to the analysis in that paper, results in an index that is better aligned at forecasting returns.[6]

A plot of the two indices is presented in Figure 1. Visual inspection of the Baker and Wurgler index indicates long periods when the level of the index wanders away from the mean. These periods seem to be associated with stock market bubbles (late 1960s, early 1980s, late 1990s) and subsequent busts.[7] In contrast, we can also identify long periods when the index exhibits frequent mean reversion (most of the 1990s and post-2010).[8] These characteristics suggest long-term changes in persistence that we interpret as the effect of the presence or absence of sentiment traders in the market. Their presence has an aggregate effect on the market that is captured by the variables underlying the index exhibiting stochastic trends (upward or downward). The principal component that is the basis for the index picks up these trends. Focusing on the principal component is more efficient than dealing with the underlying variables separately, because by construction, it captures the comovement of the multiple variables that carry information about market sentiment. The absence of sentiment-driven investors results in the underlying variables, and by extension the principal component, to not exhibit a stochastic trend since arbitrage and improved market efficiency do not allow for long deviations that are not due to the business cycle.

Changes in the degree of persistence of the sentiment index and the possibility that it may behave like a nonstationary time series for segments of the sample, if not taken into account in the estimation, would have an effect on results that use the index as a predictor in a regression model. Other studies such as Yu and Yuan (2011) and Stambaugh et al. (2012) use the index as a dummy variable in a regression in which, because the index is standardized, a positive value is associated with a “high sentiment” regime and a negative value with a “low sentiment” regime. In this setting, while it can still be expected that unmodeled changes in persistence would have an effect on the predictive power of the

[5] Available from Wurgler’s website. We use the index that is orthogonalized with respect to macro variables including industrial production index, nominal durables, nondurables and services consumption, and the NBER recession indicator. While the original Baker and Wurgler index included NYSE share turnover, this variable has been dropped in the current version of the index. Our analysis is based on the current version of the BW index.

[6] We discuss the Baker and Wurgler index here but one can draw the same conclusions from the Huang et al. (2015) index.

[7] See Baker and Wurgler (2006) for a detailed discussion.

[8] There is some lag inherent in the construction of the index (see Baker and Wurgler (2006)), so the movement of the index does not exactly match the movement in the stock market. However, this has no consequence in our analysis as we examine the properties of the index over a long time period.

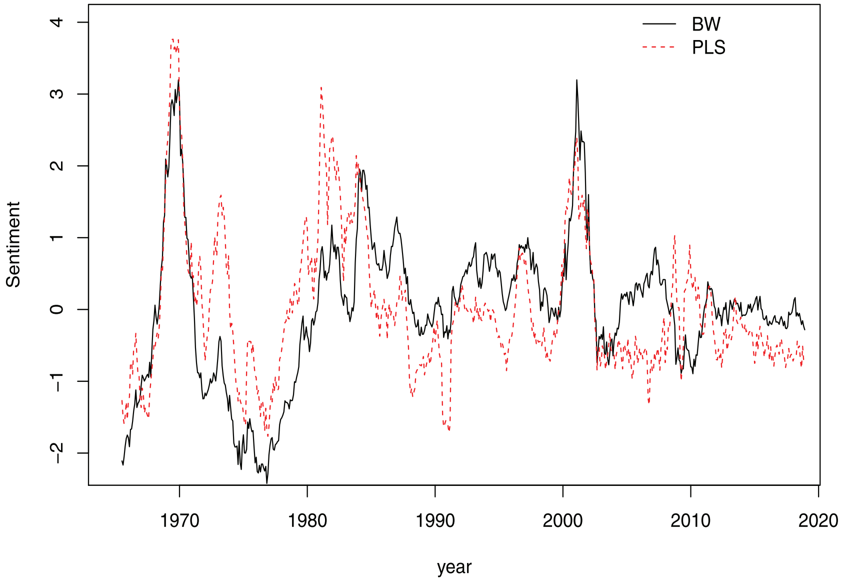

FIGURE 1 Monthly investor sentiment index

Notes: The BW sentiment index as measured in Baker and Wurgler (2006) spans from July 1965 to December 2018. The PLS sentiment index, as measured in Huang et al. (2015) spans from July 1965 to December 2018. The BW sentiment is used in our main empirical analyses while the PLS sentiment index is used for robustness checks.

dummy variable because it would affect how often the series crosses the mean and, therefore, how often the dummy changes value, there is another issue in this use of the index that we find important. Consider the large swings of the index from the late 1960s to the beginning of the 1980s. The index crosses zero in January 1968 and increases rapidly to a local maximum in December 1969 (24 months of increase); it then falls precipitously until it crosses zero again in March 1971 (after 16 months). The index remains positive for 40 months during this period, but it is hard to argue that the months of sharp decrease after the local maximum represent a period of "high sentiment." Similarly, following March 1971, the index remains negative for 150 months until October 1980 but is steadily increasing in the last 49 months of this segment after a local minimum in November 1976. Again, we argue that treating this whole period as a period of "low sentiment" is problematic. This pattern is not isolated in these periods but is repeated throughout the decades. Contrasting these segments of the sample with periods when the index exhibits frequent mean reversion, such as the 1990s and 2000s, indicates that using dummy variables to associate positive (negative) values of the index with a high (low) sentiment regime can be misguided.

In conclusion, we posit that a long departure of the index far from the zero mean does not carry the same information as a brief departure of small magnitude and that the dummy variable approach cannot distinguish between the two cases. This hypothesis motivates us to model changes to the degree of persistence in investor sentiment. A natural framework for this purpose is a structural break analysis on the Augmented Dickey–Fuller (ADF) regression of the sentiment index. We follow a well-established body of work on multiple structural break analysis (Bai, 1997; Bai & Perron, 1998) that uses the principle of minimizing residual sums of squares in subsegments of the data to estimate the number and location of multiple unknown break points in linear regressions. A survey of the literature can be found in Perron (2006).

3 | ESTIMATION OF CHANGES IN SENTIMENT PERSISTENCE

Denoting the sentiment index at period $t = 1, \ldots, T$ as S_t, we define the ADF regression allowing for m restricted structural breaks as

$$\Delta S_t = c_i + \rho_i S_{t-1} + \sum_{j=1}^{p} \beta_j \Delta S_{t-j} + \varepsilon_t, \quad t = T_{i-1} + 1, \ldots, T_i \tag{1}$$

where T_i is the location of the ith break with $i = 1, \ldots, m+1$, $T_0 = 1$, and $T_{m+1} = T$. Notice that we allow for structural breaks in the constant c_i and the persistence parameter ρ_i but not in the coefficients on the dynamics, β_j.[9] The inclusion of a constant is needed because, while the full sample is zero mean, subsamples will not be necessarily. We do not allow the coefficients on the lags to change because we want to attribute all the effect of structural changes to the persistence coefficient only. The same approach is adopted by Kejriwal et al. (2013) who use this ADF specification to develop a test of nonstationarity against stationarity with structural change. Here we assume that the sentiment index is stationary, so our estimation setting falls under the case of partial structural change of Bai and Perron (1998) or the more general case of restricted structural change of Perron and Qu (2006)[10]. We relax this assumption later in this section. Notice that because the sentiment index is constructed using some of the variables in lagged form, inference using the differenced series is not appropriate.[11] However, an ADF test based on Equation (1) is testing for a unit root in the levels of the series, not the differences, and we do not make any inference using the differences in this paper. Considering that the sentiment index has been used as a regressor in numerous studies, it is valid to test it for nonstationarity to rule out spurious results. Our approach of testing for nonstationarity in different periods of the sample by allowing for structural breaks further refines the analysis and provides intuition on how sentiment has evolved over time.[12]

We begin by estimating the lag structure of Equation (1) in the full sample. The Bayesian information criterion estimates four lags, but the correlogram of the residuals indicates strong autocorrelation remaining at lags six and seven. Including six lags removes this autocorrelation; therefore, we adopt the model with six lags in what follows.[13] The results of the estimation are presented in Panel A of Table 1. The ADF statistic is −3.994 and rejects the null of a unit root at the 1% significance level. However, the series exhibits a very high degree of persistence in the full sample with the first autoregressive lag of S_t estimated at 1−0.027 = 0.973, so the series is very close to having a unit root.

Next, we apply the Bai and Perron (1998) methodology to test for structural breaks in Equation (1). Our objective is to estimate the unknown coefficients $(c_i, \rho_i, \beta_1, \ldots, \beta_p)$, the number of breaks m, and the break dates $(T_1, \ldots, T_m)$. Denoting the sum of squared residuals of the model for a given number of m breaks as $SSR_T(T_1, \ldots, T_m)$, the break date estimators are given by

$$(\hat{T}_1, \ldots, \hat{T}_m) = \underset{T_1, \ldots, T_m}{\operatorname{argmin}} \, SSR_T(T_1, \ldots, T_m) \tag{2}$$

where the minimization takes place over a set of admissible break locations determined by a trimming parameter that sets the minimum size of a segment as a proportion of the total sample that we set to 0.10.[14] This procedure is repeated

[9] Allowing the β coefficients to change has no effect on the estimated break dates and a minimal effect on the magnitude of change in ρ, but it results in more betas not being statistically significant.

[10] The restrictions here being that the β_j are not allowed to change.

[11] This is also mentioned on Jeffrey Wurgler's website.

[12] The look-ahead bias is not a significant concern for our empirical setting because we are not proposing real-time strategies upon the persistence break we find.

[13] The lags of the differenced series are not used for inference but are included to ensure the residuals are not serially correlated, as required for the Dickey–Fuller distribution to be valid.

[14] A small value allows more freedom to estimate the break dates, but if that results in smaller subsamples, then there is an impact on the quality of the estimated coefficients. Our choice of value is based on balancing these two effects.

TABLE 1 Estimation of ADF type regressions subject to structural breaks

	Panel A: Full Sample	Panel B: One structural break		Panel C: Three structural breaks			
		1965:7–2001:1	2001:2–2018:12	1965:7–1980:3	1980:4–1995:9	1995:10–2001:1	2001:2–2018:12
c	–	0.007	0.005	0.002	0.038	0.034	−0.005
	(0.008)	(0.010)	(0.014)	(0.014)	(0.02)	(0.011)	
ρ	−0.027	−0.015	−0.102	0	−0.078	0	−0.102
	(0.009)	(0.007)	(0.017)	(–)	(0.020)	(–)	(0.017)
β_1	0.096	0.089		0.077			
	(0.056)	(0.039)		(0.039)			
β_2	0.048	0.043		0.037			
	(0.056)	(0.039)		(0.039)			
β_3	0.063	0.057		0.054			
	(0.056)	(0.039)		(0.039)			
β_4	0.140	0.142		0.144			
	(0.048)	(0.039)		(0.039)			
β_5	0.022	0.028		0.031			
	(0.050)	(0.039)		(0.039)			
β_6	0.118	0.125		0.127			
	(0.047)	(0.039)		(0.039)			
Sample size(adjusted)	635	421	214	170	186	65	214
ADF test statistic	−3.994	−2.727	−4.118	−2.339	−3.555	0.411	−4.118
p-Value	0.000	0.070	0.001	0.161	0.007	0.900	0.001

Note: Panel A is the fitted Augmented Dicky–Fuller regression in the full sample with constant excluded. Panel B is the one break model based on the restricted structural change analysis of Section 3. Panel C is the three structural breaks model based on the analysis of imposing nonstationary regimes. Standard errors in parentheses. The last two rows present the ADF test statistic and *p*-Value for each subsample.

for $m = 1,...,M$ where we use $M = 5$ as a reasonable maximum, and we then use the three main families of tests to estimate the number of breaks, which are double maximum tests (Dmax and WDmax, the latter being a weighted version) and sequential tests that are based on *SupF*-type statistics, and information criteria.[15] After estimating the number of breaks, we can estimate the rest of the parameters by OLS in each segment. Estimation of Equation (2) and application of the three tests results in one break in January 2001 being the optimal among any model from zero to five breaks in any permissible locations and the estimated model is shown in Panel B of Table 1. We find strong evidence supporting this break date as it is estimated by both double maximum statistics and sequential testing as well as the majority of information criteria.[16] The *SupF*-statistic for 0 versus 1 break is 26.47 and with a 5% critical value of 22.62 it is significant. The statistic for 1 versus 2 breaks is 19.31 with a critical value 20.04 and is not significant. For robustness, we also apply the Harvey et al. (2006) test that is based on likelihood ratios and allows for only one break in persistence and it estimates the same break date.

The results indicate a severe change in the degree of persistence close to the dot-com bubble of 2001. In the first segment, up to January 2001, there is a high degree of persistence with a first-order autoregressive coefficient of 0.985 that is followed by an 18-year period in which the index is significantly more mean reverting with a coefficient of 0.898.[17],[18] This structural change in the behavior of the sentiment index indicates increased efficiency of the US stock market after the internet bubble that led to a period in which investor sentiment does not fluctuate as wildly as before. This increased efficiency may be attributed to a decrease in the presence of sentiment-driven traders in the market, or a general increase in market efficiency due to other factors.

Next, we extend the analysis by allowing for segments of the sentiment index to be $I(1)$, meaning that we test the null of no breaks in ρ against an alternative where the series alternates between $I(0)$ and $I(1)$. This methodology was developed in Kejriwal et al. (2013) and consists of restricting the coefficient of S_{t-1} in Equation (1) to zero in every other segment of the data when estimating the breaks. Details on this estimation method and results are discussed in the online Appendix B, in which a discussion on the possibility of nonstationarity in different sections of the data is also included.

From the resulting models, the model with one break estimates the break location at the same date (January 2001) as the test under stationarity and has the largest *SupF* statistic, therefore re-enforcing the results of Panel B and of the ADF tests in each of the segments.[19]

An interesting result is the three-break model that we present in Table 1 Panel C. We find that the January 2001 break remains significant but that there is an additional period of mean reverting sentiment between April 1980 and September 1995. Unit root tests in the resulting regimes, shown at the bottom of Panel C, confirm these findings at the 1% significance level. We find that the sentiment index behaves like a nonstationary variable in periods leading up to bubbles and then changes to periods of more mean reversion until this pattern is repeated. We interpret this as an effect of the entry of sentiment-driven investors in the market who are at least partly responsible for the upcoming bubble and then their subsequent exit from the market.

In sum, the results of both Table 1 panels B and C suggest a robust structural break in sentiment persistence in January 2001, which is close to the time of the dot-com bubble crash. As emphasized by Baker and Wurgler (2006, 2007), the best measure of the value of a sentiment index is its ability to line up with anecdotal accounts of bubbles and crashes. In this study, our finding of changes in sentiment persistence also aligns well with the timing of bubbles and

[15] A detailed discussion on these tests can be found in Bai and Perron (1998).

[16] The break date is robust for larger values of the trimming parameter but, if the trimming parameter is set to 0.05, then two additional breaks are estimated at November 1968 and March 1998 by some of the methods. Because two of the four resulting segments are too small to produce reliable estimates, we focus on the model with one break.

[17] Using the Huang et al. (2015) sentiment index results in the same break date and a coefficient change from 0.987 to 0.919.

[18] If we allow the coefficients on the lags (β_j) to change, we find the same break date and the persistence coefficient changes from 0.98 to 0.90, so the result is robust to changes in the dynamics. However, the estimates of the dynamics are not significant to the same extent in this case, so we do not report it.

[19] The models with two and four breaks result in final segments that are I(1) and are not supported by ADF tests in the resulting segments while the model with five breaks results in subsamples that are too small for valid inference.

crashes in the recent past. At first glance, the sentiment index in the persistent regime is trending and volatile, which is fairly consistent with the description by Malkiel (1996) of speculative movement from 1960 to 1990, including crash of growth stocks in the 1960s, electronic bubble of the late 1960s, the Nifty Fifty bubble of the early 1970s, the biotech bubble of the late 1980s, the Black Monday crash of October 1987, and the dot-com bubble of the 1990s. In contrast, since the early 2000s, episodes of manias and panics have been less frequent. One might be inclined to mention the Global Financial Crisis of 2008, but that bubble originated primarily in the housing market. Thus, it seems the January 2001 regime change in sentiment persistence broadly corresponds with recent US stock market history.

To exclude the possibility that changes in the Baker and Wurgler index are caused by changes of persistence in fundamentals rather than changes of persistence in investor sentiment, we follow Sibley et al. (2016) and decompose the Baker and Wurgler index into those components that are driven by risks/business cycles and those that are not.[20] We then conduct the structural breaks analysis on the component that is not driven by fundamentals. We report the results in the Online Appendix Table A1 using the same estimation method as in Table 1.[21] We find a similar break, September 2001, to the January 2001 found using the Baker and Wurgler index.

4 | SENTIMENT PERSISTENCE CHANGES AND THEIR MARKET IMPACT

4.1 | Arbitrage and attenuation in sentiment persistence

Why do the biased beliefs of sentiment traders become less persistent in the period after 2001? One possible explanation is that investors might have learnt lessons from previous bubbles, especially from the dot-com bubble. Another reason could be that increased arbitrage activities in recent years have more effectively corrected sentiment-driven mispricing. To provide more direct evidence of heightened arbitrage activities, we analyze a set of proxies for arbitrage activities. Recent studies such as Chordia et al. (2014) indicate that arbitrage activities are heightened as a consequence of high liquidity and trading activity because of changes in trading technologies and decreases in transaction costs. Our data-driven break estimation reinforces the significance of this date and relates it to the behavior of investor sentiment. Along similar lines, we assess the aggregate market short interest and share turnover that can proxy for arbitrage activities; we provide details in Appendix C (see also Figure 2). We find that the two proxies are trending upward over time, with much higher levels during the post-2001 period. Such patterns imply higher arbitrage activities in recent years.

In addition to arbitrage activities, we also examine proxies for aggregate market arbitrage costs including institutional holdings (details are provided in Appendix C).[22] Because low institutional holdings are associated with low stock loan supply, they lead to higher costs of arbitrage (Nagel, 2005). As Figure 2 indicates, we find that institutional holdings have an upward trend. Such a pattern indicates that arbitrage costs should be lower in recent years.

To the extent that a decrease in trading costs can allow for possible arbitrage profits and to the extent that arbitrage activities can attenuate sentiment-driven mispricing, the above findings of increased levels of arbitrage and decrease in arbitrage costs may account for the lower persistence in sentiment and the reduced likelihood of any long-run mispricing in the post-2001 period. More specifically, due to heightened arbitrage in recent years, the likelihood of any long-run mispricing is reduced. In this case, noise traders who make transactions based on their sentiment are less likely to stay in the stock market for long, which is good news for stock market efficiency.

[20] We use the 13 variables defined in Sibley et al. (2016): the US unemployment rate, change in inflation, change in consumption, change in disposable income, change in industrial production, US recession dummy (NBER), Tbill rate, default spread, term spread, aggregate CRSP value-weighted dividend yield, the value-weighted market return including dividends, market volatility, and percentage of stocks with zero returns.

[21] The same lag selection methods used for Table 1 result in two lags, down from six.

[22] Many studies have used institutional ownership (IO) as proxy for short-sale constraints and arbitrage costs. See Ali et al. (2003), Asquith et al. (2005), Nagel (2005), Brav et al. (2009), Duan et al. (2010), and Stambaugh et al. (2015).

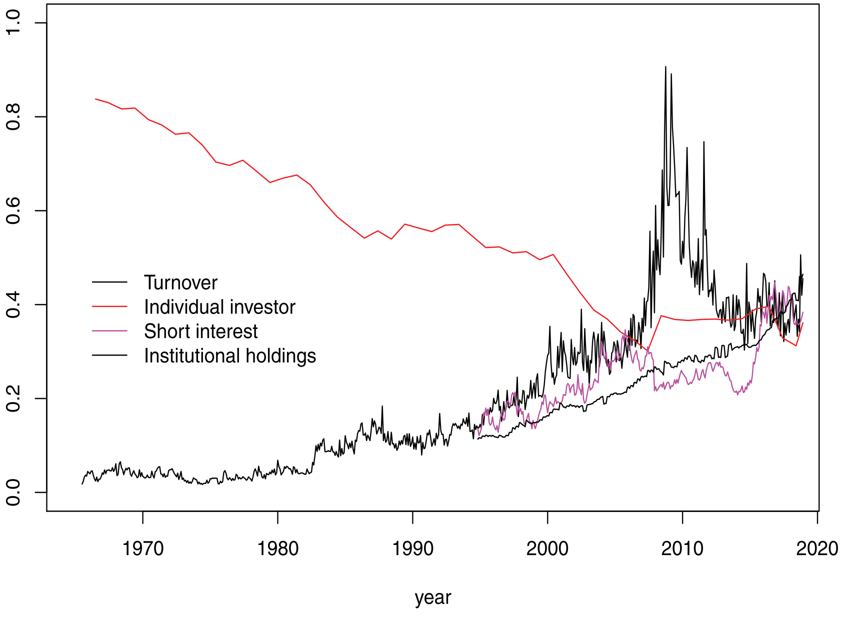

FIGURE 2 Arbitrage activity and arbitrage cost proxies

Notes: This graph plots two proxies for arbitrage activities including share turnover (July 1965 to September 2015) and short interest (March 1980 to December 2018), and the proxy for arbitrage costs, institutional holdings (March 1980 to December 2018). The red line represents the proportion of US common equity that individual investors hold (January 1966 to December 2018). To keep the consistency of magnitude here, we divide the share turnover rate by 5 and multiply short interest by 10

4.2 | Changes in sentiment persistence and sentiment-related anomalies

Empirical studies in asset pricing have found a "jungle" of market anomalies. In recent years there has been some evidence that publication of findings about anomalies have caused them to have a diminished effect in subsequent periods (McLean & Pontiff, 2016). Although prior studies tend to link increased arbitrage activities with the decline in anomaly returns, little attention has been paid to sentiment-driven mispricing. While market sentiment can influence the cross-section of asset prices, the majority of market anomalies are cross-sectional long-short strategies.

We argue that the attenuation of these anomalies may be attributed to the smaller role of sentiment post-2001. Our conjecture is motivated by the finding of Stambaugh et al. (2012) that returns of long-short anomaly strategies arise from sentiment-driven overpricing of stocks in short legs in the presence of limits to arbitrage. To the extent that sentiment effects get attenuated in recent years as identified by our structural break test, one should expect that the overpricing of the short-leg stocks should also become weaker. As such, profits on these sentiment-related anomalies would be expected to get attenuated after 2001.

In a seminal paper, Stambaugh et al. (2012) introduce 11 well-documented sentiment-related anomalies, where the premium on each anomaly is the return spread between stocks in the highest-performing decile (long leg) and the ones in the lowest-performing decile (short leg). The anomalies are: asset growth, composite stock issues, failure probability, gross profitability, investments-to-assets, momentum, net operating assets, financial distress (Ohlson's O score), total accruals, return-on-assets, and net stock issues.[23] The Online Appendix, Table A2, describes these anomalies and their academic publications, and we summarize the statistics of these return variables in Appendix Table A3.

[23] Data for these anomalies are available from Robert Stambaugh's website.

TABLE 2 Changes in sentiment persistence and 11 market anomalies

Anomalies	α_1	*t*-statistic	α_2	*t*-statistic	α_1-α_2	*p*-Value
Asset growth	0.07	0.66	−0.03	−0.22	0.11	0.57
Composite equity issue	0.35	2.84	0.18	0.97	0.16	0.45
Failure probability	0.57	1.76	0.93	2.70	−0.36	0.40
Gross profitability	0.43	3.11	0.16	0.83	0.28	0.22
Investment-to-assets	0.53	4.41	0.12	0.59	0.41	0.07
Momentum	1.74	4.77	0.66	1.39	1.08	0.05
Net operating asset	0.53	3.36	0.65	3.40	−0.12	0.60
Ohlson's O score	0.46	3.54	0.33	1.78	0.13	0.54
Total accruals	0.71	4.41	0.16	0.74	0.54	0.04
Return on assets	0.57	3.45	0.18	0.84	0.39	0.13
Net stock issues	0.42	4.17	0.30	1.76	0.12	0.54
Combination	0.54	5.52	0.31	2.90	0.23	0.09

$$R_t = \alpha_1 d_{1t} + \alpha_2 d_{2t} + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \epsilon_t \tag{3}$$

Note: This table reports the average monthly percentage alphas (relative to the Fama-French five-factor model) on the 11 long-short anomalies as documented in Stambaugh et al. (2012). The 11 anomalies are asset growth, composite stock issues, failure probability, gross profitability, investments-to-assets, momentum, net operating assets, financial distress (Ohlson's O score), total accruals, return-on-assets, and net stock issues. The return on each of the 11 anomalies is the alpha spread between stocks in the highest-performing decile (long leg) and ones in the lowest-performing decile (short leg). d_{1t} and d_{2t} are dummies that correspond to the persistent and mean reverting sentiment regimes, respectively. The parentheses report the *t*-statistics that are based on the heteroskedasticity-consistent standard errors of White (1980). *p*-Value (estimated by the Wald test) indicates the significance level of the difference in anomaly alphas between two regimes. As in Stambaugh et al. (2012), the combination is defined as the strategy that takes equal positions across the 11 long-short strategies constructed in any given month. The *t*-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

Table 2 reports alphas, relative to the Fama-French five factor model (Fama & French (2015), hereafter referred to as FF5), on the 11 long-short anomalies. The predictive regression is

$$R_t = \alpha_1 d_{1t} + \alpha_2 d_{2t} + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \epsilon_t, \tag{4}$$

where d_{1t} and d_{2t} are dummies that correspond to the persistent and mean-reverting sentiment regimes, respectively.

In the persistent sentiment regime, alphas (reported in column 2) of 10 anomalies are significantly positive at 10% significance level. In contrast, when sentiment becomes more mean-reverting, only four anomalies (failure probability, net operating asset, Ohlson's O score, and net stock issues) earn significant abnormal returns (see column 4). The last column reports the *p*-Value of the Wald test of the difference in anomaly alphas between the two regimes. We find a significant decline in the alpha between the two regimes for three of the anomalies and, importantly, the average change in alpha between the two regimes (as reported for the combination of these anomalies in the last row of Table 2) is 0.23% per month (annual alpha is 2.76%), which is both statistically (*p*-Value of 0.09) and economically significant.[24]

A possible concern is that the choice of the anomalies considered in Stambaugh et al. (2012) may be somewhat arbitrary.[25] Therefore, we choose 27 significant anomalies (mean returns are significant) considered in Hou et al. (2015)

[24] As in Stambaugh et al. (2012), the combination is defined as the strategy that takes equal positions across the 11 long-short strategies constructed in any given month.

[25] For example, Jacobs (2015) study the relation between investor sentiment and the dynamics of 100 anomalies.

TABLE 3 Post-publication and attenuation to anomaly returns

	α_1	t-statistic	α_2	t-statistic	α_1-α_2	p-Value
Asset growth	0.03	0.30	0.10	0.51	−0.07	0.75
Composite equity issue	0.28	2.40	0.36	1.50	−0.08	0.75
Failure probability	0.73	2.58	0.57	1.22	0.16	0.75
Gross profitability	0.37	3.07	−0.00	−0.01	0.37	0.39
Investment-to-assets	0.51	4.40	0.05	0.23	0.46	0.07
Momentum	1.78	5.19	0.95	1.98	0.83	0.12
Net operating asset	0.60	4.01	0.46	2.04	0.14	0.60
Ohlson's O score	0.19	1.02	0.52	3.90	−0.33	0.15
Total accruals	0.67	3.97	0.34	1.69	0.33	0.20
Return on assets	0.50	3.45	0.00	0.01	0.49	0.14
Net stock issue	0.47	4.40	0.29	2.09	0.18	0.28

$$R_t = \alpha_1 d_{1t} + \alpha_2 d_{2t} + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \epsilon_t \quad (5)$$

Note: This table reports the average monthly percentage alphas (relative to FF5 model) on the 11 long-short anomalies as documented in Stambaugh et al. (2012). The 11 anomalies are asset growth, composite stock issues, failure probability, gross profitability, investments-to-assets, momentum, net operating assets, financial distress (Ohlson's O score), total accruals, return on assets and net stock issues. The return on each of the 11 anomalies is the return spread between stocks in the highest-performing decile (long leg) and ones in the lowest-performing decile (short leg). d_{1t} and d_{2t} are dummies that correspond to the pre- and post-publication periods of anomaly strategies. d_{1t} and d_{2t} are dummies that correspond to the pre- and post-publication periods of anomaly strategies. *p*-Value (estimated by the Wald test) indicates the significance level of the difference in anomaly alphas between two regimes. The *t*-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

for robustness checks. We examine these anomalies for two reasons: (1) they cover the major anomalies categories, including momentum, value-versus-growth, investment, profitability, intangibles as well as trading frictions; and (2) they have been widely used to test the leading asset pricing models.

The test results of these anomalies are reported in Table A4. We find consistent results that these anomalies tend to be prominent in the persistent sentiment regime. Regarding the alpha (with respect to the FF5 factors), we find that the average alpha, reported in the last row of Panel B, is more significant in the persistent sentiment regime (0.39% per month with *t*-statistic of 5.94) than in the nonpersistent sentiment regime (0.23% per month with *t*-statistic of 3.51). Moreover, we test the difference of two alphas using the Wald test. We get a *p*-Value of 0.07, indicating a significant difference (at 10% significance level) between two regimes' anomaly alpha.

4.2.1 | Post-publication and attenuation to anomaly returns

An interesting question is whether our findings above can be explained by the publication effects since anomalies are often arbitraged away following their discovery by academic researchers (McLean & Pontiff (2016)). To examine how the academic publications of anomaly strategies contribute to the decline in anomaly payoffs, we compute the anomaly alphas in pre- and post-publication periods using the specification in Table 2. The publication dates of the anomalies we use are summarized in Appendix Table A2.

Table 3 reports the anomaly alphas in pre- and post-publication periods. We find mixed results. Alphas (with respect to the FF5 model) for gross profitability, investment-to-assets, momentum, total accruals, and return-on-assets experience a decline of more than 0.20% per month after their academic publications (indicated by the sixth column). However, alphas for momentum, net operating assets, Ohlson's O score, total accruals, and net stock issues still remain significant during post-publication periods (indicated by the fourth and fifth column). More importantly, the Wald test indicates that 10 out of 11 anomalies have no break in the alpha between the two regimes (indicated by the last column). Overall, the publication effect may have contributed to reduction in anomaly returns. However, it does not fully explain our findings of declines in anomaly payoffs in recent years when investor sentiment becomes more mean-reverting.

In sum, consistent with the relation between investor sentiment and the anomalies, we find that few of these anomalies yield abnormal returns in the period after January 2001. These findings support our argument that the market becomes more efficient when sentiment is more stationary.

4.3 | Changes in sentiment persistence and momentum anomalies

By forming portfolios on the basis of past returns, Jegadeesh and Titman (1993) find the decile with best past performance outperforms the one with worst past performance, which is known as the momentum anomaly. Many studies address the relation between investor sentiment and the momentum anomaly. For instance, Barberis et al. (1998) present a model of investor sentiment in which earnings of assets follow a random walk but investors mistakenly believe that a firm's earnings alternate between two states, a mean-reverting process both with a trend and without. If the path of recent earnings slows, investors will perceive that the firm's earnings are nontrending, and thus under-react to recent news, thereby leading to a short-term return autocorrelation. In addition, Antoniou et al. (2013) discover that the momentum strategy is more profitable during optimistic periods.

In a related study, Daniel et al. (1998) attribute momentum to the overconfidence and self-attribution of noise traders. In their model, investors overreact to the private signals as a result of overconfidence, causing the stock price to overreact and boosting the short-term autocorrelation of returns. However, due to self-attribution bias, even when disconfirming information comes, they hardly change their minds and thus reversal does not appear in the short term.

In the spirit of Daniel et al. (1998), we argue that the momentum anomaly should be expected to be significant only when sentiment is persistent. Specifically, persistent sentiment reflects the heavy presence of noise traders associated with long memory of past returns. Such memory may encourage sentiment-driven traders' overreaction to stocks with good past performance, causing a short-term autocorrelation of returns. However, in the less persistent regime associated with fewer sentiment traders, one should not expect effective momentum strategies.

To assess the impact of our January 2001 break in sentiment persistence, we follow Jegadeesh and Titman (1993) and construct momentum strategies. The sample involves all NYSE/AMEX stocks with share code 10 or 11 for the period from July 1965 to December 2018. At the beginning of each month, all stocks are ranked in ascending order based on their J-month lagged returns and held for K months. Following Jegadeesh and Titman (1993), we consider both formation and holding periods that vary from one to four quarters, giving a total of 16 strategies. To control for micro-structural effects such as bid-ask spread, we allow 1 month between the end of the formation period and the beginning of the holding period. The sell portfolio is the equal-weighted portfolios of stocks in the lowest past return decile while the buy portfolio is the equal-weighted portfolios of stocks in the highest return decile. The momentum profitability is the return spread on the Buy–Sell portfolio. To increase the power of the test, in each month t, the strategy holds a series of portfolios that are selected in the current month as well as the previous $K-1$ months. Under this condition, the strategy closes out the position initiated in month $t-K$, and $1/K$ of securities in the portfolio is revised in month t.

Table 4 reports alphas of the monthly returns on momentum portfolios with respect to the FF5 model (Fama & French, 2015).[26] All strategies earn significant profits during persistent sentiment periods. The most successful strategy selects stocks over 9 months and holds them for 3 months (1.44% per month with a t-statistic of 3.97). However,

[26] We report the mean returns of momentum strategies in Appendix Table A5.

TABLE 4 Sentiment persistence and alphas of momentum strategies

	α_1				α_2				*p*-Value			
J	K= 3	6	9	12	K= 3	6	9	12	K=3	6	9	12
3 Buy–Sell	0.80	0.74	0.81	0.72	0.09	0.06	0.06	−0.03	0.11	0.09	0.04	0.02
t-statistic	2.69	2.80	3.58	3.81	0.25	0.19	0.20	−0.10				
6 Buy–Sell	1.08	1.15	1.10	0.84	0.05	0.03	−0.03	−0.16	0.07	0.03	0.01	0.01
t-statistic	2.98	3.60	4.09	3.46	0.10	0.07	−0.09	−0.47				
9 Buy–Sell	1.44	1.33	1.09	0.79	0.06	−0.08	−0.17	−0.26	0.02	0.01	0.01	0.02
t-statistic	3.97	4.15	3.79	3.01	0.11	−0.17	−0.40	−0.71				
12 Buy–Sell	1.40	1.15	0.91	0.66	−0.29	−0.34	−0.37	−0.37	0.00	0.01	0.01	0.03
t-statistic	4.00	3.54	3.08	2.38	−0.58	−0.74	−0.87	−0.96				

$$R_t = \alpha_1 d_{1t} + \alpha_2 d_{2t} + \beta_1 MKT_t + \beta_2 SMB_t t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \epsilon_t \quad (6)$$

Note: This table presents monthly alpha percentage on momentum portfolios with respect to the FF5 model (2015). The sample includes all NYSE/AMEX stocks with share code 10 or 11. At the beginning of each month, all stocks are ranked in ascending orders based on their J-month lagged returns and held for *K* months. We allow 1 month between the end of the formation period and the beginning of the holding period to control for micro-structural effects, such as bid-ask spread. The sell portfolio is the equally weighted portfolio of stocks in the lowest past return decile, while the buy portfolio is the equally weighted portfolio of stocks in the highest return decile. The dependent variable R_t is the return spread on the Buy–Sell portfolio. To increase the power of the tests, in each month *t*, the strategy holds a series of portfolios that are selected in the current month as well as the previous *K*−1 months. d_{1t} and d_{2t} are dummies that correspond to the persistent and mean reverting regimes respectively. α_1 is the alphas for the period from July 1965 to January 2001, and α_2 is the alphas for the period from February 2001 to December 2018. Panel C reports the *p*-Value, which indicates the significance level of the difference in anomaly alphas between two regimes. The *t*-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

none of them yields abnormal return when sentiment follows a less persistent process. These findings confirm the impact of our estimated change in investor sentiment.

4.4 | Sentiment persistence and return predictability

Many empirical studies posit that investor sentiment can predict returns. When sentiment traders are excessively optimistic (pessimistic), their erroneous beliefs associated with high (low) demand will cause asset prices to deviate above (below) their intrinsic values.[27] As a consequence, subsequent returns will be lower (higher) with assets reverting to their fundamental values. In this sense, investor sentiment can be seen as a predictor of stock returns in the short term.

Despite well-documented evidence of the return predictability of investor sentiment, there is still some disagreement in the literature about whether the argument outlined in the above paragraph holds. Many studies, such as Stambaugh et al. (2012) and Shen et al. (2017), estimate predictive regressions of monthly returns on lagged sentiment and find its predictability on returns.[28] In contrast, other studies such as Brown and Cliff (2004) find that sentiment has little predictive power for near-term returns. Brown and Cliff (2005) further point out that sentiment is persistent and may drive asset prices away from their intrinsic value for extended periods of time. Accordingly, the mispricing caused by investors' erroneous beliefs cannot be corrected quickly and one should not expect sentiment to predict short run returns. Indeed, Brown and Cliff (2005) find that investors can predict little of short-run returns but more of

[27] Surveying investors on their subjective sentiment-creating factors, Kaplanski et al. (2015) find evidence that sentiment affects investors' return expectations.

[28] Stambaugh et al. (2014) assesses the predictive power of the Baker and Wurgler sentiment index to find it has predictive power that is not spurious.

long-run returns, and studies such as Huang et al. (2015) also suggest that sentiment has long-run predictability as a consequence of high persistence.

To identify periods with persistent sentiment, we impose the structural breaks of Section 3 on the following predictive regressions:

$$\mathrm{R}_t = \alpha_i + \beta_i \,\mathrm{Sentiment}_{t-1} + \varepsilon_t \tag{7}$$

where R_t is returns in the current period, $\mathrm{Sentiment}_{t-1}$ is the 1-month lagged sentiment, $t = T_{i-1} + 1, \ldots, T_i$ with T_i being the dates for m breaks with $T_0 = 1$ and $T_{m+1} = T$, the start and end dates of our sample. α_i and β_i are the coefficients in segment i as defined by the breaks that capture the structural change in the model. Our bottom line is that sentiment has no forecasting power for the segments of high persistence because noise investors associated with persistent biased beliefs can drive asset prices far away from fundamental values for a long period. In contrast, for the highly mean reverting sentiment segments, perhaps short-run predictability can be expected as arbitrage can correct sentiment-driven mispricing quickly. In following subsections, we first describe the return variables that we apply in the above regression and then run this regression with changes in sentiment persistence.

Our return data comes from three sources. Following Huang et al. (2015), we choose the S&P500 Index return as the market return. The market excess return is the return on the S&P 500 index in excess of the 1-month T-bill rate. The data are obtained from the Centre for Research in Security Price (CRSP).

We examine long-short strategies because sentiment effects vary cross-sectionally, and sentiment is more likely to spill over to stocks with speculative appeal. Following Stambaugh et al. (2012), we examine returns on the 11 sentiment-related long-short anomalies of Stambaugh et al. (2012), as described in Section 4.1.

Regarding short legs, stocks in the short legs are more susceptible to sentiment effects. Accordingly, investor sentiment should have strong forecasting power on these short legs (Stambaugh et al., 2014). Therefore, we also test the predictive regression of returns on them.

4.4.1 | Predictive regressions with structural breaks

Panel A of Table 5 reports results on the predictability of market returns (S&P 500 Index) and returns on long-short strategies for the whole sample period from sentiment. We find that investor sentiment has little predictive power on 1-month market excess returns. However, after considering one break in sentiment (January 2001) in the predictive regression (Panel B), there is a strong two-regime pattern: investor sentiment can significantly predict the short-run return for the post-2001 period (Regime 2), but this predictability is not evident in the pre-2001 period (Regime 1). Specifically, a one standard deviation increase in sentiment in the post-2001 regime is associated with 1.05% (t-statistic is −2.46) lower return in the next month. Such a finding is consistent with economic intuition in that high sentiment drives up stock prices but depresses subsequent returns (Yu & Yuan, 2011). It also implies that sentiment-driven mispricing is eliminated quickly so that the subsequent return is lower. In contrast, the slope coefficient on sentiment is almost zero in Regime 1. Our explanation for this finding is the long-term mispricing associated with sentiment persistence: because arbitrage cannot correct the long-run mispricing quickly, high (low) sentiment is not necessarily associated with lower (higher) returns on the subsequent month. Further, the Wald test rejects the null of no change in coefficients across regimes with a p-Value of 0.05, confirming our hypothesis that the predictability of future market returns from sentiment is subject to a structural break in January 2001.

The same two-regime pattern also appears in the predictive regressions of long-short anomaly strategies as well as their short legs. For most anomaly strategies, we find that investor sentiment has noticeably stronger predictability in the second regime than the first. The F-test of no change in the predictive coefficients rejects at the 10% level for seven out of 11 long-short anomaly strategies. To illustrate the results using the combination portfolio of anomalies, a one standard deviation increase in sentiment in Regime 1 leads to a statistically insignificant profit of 0.33% (t-statistic

TABLE 5 Predictability of returns from sentiment

Panel A: No break			Panel B: One break				Panel C: Three breaks					
Return	Full sample	R^2 (%)	Regime 1	Regime 2	R^2 (%)	*p*-Value	Regime 1	Regime 2	Regime 3	Regime 4	R^2 (%)	*p*-Value
Market excess return												
S&P 500	−0.14	−0.06	0.03	−1.05	0.58	0.05	−0.20	−0.59	−0.32	−1.05	1.09	0.04
	(−0.71)		(0.16)	(−2.46)			(−0.85)	(−1.01)	(−0.28)	(−2.45)		
Long-short market anomalies												
Accrual	0.03	−0.16	0.15	−0.58	0.94	0.01	0.37	0.33	−1.93	−0.58	1.90	0.00
	(0.17)		(0.87)	(−1.72)			(0.60)	(1.17)	(0.87)	(1.50)		
AssetGrowth	0.28	0.58	0.16	1.05	1.23	0.05	0.12	0.60	1.68	1.05	1.43	0.08
	(1.68)		(0.99)	(1.51)			(0.59)	(1.17)	(0.87)	(1.50)		
CompositeIssue	0.43	1.14	0.35	0.96	1.67	0.19	0.33	1.08	2.02	0.96	2.56	0.05
	(2.45)		(1.83)	(1.63)			(1.21)	(2.31)	(1.34)	(1.62)		
Distress	1.03	1.98	0.51	2.88	3.67	0.00	0.84	0.76	−1.23	2.88	3.22	0.05
	(2.78)		(1.43)	(2.29)			(0.80)	(1.23)	(−0.33)	(2.29)		
GrossProfit	0.19	0.10	0.13	0.52	−0.00	0.65	0.22	−0.03	−1.05	0.52	−0.36	0.78
	(1.19)		(0.76)	(1.20)			(1.03)	(−0.06)	(−0.88)	(1.19)		
InvestmentAssets	0.07	−0.01	0.03	0.37	0.32	0.06	−0.04	1.07	−0.33	0.36	0.89	0.06
	(0.59)		(0.31)	(1.27)			(−0.31)	(2.53)	(−0.47)	(1.26)		
Momentum	0.04	−0.16	−0.26	2.09	1.60	0.00	0.02	0.28	−5.83	2.09	3.07	0.00
	(0.20)		(−1.00)	(2.06)			(0.09)	(0.46)	(−2.31)	(2.05)		
NOA	0.54	3.30	0.53	0.59	3.00	0.97	0.49	0.74	0.42	0.59	3.99	0.11
	(5.29)		(4.53)	(2.59)			(2.92)	(2.15)	(0.44)	(2.58)		
Oscore	0.53	1.94	0.56	0.40	1.72	0.74	0.50	1.17	−0.43	0.40	2.05	0.36
	(3.51)		(3.35)	(1.20)			(2.10)	(2.94)	(−0.54)	(1.20)		
ROA	0.55	1.27	0.33	1.45	2.00	0.05	0.45	−0.15	2.38	1.46	2.13	0.10
	(2.69)		(1.35)	(2.81)			(0.75)	(−0.30)	(1.08)	(2.80)		

(Continued)

TABLE 5 Predictability of returns from sentiment

Panel A: No break			Panel B: One break				Panel C: Three breaks					
Return	Full sample	R^2 (%)	Regime 1	Regime 2	R^2 (%)	*p*-Value	Regime 1	Regime 2	Regime 3	Regime 4	R^2 (%)	*p*-Value
NetStockIssue	0.42	2.26	0.31	1.13	3.11	0.03	0.34	0.86	0.77	1.13	3.17	0.07
	(3.07)		(2.04)	(2.26)			(1.42)	(2.64)	(0.58)	(2.25)		
Combination	0.64	1.47	0.33	1.86	3.00	0.01	−0.64	1.59	1.51	1.86	4.10	0.00
	(2.33)		(1.19)	(1.96)			(−0.87)	(2.78)	(0.59)	(1.95)		
Short legs of long-short market anomalies												
Accrual	−0.47	0.40	−0.34	−1.26	0.35	0.44	−0.63	−1.27	0.23	−1.26	0.59	0.31
	(−1.54)		(−1.02)	(−1.30)			(−1.33)	(−1.59)	(0.11)	(−1.30)		
AssetGrowth	−0.63	0.96	−0.40	−1.95	1.54	0.06	−0.61	−1.66	−1.40	−1.95	2.08	0.04
	(−2.16)		(−1.33)	(−2.12)			(−1.46)	(−2.06)	(−0.66)	(−2.12)		
CompositeIssue	−0.53	0.73	−0.34	1.61	1.08	0.13	−0.64	−1.36	−0.34	−1.61	1.66	0.07
	(−2.01)		(−1.19)	(−2.19)			(−1.67)	(−1.74)	(−0.21)	(−2.18)		
Distress	−1.02	1.04	−0.32	−3.43	3.03	0.00	−0.95	−1.31	−0.85	−3.43	2.57	0.03
	(−2.16)		(−0.67)	(−2.33)			(−0.59)	(−1.38)	(−0.25)	(−2.32)		
GrossProfit	−0.19	−0.03	0.01	−1.29	0.69	0.04	−0.33	−0.70	0.68	−1.29	1.09	0.04
	(−0.86)		(0.06)	(−1.93)			(−1.05)	(−0.85)	(0.50)	(−1.92)		
InvestmentAssets	−0.48	0.51	−0.32	−1.36	0.62	0.26	−0.52	−1.75	0.87	−1.36	1.14	0.13
	(−1.84)		(−1.11)	(−2.27)			(−1.34)	(−2.34)	(0.63)	(−2.27)		
Momentum	−0.56	0.42	−0.20	−2.67	1.51	0.01	−0.54	−1.23	2.07	−2.67	1.71	0.03
	(−1.74)		(−0.59)	(−2.14)			(−1.18)	(−1.35)	(0.59)	(−2.13)		

(Continued)

TABLE 5 Predictability of returns from sentiment

Panel A: No break			Panel B: One break				Panel C: Three breaks					
Return	Full sample	R^2 (%)	Regime 1	Regime 2	R^2 (%)	*p*-Value	Regime 1	Regime 2	Regime 3	Regime 4	R^2 (%)	*p*-Value
NOA	−0.65	1.31	−0.45	−1.73	1.90	0.06	−0.64	−1.42	−0.51	−1.73	2.20	0.07
	(−2.66)		(−1.73)	(−2.44)			(−1.77)	(−1.87)	(−0.30)	(−2.43)		
Oscore	−0.71	1.12	−0.53	−1.72	1.30	0.21	−0.65	−1.64	−1.92	−1.72	1.44	0.24
	(−2.64)		(−1.78)	(−2.22)			(−1.55)	(−2.13)	(−0.95)	(−2.21)		
ROA	−0.63	0.57	−0.13	−2.44	1.96	0.01	−0.84	−0.75	−3.50	−2.44	2.37	0.01
	(−1.76)		(−0.35)	(−2.52)			(−0.83)	(−1.00)	(−1.09)	(−2.51)		
NetStockIssue	−0.54	0.80	−0.31	−1.77	1.52	0.04	−0.64	−1.20	0.03	−1.77	2.05	0.03
	(−2.11)		(−1.15)	(−2.30)			(−1.63)	(−1.68)	(0.02)	(−2.29)		
Combination	−0.47	0.42	−0.04	−1.93	1.51	0.01	−0.27	−1.30	−0.42	−1.93	1.43	0.07
	(−1.41)		(−0.13)	(−2.16)			(−0.21)	(−1.74)	(−0.21)	(−2.14)		

Note: Predictive regressions of returns on 1-month lagged sentiment,

$$\text{Return}_t = \alpha_i + \beta_i \text{Sentiment}_{t-1} + \epsilon_t. \tag{8}$$

The table reports estimates of β_i across different periods with Newey–West adjusted *t*-statistics in parentheses. The dependent variables are market excess returns (S&P 500 index) and returns on long-short and short leg portfolios of the 11 long-short market anomalies as documented in Stambaugh et al. (2012). In the long-short portfolio, the short leg is the bottom decile of stocks that are more susceptible to sentiment effect than stocks in top decile (the long leg). We also report combinations anomaly portfolios. Sentiment is constructed as the first principal component, as described in Baker and Wurgler (2006). Panel A looks at the whole sample period from August 1965 to December 2016. Panel B looks at the regressions imposing one structural break in sentiment persistence (January 2001). Panel C looks at the regressions with three breaks in sentiment persistence (March 1980, September 1995, and January 2001). Newey–West estimates are using the Bartlett Kernel with the Andrews Automatic bandwidth selection and allow for different variances across regimes. Adjusted R^2 values are also reported. *P*-Value refers to that of the *F*-test (Chow test) of the null hypothesis that the coefficients on sentiment do not change across regimes.

is 1.19), while this profit is larger and significant in Regime 2 (1.86% with t-statistic of 1.96). For the combination portfolio of short legs of these portfolios, a one standard deviation increase in sentiment in Regime 1 is associated with a statistically significant lower returns of 1.93% (t-statistic is −2.16) in regime 2, but this return decline is not significant in regime 1.

Overall, these findings confirm our conjecture that investor sentiment has strong short-run predictability in the post-2001 period when, as we show in Section 3, it follows a mean-reverting process. In contrast, mispricing can persist for an extended period of time in the pre-2001 regime in which sentiment behaves like a random walk, and one should not expect reliable short-run forecasting power of sentiment. Moreover, adjusted R^2s in these predictive regressions increase substantially after considering the break in sentiment persistence. For example, the R^2 for the whole sample period of S&P 500 index monthly returns is only −0.06%, but it rises to 0.58% for the two-regime model.

At this point, an interesting question is whether the forecasting regressions with three breaks can add to the pattern of results in the one break model. Panel C of Table 5 reports the results of three-break regressions, but we find little evidence that it performs drastically better than the one-break model in terms of fit because most adjusted R^2s stay roughly in the same level after including the extra two breaks. In terms of forecasting power the post-2001 results remain strong, as in the case with one break, but the additional mean-reverting period between March 1981 and September 1995 (Regime 2) is not significant. The results are better for many of the returns based on characteristics and anomalies, showing higher and more often significant coefficients in Regimes 2 and 4 than in Regimes 1 and 3, and the same is true for the combinations.

To the extent that stocks in the short legs of these long-short strategies are more susceptible to sentiment effects, there should be a strong negative relation between the returns on the short leg portfolios and the lagged sentiment level (see Stambaugh et al., 2012). Table 5 presents the regressions of returns on these short legs. For the full sample reported in Panel A, we find that sentiment has strong negative forecasting power for most short legs, which is consistent with the findings of Baker and Wurgler (2006) and Stambaugh et al. (2012). After considering the one break in sentiment persistence, we find that this negative predictability is mainly due to the second regime (from 2001). For the first regime, in which sentiment behaves like a persistent variable, sentiment cannot predict the returns on most short legs. Such a two-regime pattern confirms our conjecture that there is long-run mispricing for the pre-2001 period and that sentiment does not have short-run forecasting power. Consistent with our findings in the predictive regressions for long-short strategies, adjusted R^2s in the regressions for short-legs also increase dramatically after considering the one break in sentiment persistence. As importantly, F-tests confirm that most predictive regressions are subject to a structural break in January 2001. In conclusion, modeling the structural change results in better forecasting performance.

We assess the robustness of our results regarding the return predictability of sentiment by controlling for additional macroeconomic variables in the predictive models. To the extent that some omitted macro variables carry the same information as that in investor sentiment and may partially explain its predictive power, we follow Stambaugh et al. (2012) and Shen et al. (2017) to control for a set of variables that includes the real interest rate, the inflation rate (Fama, 1981), the term and default premia (Chen et al., 1986), and the consumption-wealth ratio (*cay*) as defined in Lettau and Ludvigson (2001).[29] Table A6 in the Online Appendix reproduces the cases examined in Table 5 with the addition of the macroeconomic regressors. Overall, the results are almost identical, demonstrating that our findings regarding the return predictability of sentiment in the regimes defined by the structural breaks estimated in this paper are robust to controlling for additional macro-related variables.

In order to further corroborate our conjecture, we add the 27 anomalies that are considered in Hou et al. (2015) for robustness check. The results are reported in Table A7. We find that returns of short legs of 26 of the 27 anomalies are

[29] The real interest rate is the difference between return on the 30-day T-bill and inflation rates. The term "premium" is defined as the spread between the average of the 30-year, 20-year, 10-year T-bill rates; and the average of the 1-year 90-day, and 30-day T-bill rates. The default premium is the difference between the yields on BAA and AAA bonds. The inflation rate and T-bill return are obtained from CRSP. The default premium comes from the St. Louis Federal Reserve and cay is obtained from Martin Lettau's website.

negatively predicted by sentiment in the post-2001 regime while this number becomes one for the pre-2001 regime. Our conclusions thus hold when considering alternative anomalies.

5 CONCLUSION

Market-wide sentiment is difficult to measure directly and can be only proxied for. Nevertheless, the topic of financial sentiment has received considerable attention in recent years. Inter alia, Baker and Wurgler (2006, 2007) construct an investor sentiment index as the first principal component of a number of proxies that contain information about the level of sentiment in the stock market. For the most part, such an index captures anecdotal accounts of bubbles and crashes. However, the majority of sentiment-related studies so far have been more concerned with the levels of sentiment and often in shorter time periods. Thus, we argue that extant literature has overlooked the important time series attributes of sentiment in the long term.

To our knowledge, this paper is the first to examine the effects of sentiment on the stock market while allowing for changes in sentiment persistence. We justify our approach using well-established theories in behavioral finance. Noise investors tend to exhibit belief perseverance, which is associated with “conservatism” and “representativeness” biases. Persistence of biased beliefs in this manner implies that sentiment may behave like a random walk, diverging from the normal range for segments of the sample associated with overconfidence and exuberance in the stock market. In this sense, the timing of the structural break in our model and market bubbles historically arguably provide some evidence in support of our model.

We assess the effect of change in sentiment persistence by testing for various associated market anomalies. Thus, we explore market efficiency in different periods as defined by distinct sentiment regimes. Consistent with the relation between investor sentiment and market anomalies, we find a two-regime pattern in which market anomalies are evident only when sentiment is persistent. Therefore, we argue and empirically demonstrate that the study of market anomalies cannot be complete without paying due attention to market sentiment, and, importantly, its degree of persistence.

Finally, we examine the predictive power of the sentiment index on returns subject to the estimated structural changes and show that the breaks significantly impact the predictive power of sentiment on market returns as well as a variety of long-short strategies based on firm characteristics and market anomalies. A natural conclusion is also to be aware of trending behavior in the sentiment index in the future, as such a development would impact negatively on the predictive power of the index. Future research can extend our work by testing alternative proxies for market sentiment as well as investigating this behavior beyond the US market.

ACKNOWLEDGMENTS

We thank the Editor Michael Goldstein and two anonymous referees for their helpful comments and thoughtful suggestions; as well as Niels Hermes, Talis Putnins, Richard Taffler, Wenzhao Wang, and seminar participants at Brunel University, University of Bath, the 2018 Scottish Doctoral Colloquium in Accounting and Finance, the 2019 Infiniti International Finance Conference, and the 2019 European Financial Management Association Conference for helpful comments and suggestions. Jo Danbolt holds the Baillie Gifford Chair in Financial Markets, and his research is partially funded by a Baillie Gifford endowment held by the University of Edinburgh Business School. Baillie Gifford has no role in or influence over the research conducted.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Han, X., Sakkas, N., Danbolt, J., & Eshraghi, A. (2022). Persistence of investor sentiment and market mispricing. *Financial Review*, 1–24. https://doi.org/10.1111/fire.12301