Persistence of investor sentiment in the past 50 years: A behavioral perspective*

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Abstract

We investigate changes in US market sentiment using structural break analysis over a 50-year period. Investor sentiment behaved like a trending, non-stationary time series from 1965 to 2001, a period associated with numerous bubbles and crashes. In the post-2001 period, sentiment has been substantially more mean reverting, implying the diminished effect of noise investors and associated mispricing. We explore how these changes in sentiment persistence affect well-documented 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.

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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 and Wurgler, 2006). Behavioural studies deem these sentiment-driven biases in expectations as 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 reinforcing themselves.

A popular way to quantify investor sentiment in financial markets (mainly due to Baker and Wurgler, 2006, 2007) has been to use principal components analysis to extract the co-movement of variables that are thought to carry information with regard to market sentiment.[1] In this paper, we investigate this monthly time series index of investor sentiment over the period 1965-2015. Borrowing language from econometrics, we associate persistence in investor sentiment with the index exhibiting unit root or near unit root behavior. Such a series is often referred to as persistent or having a high degree of persistence and is characterized by "long memory", in the sense that shocks have long-run effects and the accumulation of such shocks causes the series to wander away from the mean for long periods of time. We find that periods where investor sentiment behaves in this way are associated with equity bubbles, recessions and the emergence of market anomalies. On the other hand, regimes

[1] The variables used are: value-weighted dividend premium, first-day returns on IPOs, IPO volume, closed-end fund discount, and equity share in new issues. In order to filter out business cycle information, these variables are orthogonalized to the following macroeconomic variables: industrial production, nominal consumption on durables, non-durables, and services, employment, the CPI, and the NBER recession indicator.

associated with frequent mean reversion in the sentiment index indicate the relative absence of sentiment-driven investors in the market and thus, attenuation of observable anomalies.

To examine such changes in sentiment persistence, we employ structural break analysis on the autoregressive coefficient of the Baker and Wurgler (2006) index. We identify a substantial and robust break in January 2001 associated with a marked decrease in the degree of persistence. Unit root tests in the resulting sub-samples find evidence that the first is non-stationary while the second is stationary. Imposing non-stationarity 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.

Why did investor sentiment become markedly more mean reverting after January 2001? We approach this question by investigating a set of arbitrage cost proxies and arbitrage activities, and find that these proxies are downward trending over time. Moreover, share turnover - a natural proxy for arbitrage activities (Chordia et al., 2014) - reaches an extremely high level in recent years. We also find that the proportion of common equity held by individual investors, often considered the primary candidates for sentiment trading (Barber and Odean, 2007 and Yu and Yuan, 2011), is downward trending over time. This suggests that sentiment traders have had less impact on the aggregate market in recent years. It is also worth noting that the publication impact of the Baker and Wurgler seminal study itself cannot explain these structural breaks, since that study was published in 2006, five years after the 2001 structural break.

To the extent that a decrease in arbitrage costs can increase arbitrage opportunities and attenuate sentiment-driven mispricing, our finding that sentiment is considerably more mean reverting in the post-2001 period matters, as it indicates higher levels of market efficiency. We explore this by testing how excess returns in the cross-section of long-short strategies associated with a range of market anomalies are affected by the change in sentiment persistence that we estimate in this paper. These anomalies, documented in Stambaugh et al. (2012, 2014 and 2015) and Stambaugh and Yuan (2017), among others, have been found to produce excess returns following periods of high sentiment. We test for excess returns in different periods defined by the degree of persistence in investor sentiment and find that they are only observed when sentiment is highly persistent; that is, before 2001. Our findings support those of Chordia et al. (2014) who use market events such as decimalization as *a priori* defined change points and find an attenuation of market anomaly returns. The difference in our contribution is that we use data-based estimation of the change points and explain the attenuation of anomaly returns by changes in investor sentiment, which is more market wide and pervasive than a single event.

We also examine the effect of changes in sentiment persistence on the forecasting power of sentiment. Return forecasts have a long history, and many studies have examined whether investor sentiment can negatively predict returns.[2] While studies such as Stambaugh et al. (2012) and Shen et al. (2017) find sentiment predictability on one-month leading returns, others such as Brown and Cliff (2004, 2005) find little predictive power for near-term returns. The latter findings can be understood as sentiment driving asset prices away from their intrinsic value for extended periods of time and therefore having no short term predictive power. In addition to any other methodological differences in these studies, different sample

[2]see Neal and Wheatley (1998), Brown and Cliff (2005), Baker and Wurgler (2006), Lemmon and Portniaquina (2006), Schmeling (2009), Baker et al. (2012), Chung 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).

periods and the potential of changes in the behavior of investor sentiment over time could explain these conflicting results and highlight the need to examine changes in sentiment as we do in this paper.

To explore the predictive power of the sentiment index in light of our structural breaks analysis, we impose the one-break and three-break models of sentiment persistence that we estimate in Section 3, on one-month leading return predictive regressions. Our hypothesis is that regimes associated with highly persistent sentiment correspond with the prevalence of noise investors that drive asset prices away from fundamental values for long periods of time. This is mainly due to the noise investors' biased beliefs which result in sentiment being a weak predictor of returns. In contrast, periods of strongly mean reverting sentiment imply a smaller role for noise traders and possibly more effective arbitrage that corrects sentiment-driven mispricing. In this case, the underlying variables of the Baker and Wurgler sentiment index contain more useful information on the movements of the market and thus their predictive power is improved. We run predictive regressions subject to the breaks on market returns (S&P 500), returns on long-short characteristic portfolios (Baker and Wurgler, 2006) and long-short market anomalies (Stambaugh et al., 2012), and confirm our hypothesis: there is little predictive power when sentiment is persistent and this improves markedly when it is mean reverting. These findings also confirm our hypothesis that persistent sentiment is associated with long-run mispricing, highlight the danger of using full sample information to construct predictive models that involve sentiment, and show that sentiment is a much better predictor of returns in the post-2001 period.

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. For examples, Black (1986) shows that sentiment traders buy and sell on noise and, in doing so, introduce more noise into the market, 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 since 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 close-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. Edmans et al. (2007) find that losses in soccer affect investor mood negatively, which in turn has a negative effect on stock market performance. More recently, Chang et al. (2015) present evidence that investors exhibit significant misreaction to information and that they do not learn from past mistakes.

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 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 are consistent with their initial briefs, 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 since 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, p1540), "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".

Due to the contagion of popular ideas by personal communication and media, individuals tend to conform behaviorally (Hirshleifer, 2001) and this contagion in society facilitates an individual's bias to evolve into a social bias. 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 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 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 since 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 to 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 can 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[3] that is updated to monthly frequency and spans the period from July 1965 to September 2015, with a total of 603 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.[4]

A plot of the two indices is presented in Figure 1. Visual inspection of the Baker and Wurgler index indicates long periods where 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[5]. In contrast, we can also identify long periods where the index exhibits frequent mean reversion (most of the 1990s and post 2010s).[6] These characteristics suggest long-term changes in persistence which 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, and focusing on this is more efficient than dealing with the underlying variables separately, since by construction it captures the co-movement of the multiple variables

[3]Available at Wurgler's website.

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

[5]see Baker and Wurgler (2006) for a detailed discussion

[6]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.

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 have a stochastic trend since arbitrage and improved market efficiency do not allow for long deviations that are not due to the business cycle.

[**Insert Figure 1 about here**]

Changes in the degree of persistence of the sentiment index and the possibility that it may behave like a non-stationary 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 where, 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 un-modelled changes in persistence would have an effect on the predictive power of the 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 where 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 motivates us to model changes to the degree of persistence in investor sentiment. A natural framework for this is a structural break analysis on the Augmented Dickey-Fuller (ADF) regression of the sentiment index. We follow a well-established literature of multiple structural break analysis (Bai, 1997, Bai and Perron, 1998) that uses the principle of minimizing residual sums of squares in sub-segments 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

3.1 Estimation of structural changes in the persistence of the sentiment index

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

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

where T_i is the location of the i'th break with $i = 1, ..., m$, $T_0 = 1$ 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. The inclusion of a constant is needed because while the full sample is zero mean, sub-samples 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 found in Kejriwal et al. (2013) that use this ADF specification to develop a test of non-stationarity against stationarity with structural change. In this section we assume that the sentiment index is stationary and 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)[7]. We relax this assumption in section 3.2.

We begin by estimating the lag structure of (1) in the full sample. The Bayesian information criterion estimates 4 lags of Δy_t but the correlogram of the residuals indicates

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

strong autocorrelation remaining at lags 6 and 7. Including 6 lags removes this autocorrelation and we therefore adopt the model with 6 lags in what follows. The results of the estimation excluding the constant are presented in Panel A of Table 1. The ADF statistic is -3.916 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 since the first autoregressive lag of S_t is estimated at $1 - 0.027 = 0.973$ and so the series is very close to having a unit root.

[Insert Table 1 about here]

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

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

where the minimization takes place over a set of admissible break locations determined by a trimming parameter ϵ that sets the minimum size of a segment as a proportion of the total sample, that we set to $\epsilon = 0.10$.[8] This is repeated 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

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

information criteria. After estimating the number of breaks, the rest of the parameters can be estimated by OLS in each segment. Estimation of (1) results in one break in January 2001 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 at the 0.05 significance level as well as the majority of information criteria.[9]

The results indicate a severe change in the degree of persistence close to the dot-com bubble of 2000. In the first segment, up to January 2001, there is a high degree of persistence with a first order autoregressive coefficient of 0.99 that is followed by a fifteen year period where the index is significantly more mean reverting with a coefficient of 0.88.[10] This structural change in the behaviour of the sentiment index indicates a maturation of the US securities market after the 2000 bubble that has led to a period where investor sentiment does not fluctuate as wildly as before. This may be attributed a decrease in the presence of sentiment-driven traders in the market, or a general increase in market efficiency due to other factors.

It is worth discussing how the model with one break compares to the full sample estimation of Panel A. Firstly, by nature of the $SupF$ tests used to produce the one break model, this is compared directly to the no break model of Panel A and is found to better fit the data in the sense that it produces a smaller sum of squared residuals. It also fits the data better than any other model of up to five breaks. Secondly, while the ADF test statistic for the full sample, presented in the bottom of Panel A, strongly rejects the null of a unit

[9]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. Since two of the four resulting segments are too small to produce reliable estimates we focus on the model with one break.

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

root, it cannot distinguish between changes in the degree of persistence, which is a contribution of the structural breaks analysis employed in this paper. In fact, the unit root tests on the sub-samples of the one break model (last rows of Panel B) find strong evidence of non-stationarity in the first segment of the series and equally strong evidence of stationarity in the second segment. This presents a theoretical puzzle. If a series is stationary, or $I(0)$, then any sufficiently large sub-sample of the series should be tested $I(0)$; if a series is $I(0)$ in general but has a sufficiently large segment that is non-stationary, or $I(1)$, then unit root testing of the full sample should find that the series is $I(1)$, which is not the case here. One explanation could be that this is a small sample issue, however this cannot be the case here since the $I(1)$ segment has 428 observations while the $I(0)$ segment only 175. Time series literature has long established that small sample issues with unit root tests have to do with low power while in our case the null is rejected in the smaller of the two segments.

If the ADF test result in the full sample is misleading then it could be the case that the test is oversized. To investigate this, we conduct a small Monte Carlo experiment where we simulate the model for a sample size $T = 1000$ and $10,000$ replications. We drop the first 400 observation of each sample to avoid issues with the initial condition and test a sample size of 600 that is close to our monthly sentiment index. We use $i.i.d(0,1)$ innovations, and in order to match the sentiment index dynamics as closely as possible, we construct each series using the estimated β coefficients for the six lags as reported in Panel A of Table 1. We record the rejection rate of the ADF test when $\rho = -0.027$, which is the estimated coefficient in the Baker and Wurgler (2006) index, and find that the test rejects the unit root null in 99.999% of cases at a 5% significance level. Under the null of a unit root ($\rho = 0$) the test rejects in 12.226% of cases, indicating an empirical size that is more than twice the nominal and a bias towards rejecting the null that mirrors the result in the sentiment index sample. While recognising that an experiment such as this cannot fully account for all aspects of the sentiment index, the results suggest that whether the series has non-stationary segments or not, the test is biased towards rejecting the null of a unit root in the full sample. If one is inclined to believe that the series is stationary, then the structural break results of this section remain valid and show a substantial increase in mean reversion after January 2001. The next section explores the likelihood of non-stationary segments in the data.

3.2 Allowing for non-stationarity in sub-samples of the sentiment index

We extend the analysis of the previous section 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 has been developed in Kejriwal et al. (2013) and consists of restricting the coefficient of S_{t-1} in (1) to zero in every other segment of the data when estimating the breaks. Estimation of the breaks then follows Perron and Qu (2006) that allows imposing the necessary restrictions. Denote the restrictions $R\delta = r$ where δ is the $q(m+1) \times 1$ vector of coefficients for q regressors and m breaks, R is an $n \times m(q+1)$ matrix for n restrictions placed on the model coefficients and r is an n dimensional vector of constants. To illustrate the restrictions used here, consider that in the simple case of two breaks and one lag of ΔS_t we have $\delta = (c_1, \rho_1, \beta_1, c_2, \rho_2, \beta_2, c_3, \rho_3, \beta_3)'$, and so to impose that the first and third regime are $I(1)$ and the dynamics do not change across regimes we need

$$R = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & -1 \end{bmatrix}$$

and $r = (0, 0, 0, 0)'$. The only available test in this setting is the $SupF$ of m against zero breaks, so we examine these in turn. Critical values have to be simulated as they depend on the number of breaks, the number of regressors and the trimming parameter[11]. Visual inspection of the data and the results of the previous section indicate that the first regime is likely to be $I(1)$ and the last $I(0)$, which implies imposing $\rho_1 = 0$ and only considering models with one, three, or five breaks. The objective is then to estimate these breaks and examine the degree of persistence across regimes.

The $SupF$ statistics for $m = 1, ..., 5$ breaks are 31.99, 11.77, 11.76, 8.09, and 8.49 respectively. Using the simulated critical values, all tests strongly reject (at the 99% confidence level) the null of no structural change providing further evidence of changes in persistence.[12] We must note that this is likely due to the tests being built under the null of a unit root while there is no theory that could support testing the null of I(0) against the alternative of changes in persistence. However, the estimates of the break dates are not affected by this as the same global minimization algorithm would be used under the alternative of structural breaks regardless of the null. We may conclude that while we must be skeptical about the

[11] We simulate the distribution of the $SupF$ test for trimming parameter 0.10, $T = 600$ and 1000 replications to calculate percentiles.

[12] See the discussion in the next to last paragraph of Section 3.1.

results from the $SupF$ tests when we impose I(1) regimes, we can still draw information from the estimated break dates purely from the principle of least squares minimization. Note finally that the results of Section 3.1 are not subject to this issue as there is no assumption of non-stationarity, only a change in the degree of persistence as can be seen in Panel B of Table 1.

The model with one break estimates the break location at the same date (January 2001) as the test in the previous section and has the largest $SupF$ statistic, therefore re-enforcing the results of the previous section and of the ADF tests in each of the segments. 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 sub-samples that are too small for valid inference.

An interesting result is the three break model that we presented in Panel C of Table 1. We find that the partition of the sentiment index with the minimum sum of squared residuals is $I(1)$ until March 1980 and between October 1995 and January 2001, and stationary in the rest of the sample. Unit root tests in the resulting regimes shown at the bottom of Panel C confirm these findings. In general, we find that that sentiment index behaves like a non-stationary variable in periods leading 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 that are at least partly responsible for the upcoming bubble, and their subsequent exit from the market.

In sum, the tests of both Section 3.1 and 3.2 suggest a robust structural break in sentiment persistence in January 2001, which is close to the time of the Internet 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, the compelling evidence that can support our finding of changes in sentiment persistence is its success in explaining bubbles and 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 of 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 originated in the housing market primarily. Thus, it seems the January 2001 regime change in sentiment persistence broadly corresponds with the recent US stock market history.

4 Changes in sentiment persistence and their effects on stock market

4.1 Arbitrage and attenuated 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 analyse 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. This is due to the change in trading technologies and decreases in transaction costs. Our data driven break estimation re-enforces the significance of this date and relates it to the behaviour of investor sentiment. Along similar lines, we assess the aggregate market short interest and share turnover that can proxy for arbitrage activities—details provided in Appendix A (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.

[Insert Figure 2 about here]

In addition to arbitrage activities, we also examine proxies for aggregate-market arbitrage cost including institutional holdings (details are provided in the Appendix).[13] Since low institutional holding is associated with low stock loan supply, it leads to higher costs of arbitrage (Nagel, 2005). As Figure 2 indicates, we find that the institutional holding has an upward trend. Such a pattern indicates that arbitrage costs should be less 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 intensive arbitrage and decrease in arbitrage costs may account for the I(0) sentiment segment of the post-2001, a period where there is less persistence in noise investors'

[13] 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), Duan et al. (2010) and Stambaugh et al. (2015).

biased believes. More specifically, due to the heightened arbitrage in recent year, there should not exist any long-run mispricing. In this case, noise traders who make transactions based on their sentiment cannot survive in the stock market for long, which is good news for stock market efficiency.

4.2 Changes in sentiment persistence and market 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 and 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. To evaluate whether both sentiment effects and anomalies have attenuated effects after 2001, we test a set of anomalies that are considered to be correlated with sentiment.

4.2.1 The sentiment-related anomalies

In a seminal paper, Stambaugh et al. (2012) introduce 11 well-documented sentiment-related anomalies, which comprise 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, that arise from sentiment effects.[14] The premium on each of the 11 anomalies is the return spread between stocks in the highest-performing decile (long leg) and the ones in the lowest-performing decile (short leg). Specifically, stocks in short legs are more susceptible to sentiment-driven mispricing compared to those in long legs. If sentiment has indeed attenuated in recent years as a consequence of increased arbitrage, one should expect that the profits on these sentiment-related anomalies are less prominent post-2001.

Table 2 reports the average monthly return and Alphas, relative to the Fama-French five factor model (hereafter referred to as FF5), on the 11 long-short anomalies. In the persistent sentiment regime, we find 8 out of the 11 anomalies are significantly profitable (t-statistics range from 2.78 to 5.29). However, the FF5 model is clearly unable to capture these returns, since Alphas of 9 anomalies are significantly positive. In contrast, when sentiment becomes more mean reverting, only two anomalies earn significant abnormal returns. One is the net operating asset (0.58% with a t-statistic of 2.91), and the other is the failure probability (0.89% with a t-statistic of 2.65). In sum, consistent with the relation between investor sentiment and the said anomalies, we find that few of these anomalies yield abnormal returns in the period after January 2001. These findings support our argument that market becomes more efficient when sentiment is more stationary.

[Insert Table 2 about here]

[14]Data is available from Robert Stambaugh's website.

4.2.2 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 with a trend and without. If the path of recent earnings slows, investors will perceive that the firm's earnings are non-trending, 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 only be expected when sentiment is persistent. Specifically, persistent sentiment reflects the heavy presence of noise investors 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 the absence of 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 September 2015. 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 1 to 4 quarters. This gives a total of 16 strategies. To control for micro-structural effects such as bid-ask spread, we allow one 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 3 reports the average monthly return on the buy, sell and buy-sell portfolio for each of the 16 strategies, and the results are striking. We find that 15 of the 16 momentum strategies are significantly profitable during persistent sentiment periods (t-statistics range from 1.99 to 5.04). This profitability becomes weaker with the rise of holding periods, indicating that momentum dies out over the long run. In contrast, none of these momentum strategies yields pronounced profit in the less persistent sentiment regime. In particular, for the strategies that form and hold for more than 6 months, negative returns appear.

[Insert Table 3 about here]

Table 4 reports Alphas of the monthly returns on momentum portfolios with respect to the Fama-French five-factor model (Fama and French, 2015). All strategies earn significant profits during persistent sentiment periods. The most successful strategy selects stocks over 9 months and holds them for 3 months (1.43% per month with a t-statistic of 4.12). However, 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.

[Insert Table 4 about here]

4.3 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.[15] 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 sentiment predictability, there is still some disagree-

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

ment 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 sentiment predictability on returns. 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 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:

$$\mathrm{R}_t = \alpha + b\mathrm{Sentiment}_{t-1} + \epsilon_t$$

where R_t is the market return in the current period, and $\mathrm{Sentiment}_{t-1}$ is the one-month lagged sentiment. Our bottom line is that sentiment has no forecasting power for the highly persistent segments, since 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 one-month T-bill rate. The data is 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 like small-cap and young firms being mispriced. We follow Baker and Wurgler (2006) and construct a set of long-short characteristic portfolios, where stocks in long legs are less speculative than those in short legs. Characteristics here comprise age, beta, dividend yield, operating profitability, size and return volatility (sigma). Appendix B gives details of these characteristics. We also include 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. Table 5 summarises the statistics of these return variables.

[Insert Table 5 about here]

4.3.1 Predictive regressions with structural breaks

Panel A of Table 6 reports results on sentiment predictability on market returns (S&P 500) and returns on long-short strategies for the whole sample period. We find that investor sentiment has little predictive power on one-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, one standard deviation increase in sentiment in the post-2001 regime is associated with -1.18% (t-statistic is -3.13) 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 and 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 zero in Regime 1. Our explanation for this is the long term mispricing associated with sentiment persistence: since arbitrage cannot correct the long-run mispricing quickly, high (low) sentiment is not necessarily associated with lower (higher) returns on the subsequent month.

[Insert Table 6 about here]

The same two-regime pattern also appears in the predictive regressions of long-short strategies. We find that investor sentiment has much stronger predictability on returns of long-short characteristic portfolios in the second regime than in the first. As to the long-short anomalies, sentiment has little forecasting power for most of Regime 1 whereas the exact opposite occurs in Regime 2. To illustrate using the combination portfolio of anomalies, a one standard deviation increase in sentiment in Regime 1 leads to a statistically insignificant profit of 0.12% (t-statistic is 1.58), while this profit is larger and significant in Regime 2 (0.97% with t-statistic of 3.50). Overall, these findings confirm our conjecture that investor sentiment has strong short-run predictability in the post-2001 period where, 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 where 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 0.15%, but it rises to 0.70% 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 6 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, since 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 7 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 are consistent with the findings of Baker and Wurgler (2006) and Stambaugh et al. (2012). After considering the one break in sentiment persistence, we find this negative predictability is mainly due to the second regime (post-2001). For the first regime, where 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 a long-run mispricing for the pre-2001 period and sentiment does not have short-run forecasting power. Consistent with our findings on 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. In conclusion, modeling the structural change results in better forecasting performance.

[Insert Table 7 about here]

Finally, we assess the robustness of our results regarding sentiment predictability by controlling for additional macroeconomic variables in the predictive models. To the extent that some omitted macro-related variables carry information that coincides with 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).[16] Tables 8 and 9 reproduce the cases examined in Tables 6 and 7, respectively, with the addition of the macroeconomic regressors. Overall, the results are almost identical, showing that our findings regarding sentiment predictability in the regimes defined by the structural breaks estimated in this paper are robust to controlling for additional macro-related variables.

[**Insert Table 8 and 9 about here**]

5 Conclusion

Market-wide sentiment is difficult to measure directly and can only be 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, 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 by allowing for changes in sentiment persistence. We justify our approach using well-

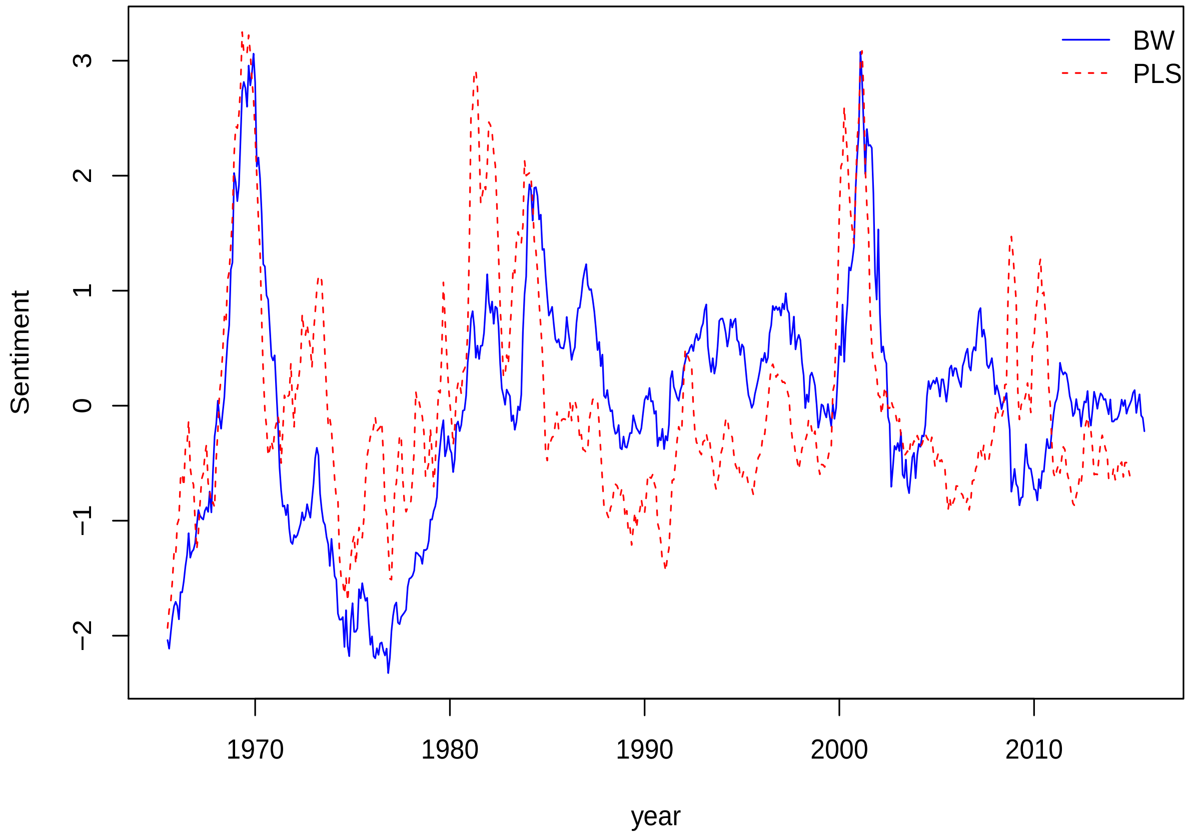
[16]The real interest rate is the difference between return on the 30-day T-bill and inflation rates. The term premium is defined as spread between 20-year T-bill and 1-year T-bill. The default premium is the difference between BAA and AAA bonds. The inflation rate and T-bill return are obtained from CRSP. The default premium comes from the St.louis Federal Reserve and cay is obtained from Martin Lettau's website.

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, wandering far away from the normal range for segments of the sample associated with overconfidence and exuberance in the stock market. In this sense, some compelling evidence in favor of our structural change model is its ability to explain market bubbles historically.

We assess the effect of change in sentiment persistence by testing for various market anomalies influenced by investor sentiment. 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 where market anomalies are only evident 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.

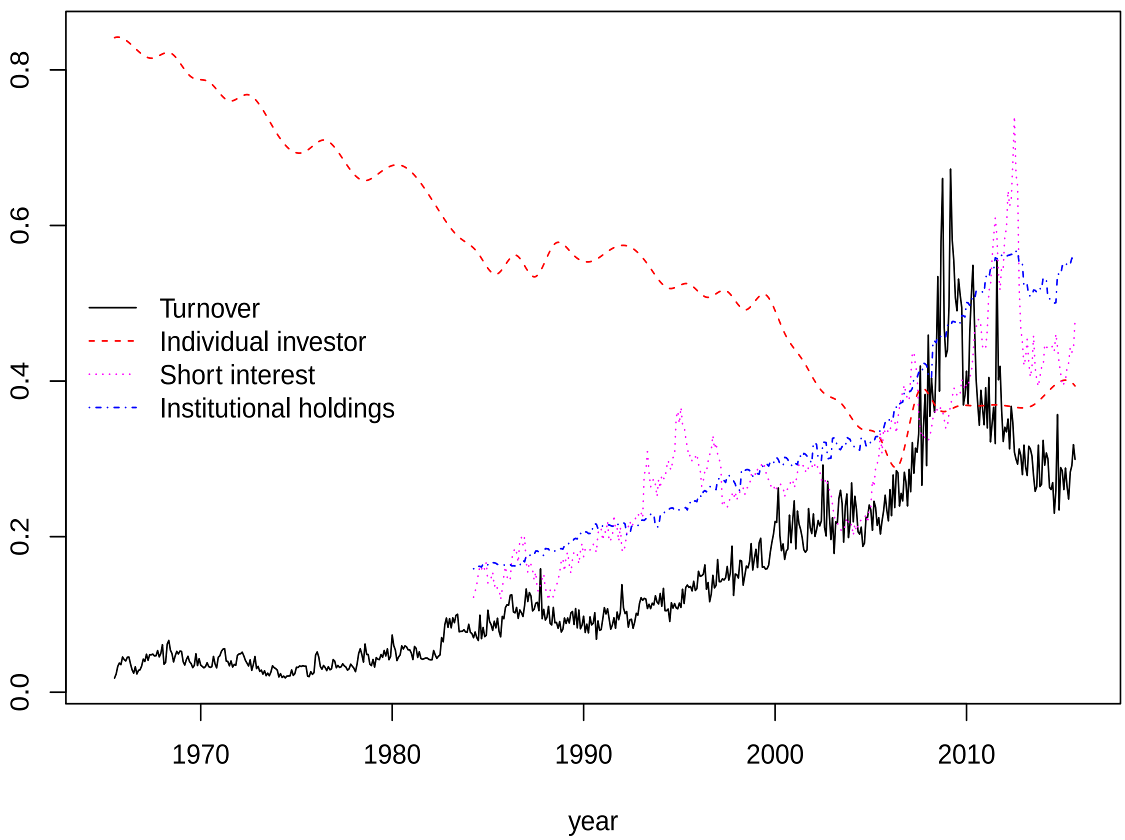
Finally, we examine the predictive power of the sentiment index on returns subject to the estimated structural changes and show that the breaks significantly impact the predictive power of sentiment on market returns as well as a variety of long-short strategies based on firm characteristics and market anomalies. We highlight the danger of using full sample models to forecast returns, since pre-2001 sentiment has little predictive power, but fortunately this has improved markedly in the post-2001 period. A natural conclusion is also to be aware of trending behavior in the sentiment index in the future, as this would impact negatively on its predictive power. Future research can extend our work by testing alternative proxies for market sentiment as well as investigating this behavior of sentiment beyond the US market.

Figure 1: Monthly Investor Sentiment Index



Notes: The BW sentiment index as measured in Baker and Wurgler (2006) spans from 1965:07 to 2015:09. The PLS sentiment index, as measured in Huang et al. (2015) spans from 1965:07 to 2014:12. The BW sentiment is used in our main empirical analyses while the PLS sentiment index is used for robustness checks.

Figure 2: Arbitrage activity and arbitrage cost proxies



Notes: This graph plots two proxies for arbitrage activities including share turnover (1965:07 to 2015:09) and short interest (1980:04 to 2015:09), and the proxy for arbitrage costs, institutional holdings (1980:04 to 2015:09). The red dash lines represents the proportion of U.S. common equity that individual investors hold (1965:07 to 2015:09). To keep the consistency of magnitude here, we divide share turnover rate by 5 and times short interest by 10.

Table 1: Estimation of ADF type regressions subject to structural breaks

Panel A is the fitted ADF regression in the full sample with constant excluded. Panel B is the one break model based on the restricted structural change analysis of Section 3.1. Panel C is the three structural breaks model based on imposing non-stationary regimes of Section 3.2. Standard errors in parentheses. The last two rows present the ADF test statistic and p-value for each sub-sample.

	Panel A:	Panel B: One structural break		Panel C: Three structural breaks			
	Full Sample	1965:7-2001:1	2001:2-2015:9	1965:7-1980:3	1981:4-1995:9	1995:10-2001:1	2001:2-2015:9
c	-	0.007 (0.008)	0.004 (0.012)	0.002 (0.012)	0.036 (0.015)	0.034 (0.02)	-0.004 (0.012)
ρ	-0.027 (0.007)	-0.015 (0.007)	-0.102 (0.018)	0 (-)	-0.081 (0.023)	0 (-)	-0.103 (0.018)
β_1	0.095 (0.040)	0.087 (0.040)		0.083 (0.039)			
β_2	0.054 (0.041)	0.048 (0.040)		0.048 (0.039)			
β_3	0.066 (0.040)	0.060 (0.040)		0.063 (0.039)			
β_4	0.143 (0.041)	0.145 (0.040)		0.150 (0.039)			
β_5	0.027 (0.041)	0.033 (0.040)		0.040 (0.040)			
β_6	0.118 (0.041)	0.124 (0.040)		0.131 (0.040)			
Sample size	603	428	175	177	186	65	175
ADF test statistic	-3.915	-2.379	-5.458	-2.352	-3.666	0.600	-5.243
p-value	0.000	0.148	0.000	0.157	0.005	0.988	0.000

Table 2: Changes in sentiment persistence and 11 market anomalies

$$\mathrm{R}_t = \alpha_1 \mathrm{d}_{1t} + \alpha_2 \mathrm{d}_{2t} + \beta_1 \mathrm{MKT}_t + \beta_2 \mathrm{SMB}_t + \beta_3 \mathrm{HML}_t + \beta_4 \mathrm{RMW}_t + \beta_5 \mathrm{CMA}_t + \epsilon_t$$

This table reports the average monthly percent return and percentage Alphas (relative to FF-5 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 persistent and mean reverting sentiment regimes respectively. Panel A looks at the period from July 1965 to January 2001, and Panel B looks at the period from February 2001 to September 2015. Return refers to the average time-series monthly return. The parentheses report Newey-West heteroskedasticity and autocorrelation consistent t-statistics.

	Panel A				Panel B			
	Return	t-statistic	α_1	t-statistic	Return	t-statistic	α_2	t-statistic
Asset growth	0.54	3.01	0.09	0.83	0.19	0.85	-0.08	-0.48
Composite equity issues	0.60	3.02	0.36	2.86	0.29	1.32	0.21	1.11
Failure probability	0.34	1.10	0.61	1.92	0.90	1.54	0.89	2.65
Gross profitability	0.26	1.46	0.44	2.99	0.34	1.03	0.18	0.98
Investment-to-assets	0.69	4.60	0.51	4.26	0.16	0.68	0.12	0.58
momentum	1.59	5.29	1.76	4.62	0.73	1.32	0.69	1.36
Net Operating asset	0.55	3.55	0.53	3.15	0.53	2.70	0.58	2.91
Ohlson's O score	0.08	0.39	0.49	3.43	-0.11	-0.43	0.24	1.44
Total accruals	0.63	3.38	0.72	4.15	-0.16	-0.78	0.06	0.27
Return on assets	0.63	2.78	0.57	3.68	0.46	1.26	0.21	1.03
Net stock issue	0.62	4.11	0.44	3.78	0.44	1.81	0.29	1.65

Table 3: Sentiment persistence and returns of momentum strategies

This table presents average monthly percent returns for momentum strategies. The sample includes all NYSE/AMEX stocks with share code 10 or 11. Panel A looks at the persistent sentiment regime for the period from July 1965 to January 2001, and Panel B looks at the mean reverting sentiment regime for the period from February 2001 to September 2015. 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 big-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. Momentum profitability 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. The parentheses report Newey-West heteroskedasticity and autocorrelation consistent t-statistics.

	Panel A				Panel B			
J	K= 3	6	9	12	K= 3	6	9	12
3 Sell	0.79	0.86	0.84	0.92	0.87	0.92	0.92	1.00
	(1.89)	(2.08)	(2.12)	(2.35)	(1.22)	(1.31)	(1.34)	(1.49)
3 Buy	1.49	1.51	1.57	1.53	1.03	1.03	1.03	0.97
	(4.70)	(4.79)	(4.91)	(4.80)	(2.14)	(2.12)	(2.14)	(1.99)
3 Buy-Sell	0.70	0.65	0.73	0.61	0.16	0.11	0.10	-0.02
	(2.67)	(2.76)	(3.65)	(3.43)	(0.35)	(0.27)	(0.28)	(-0.07)
6 Sell	0.75	0.74	0.78	0.94	0.95	0.94	0.97	1.06
	(1.66)	(1.72)	(1.86)	(2.25)	(1.22)	(1.23)	(1.32)	(1.50)
6 Buy	1.70	1.76	1.72	1.59	1.08	1.01	0.95	0.87
	(5.30)	(5.46)	(5.33)	(4.96)	(2.25)	(2.12)	(1.99)	(1.80)
6 Buy-Sell	0.95	1.02	0.94	0.65	0.13	0.07	-0.02	-0.19
	(2.93)	(3.62)	(3.80)	(2.70)	(0.22)	(0.13)	(-0.03)	(-0.46)
9 Sell	0.63	0.70	0.85	1.03	0.97	1.00	1.07	1.15
	(1.41)	(1.62)	(1.97)	(2.37)	(1.19)	(1.28)	(1.42)	(1.58)
9 Buy	1.92	1.86	1.72	1.57	1.05	0.93	0.86	0.79
	(5.82)	(5.64)	(5.26)	(4.83)	(2.20)	(1.94)	(1.80)	(1.66)
9 Buy-Sell	1.29	1.16	0.87	0.54	0.08	-0.07	-0.21	-0.36
	(4.04)	(3.92)	(3.10)	(1.99)	(0.12)	(-0.13)	(-0.41)	(-0.77)
12 Sell	0.68	0.85	1.00	1.14	1.08	1.15	1.22	1.27
	(1.49)	(1.87)	(2.20)	(2.54)	(1.33)	(1.47)	(1.60)	-(1.70)
12 Buy	1.86	1.73	1.61	1.48	0.80	0.75	0.73	0.73
	(5.60)	(5.28)	(4.92)	(4.55)	(1.70)	(1.57)	(1.55)	(1.54)
12 Buy-Sell	1.18	0.88	0.61	0.34	-0.28	-0.40	-0.49	-0.54
	(3.63)	(2.80)	(2.01)	(1.14)	(-0.44)	(-0.69)	(-0.91)	(-1.11)

Table 4: Sentiment persistence and Alphas of momentum strategies

$$\mathrm{R}_t = \alpha_1 \mathrm{d}_{1t} + \alpha_2 \mathrm{d}_{2t} + \beta_1 \mathrm{MKT}_t + \beta_2 \mathrm{SMB}_t t + \beta_3 \mathrm{HML}_t + \beta_4 \mathrm{RMW}_t + \beta_5 \mathrm{CMA}_t + \epsilon_t$$

This table presents monthly Alpha percentage on momentum portfolios with respect to the Fama-French five factor 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 one 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 September 2015. The parentheses report Newey-West heteroskedasticity and autocorrelation consistent standard errors.

	α_1				α_2			
J	K= 3	6	9	12	K= 3	6	9	12
3 Buy-Sell	0.78	0.74	0.79	0.71	0.01	0.00	0.01	-0.06
	(2.79)	(2.96)	(3.71)	(3.97)	(0.02)	(-0.01)	(0.02)	(-0.16)
6 Buy-Sell	1.08	1.14	1.08	0.82	-0.02	-0.04	-0.07	-0.17
	(3.06)	(3.75)	(4.21)	(3.55)	(-0.03)	(-0.07)	(-0.12)	(-0.36)
9 Buy-Sell	1.43	1.31	1.06	0.76	-0.07	-0.14	-0.20	-0.29
	(4.12)	(4.26)	(3.85)	(3.02)	(-0.10)	(-0.21)	(-0.33)	(-0.55)
12 Buy-Sell	1.38	1.12	0.88	0.62	-0.34	-0.38	-0.41	-0.42
	(4.14)	(3.63)	(3.10)	(2.36)	(-0.46)	(-0.56)	(-0.67)	(-0.78)

Table 5: Summary statistics of return variables

This table presents summary statistics of return variables (in percentage). Panel A looks at the market excess return (S&P 500 Index), returns on long-short characteristic portfolios, and returns on long-short market anomalies as documented in Stambaugh et al. (2012). Panel B looks at returns on short legs from these long-short strategies. Stocks in short legs are more susceptible to sentiment effects than stocks in long legs. The sample period is from August 1965 to October 2015.

		Panel A: Long-short strategies				Panel B: Short legs			
		Mean	Std	Min	Max	Mean	Std	Min	Max
Market return	S&P 500	0.22	4.37	-22.37	15.78				
Characterstics	Beta	-0.07	6.63	-25.41	23.95	0.58	8.01	-33.74	32.92
	Age	0.03	4.23	-20.84	27.81	0.46	6.46	-30.85	20.78
	DP	-0.63	6.22	-25.69	23.03	0.61	6.99	-31.12	26.64
	OP	0.13	4.11	-20.74	21.84	0.19	6.59	-32.91	16.63
	Size	-0.46	4.87	-32.21	20.94	0.63	6.44	-29.55	29.07
	Sigma	0.49	7.96	-36.03	35.16	-0.05	8.97	-34.51	33.89
	Combinantion	-0.08	4.80	-25.38	21.30	0.40	6.94	-30.23	25.20
Anomalies	Accrual	0.40	3.46	-12.21	19.69	0.64	6.39	-31.18	17.82
	AssetGrowth	0.44	3.36	-12.20	20.96	0.69	6.14	-27.81	20.96
	Composite Issue	0.51	3.49	-15.84	14.41	0.61	5.77	-26.16	20.31
	Distress	0.53	6.27	-27.44	32.75	0.53	8.30	-32.53	28.21
	GrossProfit	0.28	3.64	-10.90	17.03	0.81	5.57	-24.36	21.23
	InvestmentAssets	0.53	2.92	-7.66	10.51	0.68	5.92	-28.45	19.14
	Momentum	1.32	6.51	-39.56	29.21	0.17	7.44	-28.96	38.75
	NOA	0.54	2.95	-11.77	11.23	0.53	5.45	-28.35	18.19
	Oscore	0.03	3.68	-12.58	15.24	0.87	6.39	-31.45	22.69
	ROA	0.57	4.09	-14.01	22.02	0.54	6.56	-31.42	26.58
	NetStockIssue	0.56	2.80	-10.97	13.39	0.52	5.62	-24.68	19.58
	Combinantion	0.51	2.04	-9.22	10.70	0.58	5.74	-27.40	20.63

Table 6: Sentiment predictability on market excess returns and on long-short strategy returns

Predictive regressions of returns on one-month lagged sentiment,

$$\text{Return}_t = \alpha + \beta \text{Sentiment}_{t-1} + \epsilon_t.$$

The dependent variables include the S&P 500 excess return, returns on long-short portfolios with respect to firm characteristics and returns on 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 the top decile (the long leg). We also report combinations of characteristic portfolios and 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 October 2015. 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 1981, September 1995, and January 2001). t-statistics, adjusted by the Newey-West heteroscedasticity and autocorrelation consistent standard errors, are reported in parentheses. Adjusted R^2 values are also reported.

	Panel A: No break		Panel B: One break			Panel C: Three breaks				
Return	Full sample	R^2 (%)	Regime 1	Regime 2	R^2 (%)	Regime 1	Regime 2	Regime 3	Regime 4	R^2 (%)
sp500	-0.16	0.15	0.00	-1.18	0.70	-0.01	-0.15	0.89	-1.17	0.49
	(-0.85)		(0.00)	(-3.13)		(-0.06)	(-0.29)	1.03	(-3.07)	
Long-short characteristic portfolios										
age	0.65	2.37	0.45	1.84	3.35	0.20	1.11	1.83	1.89	3.88
	(3.25)		(2.45)	(2.50)		(1.07)	(3.26)	(1.12)	(2.61)	
beta	0.97	2.13	0.69	2.63	2.85	0.55	1.36	0.60	2.66	2.66
	(3.33)		(2.26)	(3.37)		(1.51)	(2.20)	(0.33)	(3.43)	
DP	1.02	2.66	0.88	1.80	2.60	0.63	1.48	2.51	1.86	2.74
	(3.64)		(2.99)	(2.67)		(1.78)	(2.68)	(1.41)	(2.72)	
OP	0.68	2.74	0.55	1.44	2.98	0.32	1.07	2.12	1.49	3.59
	(3.73)		(3.24)	(3.39)		(1.68)	(2.40)	(2.28)	(3.50)	
Size	0.64	1.71	0.76	-0.15	1.82	0.77	0.87	0.49	-0.15	1.51
	(2.72)		(3.49)	(-0.27)		(2.97)	(2.21)	(0.40)	(-0.27)	
sigma	1.35	2.88	1.03	3.27	3.51	0.82	1.57	2.30	3.31	3.38
	(4.12)		(3.42)	(2.72)		(2.19)	(2.51)	(1.32)	(2.77)	
Combination	0.88	3.39	0.73	1.81	3.68	0.55	1.24	1.64	11.05	3.69
	(4.31)		(3.55)	(3.06)		(2.25)	(3.25)	(1.26)	(3.16)	

Table 6 – continued from previous page

Long-short market anomalies										
Accrual	0.03	0.01	0.15	-0.67	0.37	0.21	0.13	-0.46	-0.68	0.19
	(0.19)		(0.38)	(-2.65)		(0.91)	(0.40)	(-0.66)	(-2.69)	
AssetGrowth	0.41	0.76	0.16	1.08	1.32	0.03	0.38	1.23	1.10	1.55
	(1.63)		(0.94)	(2.05)		(0.16)	(0.82)	(1.32)	(2.09)	
CompositeIssue	0.45	1.64	0.36	0.93	1.63	0.18	0.73	1.72	0.97	2.19
	(2.42)		(1.77)	(2.70)		(0.70)	(1.75)	(1.64)	(2.80)	
Distress	1.04	2.21	0.53	2.93	3.76	0.77	0.53	-1.10	2.90	3.74
	(3.27)		(1.84)	(3.11)		(1.89)	(0.98)	(-0.62)	(3.04)	
GrossProfit	0.19	0.26	0.13	0.50	0.05	0.23	-0.14	-0.27	0.48	-0.14
	(1.17)		(0.77)	(1.43)		(1.07)	(-0.31)	(-0.48)	(1.35)	
InvestmentAssets	0.08	0.07	0.03	0.34	0.00	-0.13	0.78	0.18	0.34	0.42
	(0.63)		(0.25)	(1.34)		(-0.80)	(2.01)	(0.42)	(1.34)	
Momentum	0.03	0.00	-0.28	1.92	1.11	-0.17	0.07	-2.58	1.90	1.39
	(0.14)		(-1.05)	(2.11)		(-0.62)	(0.14)	(-1.27)	(2.04)	
NOA	0.57	0.26	0.55	0.65	3.36	0.51	0.36	1.59	0.66	3.73
	(5.40)		(4.89)	(3.38)		(4.16)	(1.16)	(3.11)	(3.43)	
Oscore	0.55	2.20	0.57	0.38	1.91	0.48	0.86	0.99	0.40	1.73
	(3.82)		(3.88)	(1.22)		(2.63)	(2.69)	(1.42)	(1.29)	
ROA	0.56	1.50	0.33	1.43	2.04	0.19	0.27	1.49	1.45	2.13
	(2.75)		(1.64)	(3.25)		(0.65)	(0.63)	(1.52)	(3.33)	
NestStockIssue	0.44	2.47	0.32	1.15	3.20	0.24	0.59	0.60	1.16	3.05
	(3.05)		(2.03)	(3.60)		(1.18)	(1.74)	(0.78)	(3.66)	
Combination	0.34	2.74	0.12	0.97	3.99	0.18	0.44	0.34	0.98	3.82
	(4.02)		(1.58)	(3.50)		(1.74)	(2.39)	(0.56)	(3.57)	

Table 7: Sentiment predictability on short leg strategy returns

Predictive regressions of returns on one-month lagged sentiment,

$$\text{Return}_t = \alpha + \beta \text{Sentiment}_{t-1} + \epsilon_t.$$

The dependent variables include returns on short legs of long-short characteristic portfolios and returns on short legs 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 of characteristic portfolios and 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 October 2015. 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 1981, September 1995, and January 2001). t-statistics, adjusted by the Newey-West heteroscedasticity and autocorrelation consistent standard errors, are reported in parentheses. Adjusted R^2 values are also reported.

	Panel A: No break		Panel B: One break			Panel C: Three breaks				
Return	Full sample	R^2 (%)	Regime 1	Regime 2	R^2 (%)	Regime 1	Regime 2	Regime 3	Regime 4	R^2 (%)
Short legs of long-short characteristic Portfolios										
Low age	-0.75	1.36	-0.44	-2.65	2.45	-0.27	-1.00	-1.01	-2.68	2.26
	(-2.49)		(-1.44)	(-2.98)		(-0.74)	(-1.52)	(-0.58)	(-3.03)	
High beta	-1.01	1.58	-0.68	-2.98	2.25	-0.66	-1.06	0.20	-2.98	2.02
	(-2.75)		(-1.68)	(-3.46)		(-1.32)	(-1.33)	(0.13)	(-3.43)	
Low dp	-0.95	1.86	-0.77	-2.05	1.94	-0.73	-1.06	-0.51	-2.01	1.64
	(-2.77)		(-1.99)	(-3.45)		(-1.48)	(-1.53)	(-0.38)	(-3.44)	
Low op	-0.84	1.61	-0.58	-2.39	2.20	-0.36	-1.30	-1.32	-2.43	2.01
	(-2.93)		(-2.26)	(-2.93)		(-1.00)	(-1.89)	(-1.05)	(-3.58)	
Small size	-0.78	1.45	-0.73	-1.05	1.15	-0.74	-0.98	0.10	-1.04	0.93
	(-2.52)		(-2.13)	(-2.09)		(-1.52)	(-1.87)	(-0.74)	(-2.94)	
High sigma	-1.30	2.11	-0.92	-3.61	2.88	-0.79	-1.37	-1.22	-3.64	2.59
	(-3.24)		(0.58)	(-1.33)		(0.09)	(0.53)	(1.55)	(-1.24)	
Combination	-0.94	1.82	-0.68	-2.55	2.28	-0.59	-1.13	-0.62	-2.47	2.01
	(-2.95)		(-1.98)	(-3.18)		(-1.35)	(-1.68)	(-4.55)	(-3.19)	
Short legs of long-short market anomalies										
Accrual	-0.50	0.59	-0.35	-1.32	0.53	0.00	-0.31	0.15	-1.31	0.23
	(-1.65)		(-1.05)	(-2.63)		(-0.94)	(-0.50)	(0.14)	(-2.57)	

Table 7 – continued from previous page

AssetGrowth	-0.66	1.14	-0.42	-2.06	1.68	-0.03	-0.53	-0.55	-2.06	1.35
	(-2.22)		(-1.33)	(-3.84)		(-0.97)	(-0.79)	(-0.45)	(-3.81)	
CompositeIssue	-0.55	0.91	-0.36	1.68	1.21	-0.41	-0.27	0.03	-1.67	0.91
	(-2.00)		(-1.14)	(-3.41)		(-1.02)	(-0.40)	(0.03)	(-3.32)	
Distress	-1.04	1.25	-0.35	-3.60	2.88	-0.38	-0.56	0.43	-3.59	2.56
	(-2.17)		(-0.72)	(-3.58)		(-0.53)	(-0.67)	(0.22)	(-3.52)	
GrossProfit	-0.20	0.12	0.00	-1.38	0.55	-0.17	0.32	1.30	-1.35	0.53
	(-0.85)		(0.00)	(-2.62)		(-0.55)	(0.48)	(1.26)	(-2.48)	
InvestmentAssets	-0.50	0.71	-0.34	-1.45	0.81	-0.34	-0.62	0.52	-1.45	0.61
	(-1.86)		(-1.11)	(-3.57)		(-0.90)	(-0.99)	(0.52)	(-3.52)	
Momentum	-0.57	0.58	-0.21	-2.67	1.57	-0.30	-0.35	1.24	-2.65	1.44
	(-1.75)		(-0.60)	(-2.77)		(-0.68)	(-0.48)	(0.72)	(-2.70)	
NOA	-0.67	1.51	-0.47	-1.85	1.95	-0.50	-0.34	-0.40	-1.84	1.63
	(-2.66)		(-1.73)	(-4.06)		(-1.52)	(-0.53)	(-0.34)	(-3.98)	
Oscore	-0.74	1.33	-0.55	-1.82	1.47	-0.47	-0.81	-0.93	-1.84	1.18
	(-2.75)		(-1.89)	(-3.20)		(-1.26)	(-1.28)	(-0.83)	(-3.22)	
ROA	-0.64	0.78	-0.15	-2.55	2.11	0.16	-0.51	-1.35	-2.55	1.98
	(-1.78)		(-0.42)	(-3.60)		(0.30)	(-0.76)	(-0.82)	(-3.60)	
NestStockIssue	-0.56	0.98	-0.34	-1.88	1.57	-0.45	-0.17	0.70	-1.86	1.42
	(-2.14)		(-1.13)	(-3.60)		(-1.22)	(-0.27)	(0.64)	(-3.47)	
Combination	-0.55	0.92	-0.30	-2.02	1.67	-0.33	-0.36	0.13	-2.01	1.37
	(-2.16)		(-1.1)	(-3.57)		(-0.97)	(-0.57)	(0.11)	(-3.51)	

Table 8: Sentiment predictability on log-short strategy returns, controlling for macro-related variables.

Predictive regressions of returns,

$$Return_t = \alpha + \beta \text{Sentiment}_{t-1} + \alpha_1 \text{RI}_{t-1} + \alpha_2 \text{INF}_{t-1} + \alpha_3 \text{TERM}_{t-1} + \alpha_4 \text{DEF}_{t-1} + \alpha_5 \text{CAY}_{t-1} + \epsilon_t.$$

The dependent variables include excess returns on the S&P 500 index, returns on long-short portfolios with respect to firm characteristics and returns on 11 long-short market anomalies as documented in Stambaugh et al. (2012). Control variables are the real interest rate (RI), inflation (INF), the term spread(TERM), the default premium (DEF) and the consumption-wealth ratio (CAY). The table reports coefficients on lagged sentiment in the full sample, and in regimes defined by the breaks. t-statistics, adjusted by the Newey-West heteroscedasticity and autocorrelation consistent standard errors, are reported in parentheses. Adjusted R^2 values are also reported.

	Panel A: No break		Panel B: One break			Panel C: Three breaks				
Return	Full sample	R^2 (%)	Regime 1	Regime 2	R^2 (%)	Regime 1	Regime 2	Regime 3	Regime 4	R^2 (%)
sp500	-0.16	0.15	0.00	-1.04	1.20	-0.01	-0.07	0.79	1.01	1.05
	(-0.85)		(0.00)	(-3.05)		(-0.24)	(-0.13)	(0.82)	(-2.88)	
Long-short characteristic Portfolios										
age	0.65	2.37	0.43	1.70	3.27	0.23	1.08	1.68	1.78	3.55
	(1.73)		(2.27)	(2.34)		(1.22)	(2.48)	(0.98)	(2.49)	
beta	0.97	2.13	0.74	2.37	2.80	0.63	1.55	0.36	2.38	2.66
	(3.33)		(2.35)	(3.35)		(1.73)	(1.95)	(0.19)	(3.38)	
DP	1.02	2.66	1.03	1.60	3.05	0.73	2.14	2.75	1.72	3.35
	(3.64)		(3.27)	(2.56)		(2.09)	(3.00)	(1.52)	(2.68)	
OP	0.68	2.74	0.51	1.47	3.89	0.37	0.77	2.16	1.56	3.17
	(3.73)		(2.95)	(3.33)		(1.90)	(1.40)	(2.18)	(3.44)	
Size	0.64	1.71	0.84	-0.37	2.40	0.87	0.95	0.17	-0.40	2.16
	(2.72)		(3.66)	(-0.74)		(3.32)	(1.79)	(0.14)	(-0.76)	
sigma	1.35	2.88	1.09	3.11	3.74	0.94	1.51	2.32	3.19	3.55
	(4.12)		(3.52)	(2.88)		(2.68)	(1.77)	(1.34)	(2.94)	
Combination	5.30	3.39	0.78	1.64	3.88	0.63	1.34	1.58	1.71	3.81
	(4.31)		(3.65)	(3.01)		(2.63)	(2.56)	(1.14)	(3.12)	
Long-short market anomalies										
Accrual	0.03	0.01	0.16	-0.86	0.93	0.25	0.03	-0.88	-0.92	1.01

Table 8 – continued from previous page

	(0.19)		(0.88)	(-2.94)		(1.16)	(0.08)	(-1.29)	(-3.16)	
AssetGrowth	0.41	0.76	0.12	1.07	1.10	0.03	0.23	1.30	1.13	1.31
	(1.63)		(0.72)	(1.99)		(0.16)	(0.44)	(1.31)	(2.11)	
CompositeIssue	0.45	1.64	0.36	0.78	1.81	0.21	0.80	1.51	0.86	2.09
	(2.42)		(1.61)	(2.38)		(0.77)	(1.74)	(1.33)	(2.48)	
Distress	1.04	2.21	0.48	3.03	3.31	0.71	0.45	-0.98	2.93	3.21
	(3.27)		(1.39)	(3.14)		(1.69)	(0.67)	(-0.57)	(3.05)	
GrossProfit	0.19	0.26	0.06	0.56	0.23	0.17	-0.38	-0.37	0.52	0.52
	(1.17)		(0.34)	(1.83)		(0.78)	(-0.71)	(-0.58)	(1.64)	
InvestmentAssets	0.08	0.07	0.02	0.34	0.13	-0.13	0.78	0.23	0.38	0.55
	(0.63)		(0.14)	(1.34)		(-0.75)	(1.71)	(0.48)	(1.46)	
Momentum	0.03	0.00	-0.23	1.50	2.31	-0.13	0.33	-3.27	1.37	3.10
	(0.14)		(-0.93)	(2.24)		(-0.58)	(0.54)	(-1.59)	(2.09)	
NOA	0.57	3.68	0.52	0.57	3.35	0.46	0.55	1.46	0.61	3.46
	(5.40)		(4.66)	(2.64)		(3.62)	(1.48)	(2.67)	(2.89)	
Oscore	0.55	2.21	0.57	0.26	1.58	0.48	0.96	0.80	0.29	1.38
	(3.82)		(3.75)	(0.84)		(2.67)	(2.13)	(1.16)	(0.91)	
ROA	0.56	1.50	0.24	1.44	2.04	0.21	-0.13	1.50	1.50	2.29
	(2.75)		(0.95)	(3.05)		(0.67)	(0.63)	(1.41)	(3.03)	
NestStockIssue	0.44	2.47	0.29	1.04	3.22	0.25	0.53	0.32	1.05	2.97
	(3.05)		(1.71)	(3.55)		(1.18)	(1.37)	(0.38)	(3.50)	
Combination	3.72	2.74	0.21	0.89	4.28	0.18	0.39	0.16	0.89	4.05
	(4.02)		(2.51)	(3.48)		(1.87)	(1.62)	(0.56)	(3.53)	

Table 9: Sentiment predictability on short leg strategy returns, controlling for macro-related variables.

Predictive regressions of returns,

$$Return_t = \alpha + \beta \text{Sentiment}_{t-1} + \alpha_1 \text{RI}_{t-1} + \alpha_2 \text{INF}_{t-1} + \alpha_3 \text{TERM}_{t-1} + \alpha_4 \text{DEF}_{t-1} + \alpha_5 \text{CAY}_{t-1} + \epsilon_t.$$

The dependent variables include returns on short legs of long-short characteristic portfolios and returns on short legs of 11 long-short market anomalies as documented in Stambaugh et al. (2012). Control variables are the real interest rate (RI), inflation (INF), the term spread(TERM), the default premium (DEF) and the consumption-wealth ratio (CAY). The table reports coefficients on lagged sentiment in the full sample, and in regimes defined by the breaks. t-statistics, adjusted by the Newey-West heteroscedasticity and autocorrelation consistent standard errors, are reported in parentheses. Adjusted R^2 values are also reported.

	Panel A: No break		Panel B: One break			Panel C: Three breaks				
Return	Full sample	R^2 (%)	Regime 1	Regime 2	R^2 (%)	Regime 1	Regime 2	Regime 3	Regime 4	R^2 (%)
Short legs of long-short characteristic Portfolios										
Low age	-0.75	1.36	-0.47	-2.36	3.14	-0.35	-1.07	-0.74	-2.40	2.91
	(-2.49)		(-1.59)	(-2.81)		(-1.04)	(-1.29)	(-0.38)	(-2.84)	
High beta	-1.01	1.58	-0.75	-2.66	2.58	-0.75	-1.26	0.58	-2.61	2.30
	(-2.75)		(-1.90)	(-3.44)		(-1.62)	(-1.26)	(0.35)	(-3.34)	
Low DP	-0.95	1.86	-0.85	-1.80	2.38	-0.82	-1.24	-0.30	-1.79	2.12
	(-2.77)		(-2.23)	(-3.18)		(-1.80)	(-1.39)	(-0.20)	(-3.03)	
Low OP	-0.84	1.61	-0.60	-2.20	2.93	-0.47	-1.17	-1.15	-2.25	2.71
	(-2.93)		(-2.05)	(-3.43)		(-1.41)	(-1.31)	(-0.83)	(-3.43)	
Small size	-0.78	1.45	-0.83	-0.72	2.57	-0.87	-1.05	0.48	-0.67	2.45
	(-2.52)		(-2.49)	(-1.23)		(-2.28)	(-1.23)	(0.39)	(-1.10)	
High sigma	-1.30	2.11	0.10	-0.24	1.17	-0.93	(-1.27)	(-1.03)	(-3.36)	3.07
	(-3.24)		(0.56)	(-0.86)		(-1.95)	(-1.23)	(-0.57)	(-3.08)	
Combination	-5.63	1.82	-0.65	-3.39	2.15	-0.70	-1.18	-0.36	-2.01	2.70
	(-2.95)		(-1.28)	(-3.47)		(-1.76)	(-1.33)	(-0.23)	(-3.12)	
Short legs of long-short market anomalies										
Accrual	-0.50	0.59	-0.41	-1.03	1.17	-0.45	-0.51	0.63	-0.98	0.96
	(-1.65)		(-1.22)	(-2.08)		(-1.13)	(-0.64)	(0.49)	(-1.93)	
AssetGrowth	-0.66	1.14	-0.47	-1.85	1.90	-0.04	-0.87	-0.32	-1.85	1.61

Table 9 – continued from previous page

	(-2.22)		(-1.47)	(-3.45)		(-1.07)	(-1.03)	(-0.23)	(-3.35)	
CompositeIssue	-0.55	0.91	-0.41	-1.45	1.62	-0.43	-0.59	0.39	-1.42	1.39
	(-2.00)		(-1.28)	(-3.16)		(-1.14)	(-0.71)	(0.31)	(-3.01)	
Distress	-1.04	1.25	-0.32	-3.69	2.79	-0.24	-0.73	0.28	-3.67	2.46
	(-2.17)		(-0.57)	(-3.65)		(-0.34)	(-0.67)	(0.13)	(-3.58)	
GrossProfit	-0.20	0.12	-0.03	-1.36	0.63	-0.16	0.14	1.40	-1.28	0.60
	(-0.85)		(-0.12)	(-3.01)		(-0.54)	(0.16)	(1.20)	(-2.79)	
InvestmentAssets	-0.50	0.71	-0.36	-1.29	1.18	-0.36	-0.86	0.83	-1.25	1.13
	(-1.86)		(-1.18)	(-3.24)		(-0.98)	(-1.04)	(0.73)	(-3.11)	
Momentum	-0.57	0.58	-0.30	-2.33	2.48	-0.36	-0.70	1.73	-2.25	2.53
	(-1.75)		(-0.86)	(-2.87)		(-0.92)	(-0.73)	(0.93)	(-2.75)	
NOA	-0.67	1.51	-0.50	-1.69	2.26	-0.50	-0.65	-0.17	1.69	1.96
	(-2.66)		(-1.80)	(-3.73)		(-1.54)	(-0.81)	(-0.13)	(-3.58)	
Oscore	-0.74	1.33	-0.63	-1.64	2.17	-0.53	-1.15	-0.78	-1.66	1.92
	(-2.75)		(-2.11)	(-2.89)		(-1.50)	(-1.36)	(-0.63)	(-2.89)	
ROA	-0.64	0.78	-0.13	-2.52	2.64	0.18	-0.48	-1.41	-2.63	2.50
	(-1.78)		(-0.30)	(-3.43)		(0.37)	(-0.60)	(-0.79)	(-3.47)	
NestStockIssue	-0.56	0.98	-0.37	-1.72	1.82	-0.45	-0.45	1.05	-1.65	1.79
	(-2.14)		(-1.23)	(-3.54)		(-1.28)	(-0.56)	(0.83)	(-3.32)	
Combination	-6.05	0.92	-0.35	-1.85	2.12	-0.35	-0.62	0.37	-1.83	1.89
	(-2.16)		(-1.28)	(-3.47)		(-1.12)	(-0.76)	(0.27)	(-3.36)	

Appendix

A. Arbitrage proxies

Share turnover. The aggregate-market share turnover is calculated monthly as the total trading volumes divided by the total share outstanding in NYSE, AMEX and Nasdaq stock market. The data is obtained from the Central for Research in Security Prices (CRSP).

Short interest. Following Duan et al. (2010), Short interest is measured as shares shorted divided by shares outstanding. We examine the equal weighted market short interest in the NYSE, AMEX and Nasdaq stock markets. The data is obtained from CRSP.

Institutional Ownership. Institutional ownership (IO) of individual stocks is measured as the fraction of shares outstanding held by institutional investors (Nagel (2005)). We examine the equal weighted market IO in the NYSE, AMEX and Nasdaq stock markets. The data is obtained from Thomson Financial Institutional Holdings, covering the period from April 1980 to September 2015.

Equity holdings by individual investors. The data of equity holdings by individual investors comes from the Federal Reserve Board's Flow of Funds Accounts.[17] The proxy for individual investors is calculated as the proportion of the aggregate corporate equity that Household sector holds. We then use linear interpolation to transform the annual data into monthly frequency.

[17]Prior (after) 2007, Table L.213 (L.215) of the Flow of Funds Accounts reports the value of corporate equity held by various groups of investors.

B. Characteristic portfolios

We construct a set of long-short characteristic portfolios, where stocks in the bottom (top) decile is in short (long) legs and are more (less) susceptible to sentiment. Characteristics comprise of: age, beta, dividend yield, operating profitability, size and return volatility.

Age Baker and Wurgler (2006) discover that firms that are young are more difficult to value and arbitrage. Following Baker and Wugler, we measure the firms' age as the number of month since they firstly appeared in CRSP.

Beta. According to Hong and Sraer (2016), high-beta stocks are more susceptible to speculative overpricing. In addition, Antoniou et al. (2015) discover that firms with high-beta appeal to sentiment traders during high sentiment periods. Here, beta is measured by the methodology of Fama and French (1992).

Dividends Yield. According to Pontiff (1996), stocks with low dividends are more likely to deviate from their true values. Dividends reduce holding cost, which in turn promotes arbitrage profitability. However, if firms pay no or small dividends, arbitrage will be more costly and difficult.

Operating Profitability. Baker and Wurgler (2006) suggest that firms with lower profitability are harder to value and arbitrage. In this study, we measure operating profitability as annual revenues minus cost of goods sold, interest expense and selling, general and administrative expenses, divided by total assets at the fiscal year-end.

Size Baker and Wurgler (2006) find that small-cap stocks are more susceptible to sentiment influence. According to Wurgler and Zhuravskaya (2002), firms with small size have higher arbitrage risk since they have fewer substitutes. According to this view, mispricing on small-cap stocks should be more difficult to arbitrage. Here, firm size is measured as the market value of equity (share close price times shares outstanding) in June of each year.

Return Volatility (sigma). According to Baker and Wurgler (2007), return volatility can be a natural measure of firms' speculative appeal. Further, they discover that stocks with higher volatility are more sensitive to shocks in sentiment, and thus more difficult to arbitrage. Following Baker and Wurgler, in June of each year t, sigma is computed as the standard deviation of returns over last 12 months (with a minimum window of 6 months).

The return data on portfolios of size , dividend yield and operating profitability are come from Kenneth French's website.

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