Sentiment Bubbles

Citation	Berger, D., & Turtle, H. J. (2015). Sentiment bubbles. Journal of Financial Markets, 23, 59-74. doi:10.1016/j.finmar.2015.01.002
DOI	10.1016/j.finmar.2015.01.002
Publisher	Elsevier
Version	Accepted Manuscript
Terms of Use	http://cdss.library.oregonstate.edu/sa-termsofuse

Sentiment bubbles

by

David Berger[a] and H. J. Turtle[b]

We examine cumulative changes in investor sentiment and find that these changes relate to extended periods of increasing overvaluation, followed by price corrections. The relation between sentiment and returns is path dependent — short-term increases in sentiment precede strong positive returns, while prolonged periods of increasing sentiment precede negative returns. Positive short-run returns are consistent with bubble dynamics and mitigate the backwards induction conundrum described by Abreu and Brunnermeier (2003). Our results hold for the market portfolio, and are especially strong for opaque portfolios with high levels of uncertainty, as well as portfolios with greater market frictions that limit arbitrage.

JEL classification: G11, G12

Keywords: Investor sentiment; Bubbles; Price-correction

*Berger thanks the Oregon State University College of Business for a summer research grant supporting this project.
[a] Corresponding author. Affiliation: Oregon State University. Address: 443 Austin Hall, College of Business, Corvallis, OR 97331-2603, United States. E-mail: dave.berger@bus.oregonstate.edu. Phone: (541) 737-2636.
[b] Affiliation: West Virginia University. Address: College of Business and Economics, West Virginia University, 1601 University Ave., Morgantown, WV 26506-6025, United States. E-mail: harry.turtle@mail.wvu.edu. Phone: (304) 293-7836.

1. Introduction

Negative returns following periods of high investor sentiment are reported in multiple studies. These studies examine sentiment sensitivities in the cross-section (e.g., Baker and Wurgler, 2012, 2006; Berger and Turtle, 2012; Neal and Wheatley, 1998), in aggregate domestic portfolios (e.g., Brown and Cliff, 2005), and in international markets (e.g., Baker et al., 2011; Schmeling, 2009). Considering the apparently robust role of sentiment as a contrarian indicator, it remains unclear why rational traders fail to use publicly available data to correct predictable price movement. Abreu and Brunnermeier (2003) summarize this backwards induction problem succinctly: Essentially, if sentiment predicts a correction tomorrow, then rational arbitrageurs should sell today, and prices should fall immediately, eliminating the informational content of investor sentiment. Yet, empirical evidence suggests a consistent predictive role for sentiment.[1]

To examine how cumulative sentiment changes affect equity returns, we link investor sentiment with economic bubble models. De Long et al. (1990) present a bubble model in which rational speculators trade in advance of positive feedback noise traders, and the buying pressures from both groups exacerbate price deviations. Abreu and Brunnermeier (2002) suggest that rational traders initially ride the bubble to capture strong returns due to the increased buying pressure of behavioral or noise traders. Abreu and Brunnermeier (2003) also model a role for rational traders in the evolution of bubble episodes. To correct mispricing, arbitrageurs must engage in coordinated action, whereas their lack of immediate synchronization allows the bubble to persist, prompting them to increase or maintain their long positions to capture returns as the overvaluation builds. Consequently, prices increase substantially above their fundamentals, before the ultimate correction. Matsushima (2013)

[1] Rosenthal (1981) also provides experimental evidence that economic agents often violate backwards induction principles — agents continue to play when stopping is the only rational strategy.

presents a similar model in which there is a small, uncertain probability that some arbitrageurs display behavioral biases and remain committed to riding a bubble.

Recent anecdotal work contends that sophisticated arbitrageurs may contribute to mispricing. Griffin et al. (2011) and Brunnermeier and Nagel (2004) reveal that institutions actively purchased technology stocks during the tech bubble; Xiong and Yu (2011) conclude that rational arbitrageurs chose to ride a bubble for Chinese warrants between 2005 and 2008. In an investigation of Hoare's Bank, a sophisticated economic agent, during the South Sea Bubble, Temin and Voth (2004) provide evidence that the bank actively rode the bubble to reap substantial profits. According to Guenster et al. (2013), it is optimal for investors to ride asset bubbles, given plausible utility specifications and a real-time indicator for bubble periods. McQueen and Thorley (1994) also find that the probability of observing an end to a run of consecutive positive abnormal returns decreases with the length of the run. In addition, DeVault et al. (2014) argue that institutional traders appear on both sides of most sentiment-related trades and that most sentiment trades are due to managerial discretion, not forced, flow-related trades.

In turn, Abreu and Brunnermeier (2003) suggest several testable hypotheses with respect to price dynamics during a bubble period. Initially, mispricing should increase, due to buying pressure from rational arbitrageurs who choose to ride the bubble, so we hypothesize that initial positive changes in sentiment provide a positive indicator of future returns. However, as the bubble persists, an increasing number of rational arbitrageurs liquidate their holdings and potentially establish positions against the bubble. Therefore, the initial positive relation between behavioral trader optimism and subsequent returns might dampen over the bubble period, as selling pressure from rational arbitrageurs increases. We also anticipate a price correction when the selling pressure from arbitrageurs exceeds the absorption capacity of noise traders, so in the long run, indicators of overly optimistic behavioral trading should relate negatively to future returns.

Our findings align with these predictions and clarify the role of investor sentiment in asset pricing. In the short run, increases in sentiment precede positive, large subsequent returns, consistent with building overvaluation early in a bubble episode. This novel result contrasts with the literature in which sentiment appears solely as a contrarian indicator.[2] After an extended overvaluation period, we find an even larger offsetting reversal. These empirical results highlight the impact of cumulative sentiment changes on returns, because they are economically larger than the impact of sentiment levels, although neither impact subsumes the other. That is, the strong short-run returns provide incentive for arbitrageurs to remain in the market, which represents a possible explanation for the backward induction problem. We also capture nonlinearity in the relation between investor sentiment and subsequent returns by including a quadratic measure of sentiment; the significant negative impact of squared sentiment on subsequent returns is consistent with a diminishing bubble growth rate as selling pressures increase. We further condition the relation between sentiment changes and subsequent returns based on the length of a sentiment episode. The results show that prolonged increases in sentiment have a negative impact on subsequent returns, because extended periods of cumulative sentiment increases ultimately induce corrections.

In addition to these primary hypotheses, we consider cross-sectional variation among portfolios. We predict that sentiment dynamics should be greatest in magnitude for firms that are difficult to value or costly to trade. The synchronization problem in Abreu and Brunnermeier (2003) should be greatest for firms with high levels of uncertainty. Further, misvaluation should be most extreme for firms with large market frictions that limit arbitrage. Baker and Wurgler (2007) also claim that opaque stocks, and stocks for which limits to arbitrage are most prevalent, are most prone to the impacts of investor sentiment. In addressing these various portfolio types, we provide a cross-sectional analysis

[2] It also contrasts with experimental results that indicate bubbles can be mitigated by rational arbitrageurs, such as Smith et al.'s (1988) finding that trader experience dampens bubbles, and Hommes et al.'s (2005) assertions that bubbles do not occur in the presence of fundamentalist traders.

of the extent to which market frictions facilitate the persistence of sentiment-related mispricings. We find opaque and high transaction cost portfolios are the most sentiment prone, exhibiting the greatest mispricing with the strongest returns following moderate increases in sentiment, as well as the largest corrections following prolonged sentiment episodes. These results are also consistent with the idea that greater misvaluation occurs in stocks that are short sale constrained.[3]

We adopt the Baker and Wurgler (2006) orthogonalized measure of sentiment changes with extensive tests to confirm that our findings are robust to the inclusion of orthogonalized measures of sentiment levels. We do not find comparable results with retail-based measures of consumer sentiment (e.g., University of Michigan Consumer Sentiment Index). Because recent findings indicate that institutions are the primary sentiment traders (DeVault et al., 2014), it is perhaps not surprising that consumer sentiment-based indicators have less value in describing equity market dynamics. Other factors, such as the link between product markets and financial markets, could also affect this relationship.

In sum, our study affirms a contrarian role of investor sentiment for future returns; and also offers an explanation for why standard backward induction arguments fail. Although prices likely decrease when sentiment levels are high, the effect of cumulative positive sentiment changes is nonlinear, and amplified especially when uncertainty and market frictions are greatest. These path-dependent sentiment dynamics suggest that arbitrageurs initially choose to ride speculative bubbles. These actions may be especially prevalent in opaque securities, for which bubble identification is difficult and bubble duration is uncertain, such that bubble riding is most likely. High market frictions create similar problems, limiting arbitrage, which can hamper price corrections.

[3] In unreported analyses, we consider low levels of institutional holdings to proxy for short sale constraints. We find large magnitude sentiment dynamics for these portfolios, suggesting that the impact of sentiment is greatest in constrained equities.

2. Data and sentiment measures

We examine macro-level sentiment effects related to the value-weighted excess market return (*Mkt*), as well as cross-sectional effects associated with value-weighted excess returns to sentiment-prone portfolios. The market return and riskless rate come from Ken French's data library. We identify sentiment-prone portfolios on the basis of volatility, age, size, and bid-ask spread, such that high volatility, young, and small value-weighted portfolios are opaque, whereas the large bid-ask spread value-weighted portfolio captures high trading frictions. We use the CRSP standard deviation sorted portfolios as the volatility portfolios for this study. Volatility portfolios, σ_{low} and σ_{high}, consist of the first and tenth decile of equities sorted according to standard deviations. We construct age, size, and spread portfolios from the universe of CRSP firms listed on the NYSE, AMEX, or NASDAQ that have a share code of 10 or 11 and sufficient available data for us to calculate returns and market capitalization. *Age* is the number of months since the firm's first appearance in the CRSP database. *Size* is the number of shares outstanding multiplied by the closing stock price at the end of month *t*-1. We assign firms to their *Age* and *Size* deciles for month *t*, according to their ranking at the end of month *t*-1. *Spread* is based on Corwin and Schultz's (2012, Eqs. (7), (10), (14), and (18)) measure of trading costs for firm *j* on day *t*. Following Corwin and Schultz, we calculate the monthly spread for each firm using all possible overlapping two-day periods within the month, then assign firms to *Spread* deciles for month *t*, using the average monthly spread value over the preceding six months. We adopt this measure as a proxy for the arbitrage limits faced by market participants that seek to eliminate mispricings. Following Stoll (2000) and Halling et al. (2013), we expect the spread measure to be highly correlated with other measures of market frictions (as well as with our opaqueness measures). For brevity, we report the results for the first and tenth decile portfolios, as well as a corresponding long-short portfolio formed with a long position in the most sentiment-prone portfolio for each characteristic. To match the available sentiment data, the monthly sample runs from July 1965 to December 2010.

As the summary statistics in Table 1 show, more opaque portfolios tend to display higher sample means and standard deviations. For example, the mean returns increase from 0.472 to 3.694 when we move from the low to the high volatility portfolios, and their standard deviations similarly increase from 3.011 to 11.039. Comparing the smallest and largest spread portfolios similarly reveals larger means and standard deviations for the large spread portfolio.

[Insert Table 1 about here]

We focus on periods in which prices may be inflated above fundamental values. Bubble models (Abreu and Brunnermeier, 2003) allow overvaluation to build throughout a bubble episode, prior to the ultimate correction. We hypothesize that the magnitude of this correction depends on the total level of overvaluation that has accumulated in previous periods, such that returns should be a path-dependent function of the accumulated sentiment changes, rather than simply a function of the most recent change in (or level of) sentiment. A simple specification that ignores the accumulated effects likely fails to acknowledge the dynamic nature of the impact of building sentiment on pricing. Our sentiment measures instead reflect positive increases in sentiment aggregated across a given episode. With these sentiment variables, we can detail the evolution of sentiment during positive bubble periods, then assess the path-dependent relation between sentiment and subsequent returns.

To measure path-dependent mispricing, we begin with the Baker and Wurgler (2006, 2007) sentiment index, developed to capture periods of mispricing and discern bubbles.[4] The sentiment index consists of the first principal component of several market variables, orthogonalized to macroeconomic conditions. We measure the extent to which multiple periods of sentiment *growth* affect subsequent returns in a path-dependent manner. As a measure of sentiment changes, Baker and

[4] We thank Jeffrey Wurgler for providing the sentiment data.

Wurgler (2007) suggest using the changes index, constructed from the first principal component of changes in the underlying proxies, rather than simply differencing the levels index. Accordingly, to measure sentiment as it builds through time, we calculate $Sum_{t-1,\Delta sent+}$ as the sum of successive (orthogonalized) sentiment increases through month *t*-1. For the initial month in the sample, we set $Sum_{t-1,\Delta sent+}$ equal to zero.[5] Then for each subsequent month, if the change in sentiment is positive, the value of the sentiment change is added to the previous value of $Sum_{t-1,\Delta sent+}$. If the change in sentiment is negative, we reset $Sum_{t-1,\Delta sent+}$ to zero, to capture periods of *increasing* sentiment.[6] We similarly define $Count_{t-1,\Delta sent+}$ as the number of months of consecutive sentiment increases through month *t*-1, which resets to zero for every month following a decrease in sentiment, consistent with the intuition of McQueen and Thorley's (1994) investigation of empirical runs of positive or negative abnormal returns. All our sentiment variables are defined for month *t* -1 and relate to returns during month *t*. We present the summary statistics in Table 2.

[Insert Table 2 about here]

The median of $Sum_{t-1,\Delta sent+}$ is 0, indicating that more than half of our observations correspond to periods of decreasing sentiment (due to the zero mean of the normalized Baker and Wurgler variable). In addition, $Sum_{t-1,\Delta sent+}$ increases at an increasing rate with bubble duration; for example, the 25th percentile of positive realizations of $Sum_{t-1,\Delta sent+}$ is 0.420 and the 50th percentile is 0.983, an increase of 0.563. However, from the conditional 50th to the 75th percentile, the variable increases by 0.85, then increases by 2.082 from the conditional 75th to the conditional 95th percentile.[7]

[5] The first available observation of the monthly sentiment change variable is a decrease during August 1965. The reported level of the sentiment variable was negative during July 1965. We set the *Sum* and *Count* variables equal to zero for August 1965. Results remain qualitatively similar if we omit August 1965 and begin with September 1965, which corresponds with the first observed increase in sentiment following a decrease.

[6] Sentiment changes involve improvements relative to the levels at the beginning of the period. We consider the underlying levels of sentiment in more detail in our robustness analysis.

[7] By design, our empirical measure captures a small number of extreme observations in which sentiment has built for several consecutive months. We expect the impact of sentiment on subsequent returns to manifest

In our empirical analysis, we use these sentiment variables to proxy for mispricing in subsequent equity returns. Although our focus is on positive bubbles, for comparison and a robustness analysis, we also consider $Count_{t-1,\Delta sent-}$, for which the negative subscript denotes consecutive decreases in sentiment. With this variable we can differentiate the impact of positive and negative runs of sentiment on subsequent returns. We predict an asymmetric relation between sentiment and returns that manifests mainly during periods of increasing sentiment.

From the *count* variables, we further create indicator variables that denote consecutive increases or decreases in sentiment, such that $I^{+}_{ST,t-1}$, $I^{+}_{Med,t-1}$, and $I^{+}_{LT,t-1}$ define the length of positive sentiment episodes. The short-term indicator $I^{+}_{ST,t-1}$ takes the value of 1 when sentiment has increased for one or two consecutive months through month *t*-1, and 0 otherwise. The medium-term indicator $I^{+}_{Med,t-1}$ equals 1 if there have been three to five months of consecutive increases in sentiment, and the long-term indicator $I^{+}_{LT,t-1}$ equals 1 in months in which sentiment has increased for six or more consecutive months through *t*-1. We define these indicator variables in a mutually exclusive and exhaustive manner, so that a six-month increase in sentiment implies that only the long-term indicator, $I^{+}_{LT,t-1}$, is nonzero, for example. Comparable indicator variables, $I^{-}_{ST,t-1}$, $I^{-}_{Med,t-1}$, and $I^{-}_{LT,t-1}$, pertain to consecutive decreases in sentiment. In Table 3, we partition the sample across these six indicator variables measured during month *t*-1, and then report conditional excess returns during month *t* for the test portfolios. We exclude the initial month of the sample from this analysis.

[Insert Table 3 about here]

The results in Table 3 offer several empirical regularities that are consistent with building overvaluation followed by an ultimate correction. First, we observe negative point estimates of

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during these periods. Importantly, within the robustness analysis in Section 3.2, we find our primary results are qualitatively similar when we exclude months in which sentiment increased for six or more months.

conditional returns following six or more consecutive monthly increases in sentiment, $I^{+}_{LT,t-1}$, across all portfolios considered. For example, the market portfolio loses 2.08% in this scenario. Further, the impact is greatest for the most sentiment-prone portfolios. The average conditional return across all long decile portfolios is -3.09%, whereas the average long-short portfolio conditional return is -3.10%. After six consecutive positive changes in sentiment, young firms lose 5.85%, but old firms lose only 1.64%. We observe similar large magnitude differential impacts across trading cost portfolios such that the largest decile spread companies lose 5.42%, whereas small spread companies lose only 1.61%. Second, we find that large conditional returns follow short-run increases in sentiment, consistent with building overvaluation during the early portion of a bubble episode. For example, following three to five consecutive sentiment increases (Column 5), conditional returns to the high and low volatility portfolios are 8.00% and 0.63%, respectively. The average mean return for the long-short portfolios following three to five consecutive increases in sentiment is 3.99%, indicating the greatest impact of short-run sentiment within opaque and high transaction cost portfolios

The partitions across consecutive increases and decreases in Table 3 enable us to consider the potential asymmetries with respect to sentiment. In the final three columns of Table 3, we report *F*-statistics that compare conditional returns across economic states. We reject the null hypothesis of mean equality across all sentiment categories for the high volatility and small firm portfolios at the 5% level (young firms are significantly different across all conditions at the 10% level (unreported)). The relevant tests for the related long-short portfolios for high volatility, young, and small firms are all significant at the 5% level (or better). We do not reject the null hypothesis for the large spread portfolio or the related long-short trading cost portfolio (unreported *p*-values of 12% and 11%, respectively). Comparing mean returns across all positive sentiment conditions reveal that the rejections in the initial column of *F*-statistics reflect mean differences within these positive conditions. That is, differences in returns across the positive sentiment states are significantly different at the 5% level or more for all opaque portfolios and their long-short portfolios. Furthermore, the difference in mean returns across positive sentiment conditions is significant for the high trading cost portfolio and its long-short portfolio.

Next, across the negative sentiment states, the highest point estimates occur for the market portfolio, the four low sentiment portfolios, and two high sentiment portfolios in the condition in which sentiment has decreased for six or more consecutive months. These estimates appear economically meaningful, but the final column shows that none of the portfolios display significant differences in mean returns across the negative sentiment categories. The impact of sentiment on returns thus appears significantly asymmetric, with strong impacts after consecutive positive increases but lesser effects after consecutive negative sentiment periods. These findings are consistent with the notion that sentiment changes relate primarily to positive asset pricing bubbles and are predominant in opaque portfolios, as well as portfolios with large trading costs.

3. The nonlinear relationship between sentiment changes and excess returns

In this section, we test two hypotheses related to cumulative sentiment changes. First, we predict that initial increases in sentiment produce positive returns. Second, as the bubble persists and sentiment increases accumulate, we predict that the relation between positive sentiment and subsequent returns weakens. Increased selling pressure from rational arbitrageurs slows the growth rate of the bubble, ultimately leading to negative returns when the mispricing gets resolved. We test these two hypotheses with the following quadratic regression:

$$R_{j,t} = \alpha_j + \theta_j Sum_{t-1,\Delta sent+} + \varphi_j Sum^2_{t-1,\Delta sent+} + e_{j,t}, \qquad (1)$$

where $R_{j,t}$ represents the excess return to test asset *j* during month *t*, $Sum_{t-1,\Delta sent+}$, is as previously defined, and its square is $Sum^2_{t-1,\Delta sent+}$. Following Baker et al. (2011), we do not include risk factors that could attenuate the empirical findings.[8] We expect a positive estimate for the θ_j parameter because increasing sentiment should precede increasing returns in the short run. We also, anticipate a negative coefficient estimate for the φ_j parameter, because selling pressure from rational arbitrageurs should increase as the bubble expands and thereby dampen the growth rate of the bubble.

3.1 Estimates of the impact of changes in sentiment on excess returns

We report the parameter estimates and associated *t*-statistics for equation (1) in Table 4. Because extant literature focuses on levels of sentiment rather than changes in sentiment, we append this variable to equation (1) and present these results within Panel B.[9]

[Insert Table 4 about here]

The estimates in Table 4 indicate persistence in bubbles with ultimate corrections. In the initial row of Panel A, the coefficient estimates for θ_j and φ_j are 0.880 and -0.244, respectively (both significant at the 1% level), implying a nonlinear relation between sentiment and excess market returns. Returns initially increase with sentiment, but the effect diminishes as sentiment continues to grow, as evidenced by the coefficient of the squared term. Sufficiently large sentiment increases then reduce future expected market excess returns.[10] This nonlinear relation is consistent with the notion that sentiment positively affects future returns as mispricing builds, and corrections emerge only in the long run.

The parameters from this specification can identify the maximum of the fitted functions. For any

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[8] In our robustness analysis, we demonstrate that our primary results also persist within the standard four-factor model. Unreported analyses also support our primary empirical results with both a single and three-factor risk specification.

[9] In an earlier version of the paper, we consider alternative robustness specifications related to equation (1) that include changes in the levels of previous sentiment, and regressors based on consecutive decreases in sentiment. Coefficient estimates for these additional variables are insignificant in the regressions considered.

[10] Although we include the full 545-month sample within our estimation, our independent variables are only non-zero for the 271 months in which sentiment increased in month *t*-1. If we restrict our sample to solely consider periods in which the sentiment variables are non-zero, inferences are largely unchanged for parameter estimates, but model fit often improves.

portfolio *j*, the maximum forecast value from equation (1) conditional on sentiment changes occurs when $Sum_{t-1,\Delta sent+} = \frac{-\theta_j}{2\varphi_j}$. The market portfolio estimates indicate that an indirect estimate of the maximum occurs when the sentiment variable is 1.803, near the 75th percentile of our positive sentiment measure (P_{75^+}=1.833 in Table 2). Similarly, when the sentiment measure $Sum_{t-1,\Delta sent+}$ equals 3.882, the conditional forecast crosses the horizontal axis, proximate to the 95th percentile of our positive sentiment measure in Table 2. Sentiment values above this threshold imply negative indirect estimates of the conditional market excess return.

In Figure 1 we present the estimated dynamic relationship between sentiment and excess market returns, using parameter estimates from the initial row of Panel A in Table 4. According to the estimated quadratic relation, marginal increases in sentiment improve future returns, and then after sufficiently large increases, the impact weakens and ultimately becomes negative. The relationship in Figure 1 highlights the importance of including a quadratic sentiment term; models that ignore the nonlinear impact yield a nearly flat, linear relationship between sentiment and future returns (with a negative, but insignificant, slope estimate for the market (unreported)).

[Insert Figure 1 about here]

The estimation results from equation (1) for the high and low sentiment portfolios offer further support for the hypothesis regarding the short- and long-run dynamics of sentiment with respect to subsequent returns. Panel A of Table 4 reports positive and significant estimates of the linear parameter, θ_j, for every portfolio. When we compare the estimates of sentiment responsiveness between decile portfolios, we find consistent evidence that estimates for opaque and high trading cost portfolios are meaningfully larger than those for translucent and low trading cost portfolios. For example, the θ_j parameter estimate for the lowest volatility portfolio (0.416, significant at the 5% level) is approximately one-tenth the magnitude of the highest volatility portfolio estimate (4.093, significant at the 1% level). The long-short volatility portfolio has an estimated θ_j of 3.677 (significant at the 1% level), indicating a dramatic increase in returns for high relative to low volatility portfolios. Furthermore, the average long-short portfolio estimate of sensitivity to short-run sentiment, θ_j, is 2.247. The positive parameter estimates document that initial sentiment increases relate positively to subsequent returns.

The φ_j estimates in column 3 of Table 4, which indicate the impact associated with previous squared sentiment changes ($Sum^2_{t-1,\Delta sent+}$), present strong evidence that overvaluation decreases with ever larger sentiment changes. All quadratic parameter estimates are negative and significant (1% level). In addition, the magnitude of the negative impact increases with opacity and trading costs. For example, the φ_j parameter estimates are -0.117 and -0.801 for the low and high volatility portfolios, respectively. The long-short volatility portfolio estimate is -0.684 and is significant at the 1% level. This effect is consistent with the Abreu and Brunnermeier (2003) model in which selling pressure from arbitrageurs increases as the bubble persists. Because the onset of the bubble is more difficult to discern in opaque portfolios and more difficult to correct in portfolios with greater trading costs, we expect bubble growth to be more persistent, then lead to larger ultimate reversals in these portfolios.

In addition to the market frictions captured by the trading cost portfolios, we expect greater misvaluation in short sale constrained equities. Therefore (in unreported results), we consider institutional holdings as a proxy for short sale constraints. Using Thompson-Reuters data, we designate high and low value-weighted decile portfolios according to their previous quarter-end institutional holdings beginning April 1980. The greatest sentiment effects manifest in the most short sale constrained portfolio. The θ_j and φ_j parameter estimates, which are comparable to the specification in Panel A of Table 4, are 2.441 (significant at the 1% level) and -0.539 (significant at the 5% level) in the low institutional holding portfolio, whereas these values are 1.213 (insignificant) and

-0.347 (significant at the 10% level) for the high institutional holding portfolio. These results also indicate that short sale constraints influence misvaluation.[11]

Analogous to our development of Figure 1, we compute indirect estimates of the maximum for the underlying quadratic function for each portfolio in Table 4. The maximum for the fitted functional form generally occurs at larger sentiment values for opaque and high transaction cost portfolios, relative to their transparent or low transaction cost counterparts. Consider the lowest volatility portfolio, with θ_j and φ_j estimates of 0.416 and -0.117, respectively. Here, we find an implied maximum when the sentiment variable equals 1.778, whereas the maximum for the highest volatility portfolio occurs when the sentiment variable is equal to 2.555. The maxima fall between 1.570 and 1.778 for the transparent or low transaction cost portfolios, compared with a range of 1.844 to 2.941 for the opaque and high transaction cost portfolios. These results imply that overvaluation builds for a longer period within opaque assets. Moreover, the maxima for the long-short portfolios range from 1.934 (age) to 3.631 (size). In an interesting implication, these empirical results show that the optimal time to "ride the bubble" may change with portfolio opacity or market frictions.

To illustrate the path-dependent relation, we plot the fitted quadratic function for the decile portfolios and present results in Figure 2. The results relate to the point at which arbitrageurs recognize that the price of an asset exceeds its fundamental value, an important consideration in Abreu and Brunnermeier (2003). We expect greater uncertainty regarding the start of a bubble for opaque assets, and our results indicate that inflated prices persist longer in opaque portfolios. Similarly, we expect difficulty in correcting bubbles when trading costs are large, as indicated by the spread variable. Supporting this hypothesis, we find the forecasts cross the horizontal axis at sentiment values of 4.336 and 5.625 for the lowest and highest volatility portfolios, respectively. Similar patterns emerge for

[11] We thank an anonymous referee for suggesting this analysis.

other measures of opaqueness and trading costs. The average horizontal axis cross-over points for the four characteristics are 3.951 and 4.922 for the low and high sentiment portfolios, respectively.

[Insert Figure 2 about here]

Extant literature relates levels of investor sentiment to future returns. In Panel B of Table 4 we append the lagged level of the Baker and Wurgler (2006) orthogonalized sentiment index, $Sent_{t-1}$, to equation (1), and find consistent evidence that all θ_j parameter estimates for $Sum_{t-1,\Delta sent+}$ remain positive, all φ_j parameter estimates for the $Sum^2_{t-1,\Delta sent+}$ variable are still negative, and all estimates are significant. For example, for the market portfolio, the inclusion of the levels variable causes the linear θ_j coefficient to decrease slightly from 0.880 to 0.828, and the quadratic estimate is mitigated in absolute magnitude, from -0.244 to -0.239. The estimated coefficient for the level of sentiment is -0.315 for the market portfolio (with the sign consistent with the contrarian view in extant literature, but an insignificant coefficient). We find negative, significant $Sent_{t-1}$ parameter estimates for the sentiment-prone portfolios, as well as the long-short portfolios, although including the levels variable has little impact on path-dependent sentiment estimates. For example, in the large spread portfolio, the θ_j parameter estimate is 1.911, while the φ_j parameter estimate is -0.499 (see Panel B), so the comparable values of 2.107 and -0.516 (see Panel A), indicate a marginal impact of the levels variable on the parameter estimates. In this sense, our results coexist with extant literature but also provide important information about the path dependent nature of sentiment changes, distinct from the impacts of sentiment levels.

Our empirical findings are consistent with the interpretation that initial increases in sentiment lead to strong subsequent returns as overvaluation builds. As the bubble persists for more time, the rate of bubble growth slows. These novel results contrast with the literature that indicates sentiment is purely a contrarian indicator (e.g., Baker et al., 2011). Our empirical results reveal that the impact of cumulative sentiment changes on returns is economically greater than the impact of sentiment levels reported in existing studies; however, neither impact subsumes the other (though sentiment levels exert a modest impact in the low sentiment portfolios).

3.2 Robustness analyses

We investigate several modifications to our primary empirical model, to confirm the robustness of our results. We focus this analysis on the market portfolio and the high sentiment-prone portfolios only, and report the results in Table 5. Column 1 describes the model modifications relative to our primary specification.

[Insert Table 5 about here]

To discern the impact of different risk factor specifications on our estimates, we include excess market returns, the Fama and French (1993) size and value factors, and Carhart's (1997) momentum factor in our modified sentiment regressions, using data obtained from Ken French's data library. The initial rows of Table 5 indicate the marginal impact of sentiment changes, after controlling for all four risk factors.[12] The results remain largely robust to this inclusion of a four-factor risk model. For the highest volatility portfolio, the highly significant parameter estimates, 1.818 for θ_j and -0.264 for φ_j, are dampened, but they continue to indicate a significant quadratic relation. The estimates for the smallest portfolio (1.972 and -0.228, both highly significant) are comparable to our original model. The φ_j estimate is negative (and significant at the 10% (unreported)) for the young portfolio. Furthermore, for the young and large spread portfolios, including additional risk factors leads to insignificant estimates of γ_j, the parameter estimate associated with $Sent_{t-1}$, as well as insignificant estimates for the path-dependent variables.

[12] We omit these factors in our primary specification, with the recognition that the impact of sentiment changes on excess returns gets mitigated in factor model disturbances, to the extent that the underlying risk factors capture impacts on sentiment (Baker et al., 2011).

In model 2 of Table 5, we consider a different specification of sentiment, such that we define the sentiment variable, $Sum_{t-1,\Delta sent+}$, conditional on periods of increasing and positive sentiment (i.e., the Baker and Wurgler sentiment level index must also be positive). The results remain qualitatively unchanged, or even appear stronger. For example, the θ_j estimate for the market portfolio is 1.396, compared with an estimate of 0.880 in the full model (Table 4).

In model 3 of Table 5, we report the results when we replace $Sum_{t-1,\Delta sent+}$ and $Sum^2_{t-1,\Delta sent+}$ with analogous variables that count consecutive months of sentiment increases. In the Abreu and Brunnermeier (2003) model, each arbitrageur liquidates shares a fixed period of time after becoming aware of the mispricing. Therefore, the length of a sentiment episode might relate to subsequent returns. The positive and significant estimates for $Count_{t-1,\Delta sent+}$, and the negative and significant estimates for $Count^2_{t-1,\Delta sent+}$ for all of the opaque portfolios (with insignificant results for the market portfolio) imply a comparable, quadratic impact of the consecutive number of sentiment increases on a bubble, relative to our summed variables.

Finally, we exclude the months in which sentiment increased for six or more consecutive months, to address the relation between sentiment changes and subsequent returns without the impact of the most extreme observations. The reported parameter estimates continue to confirm our primary results. In particular, the θ_j estimate of 0.882 for the market portfolio is marginally significant, and comparable with the results from the full model. The θ_j estimates are positive, large in magnitude, and highly significant for the four top decile portfolios, ranging from 1.946 to 3.886. The nonlinear coefficient estimate of φ_j for the market portfolio is -0.271 and significant at the 5% level. The remaining estimates are significant, ranging from -0.786 to -0.324 across the high volatility, young, and high trading cost portfolios (with an insignificant φ_j estimate for the smallest decile portfolio).

4. Sentiment-related overvaluation and price corrections

We next examine the dynamic relation between the magnitude of cumulative sentiment changes and subsequent returns, conditioned on the length of a positive sentiment episode. We hypothesize that as the length of a sentiment episode increases and overvaluation builds, future excess returns become more likely to be negative. To test this hypothesis, we specify the following model:

$$R_{j,t} = \alpha_j + \theta_{j,ST} I^{+}_{ST,t-1} Sum_{t-1,\Delta sent+} + \theta_{j,Med} I^{+}_{Med,t-1} Sum_{t-1,\Delta sent+}$$

$$+\theta_{j,LT} I^{+}_{LT,t-1} Sum_{t-1,\Delta sent+} + \gamma_j Sent_{t-1} + e_{jt}, \qquad (2)$$

where all variables are as previously defined. In this specification, the $\theta_{j,ST}$, $\theta_{j,Med}$, and $\theta_{j,LT}$ parameters describe the estimated path dependence between sentiment and returns for consecutive increases in sentiment over one to two months, three to five months, and six or more months, respectively.[13] We also include the sentiment level variable, $Sent_{t-1}$, to nest our results in extant literature and differentiate the impact of a high level of sentiment versus our path-dependent hypotheses. We report the parameter estimates and *t*-statistics in Table 6.

[Insert Table 6 about here]

The regression results in Table 6 provide further evidence in support of bubble growth and corrections. In particular, the $\theta_{j,LT}$ parameter reflects the estimated impact of six or more consecutive sentiment increases on subsequent returns. We find the long-run parameter is a strong contrarian indicator of subsequent returns. For the market portfolio, we estimate a highly significant negative coefficient of -0.704. This parameter estimate is significant at the 10% level for the largest size portfolio. All remaining $\theta_{j,LT}$ estimates are negative and significant at the 5% (or better) for the various decile portfolios. Estimates for the low volatility, old, large, and low trading cost portfolios range from to -0.620 to -0.440; estimates for the high volatility, young, small, and high trading cost portfolios

[13] Results are qualitatively similar for alternative specifications of the indicator variables.

appear much larger in absolute magnitude, with a range from -1.693 to -1.072. We interpret these negative parameter estimates as evidence of corrections, such that prices revert back to fundamental values after six or more months of building overvaluation. The relation of short and moderate periods of sentiment increases with subsequent returns, as indicated by $\theta_{j,ST}$ and $\theta_{j,Med}$, reveal significant estimates of 1.554 and 1.252 (high volatility) and 1.552 and 1.651 (small size portfolio), respectively. That is, initial increases in sentiment relate to increasing returns for these portfolios. Considering long-short portfolios, the $\theta_{j,ST}$ and $\theta_{j,Med}$ estimates are positive and significant at the 5% level or better for the volatility and size long-short portfolios.[14]

To specify the economic significance of the correction results, we develop forecasts of portfolio excess returns conditional on realizations of the sentiment levels and changes variables in conjunction with the Table 6 parameter estimates. First, we find large positive forecast returns for sentiment prone portfolios following moderate increases in sentiment, when sentiment levels are either neutral or high. If sentiment increases over the medium term, and $I^{+}_{Med,t-1}Sum_{t-1,\Delta sent+}$ equals its 75th percentile of positive realizations, the average long-short portfolio return is 3.68% when the sentiment levels variable equals 0 and 2.221 when the levels variable is set to the 75th percentile of its positive realizations. Next, large magnitude corrections occur following six or more months of consecutive sentiment increases, and high sentiment levels exacerbate these corrections. For example, when the long-term sentiment increase variable equals the 75th percentile of positive realizations, the conditional forecast for the market is -4.92% if sentiment levels is equal to 0, but if sentiment levels reach their

[14] These results demonstrate the interaction between the length of the sentiment window and the magnitude of the sentiment variable. By design, the value of the sentiment variable is increasing with the length of the sentiment episode. In an unreported analysis, we examine the impact of the length of the sentiment window without the interaction effect associated with the magnitude of the sentiment variable (by solely including the indicators as independent variables). This analysis provides a direct estimate of the impact of the sentiment path on subsequent returns within a bubble and again reveals large economic corrections, especially in sentiment-prone portfolios. Further, these results are robust to the inclusion of the Baker and Wurgler orthogonalized sentiment levels variable.

75th conditional percentile, this negative forecast decreases to -5.37%. Following six or more consecutive sentiment increases, the average conditional forecasts for the long-short portfolios are -5.87% and -7.33% if sentiment levels are neutral or high, respectively. Therefore, the magnitude of economic corrections relates primarily to the sentiment path, not just the level. Corrections seem due primarily to consecutive sentiment changes, and high sentiment levels intensify corrections.

5. Conclusion

We confirm the predicted links between investor sentiment and asset bubbles. First, we find a positive effect of increased sentiment on subsequent returns in the short term as overvaluation builds. Second, the positive relation between sentiment and subsequent returns becomes dampened as the bubble episode persists, because rational arbitrageurs seemingly trade against behavioral traders. Third, we find corrections in prices, as a function of both sentiment changes and the length of the bubble. These results are consistent with the expectation that selling pressures from rational arbitrageurs eventually exceed the capacity of behavioral traders and ultimately yield a negative relation between multiple consecutive price increases and subsequent returns. These results are most notable in opaque portfolios, where differences between price and value are most difficult to detect. These findings thus provide empirical support for Abreu and Brunnermeier's (2003) model, using investor sentiment as a measure of behavioral trading and related mispricing.

Whereas existing research finds investor sentiment is solely a contrarian indicator for subsequent returns, with little guidance about why rational arbitrageurs do not correct these avoidable mispricings, we show with this study that the coordination and synchronization problem included in Abreu and Brunnermeier's (2003) model might define the relationship. Ignoring the path dependency and nonlinearity of the impact of sentiment on returns can obscure interesting dynamic effects. Future returns increase with sentiment at a decreasing rate, which ultimately reverses for either large changes in sentiment or after multiple previous periods of accumulating sentiment. Our results thus shed light on how equity bubbles grow, and then potentially burst, with sentiment.

References

Abreu, D., Brunnermeier, M., 2002. Synchronization risk and delayed arbitrage. J. Financ. Econ. 66, 341-360.

Abreu, D., Brunnermeier, M., 2003. Bubbles and crashes. Econometrica 71, 173-204.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Financ. 61, 1645-1680.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. J. Econ. Perspectives 21, 129-151.

Baker, M., Wurgler, J., 2012. Comovement and predictability relationships between bonds and the cross-section of stocks. Rev. Asset Pric. Stud. 2, 57-87.

Baker, M., Wurgler, J., Yuan, Y., 2011. Global, local, and contagious investor sentiment. J. Financ. Econ. 104, 272-287.

Berger, D., Turtle, H., 2012. Cross-sectional performance and investor sentiment in a multiple risk factor model. J. Bank. Financ. 36, 1107-1121.

Brown, G., Cliff, M., 2005. Investor sentiment and asset valuation. J. Bus. 78, 405-440.

Brunnermeier, M., Nagel, S., 2004. Hedge funds and the technology bubble. J. Financ. 59, 2013-2040.

Carhart, M., 1997. On persistence in mutual fund performance. J. Financ. 52, 57-82.

Corwin, S., Schultz, P., 2012. A simple way to estimate bid-ask spreads from daily high and low prices. J. Financ. 67, 719-759.

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Positive feedback investment strategies and destabilizing rational speculation. J. Financ. 45, 379-395.

DeVault, L., Sias, R., Starks, L., 2014. Who are the sentiment traders? Evidence from the cross-section of stock returns and demand. Working paper, University of Arizona, University of Arizona, and University of Texas.

Fama, E. F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33, 3-56.

Griffin, J., Harris, J., Shu, T., Topaloglu, S., 2011. Who drove and burst the tech bubble? J. Financ. 66, 1251-1290.

Guenster, N., Kole, E., Jacobsen, B., 2013. Riding bubbles. Working Paper, Erasmus University.

Halling, M., Moulton, P.C., Panayides, M., 2013. Volume dynamics and multimarket trading. J. Financ. Quant. Anal. 48, 489-518.

Hommes, C., Sonnemans, J., Tuinstra, J., van de Velden, H., 2005. Coordination of expectations in asset-pricing experiments. Rev. Financ. Stud. 18, 955-980.

Matsushima, H., 2013. Behavioral aspects of arbitrageurs in timing games of bubbles and crashes. J. Econ. Theory 148, 858-870.

McQueen, G., Thorley, S., 1994. Bubbles, stock returns and duration dependence. J. Financ. Quant. Anal. 29, 379-401.

Neal, R., Wheatley, S., 1998. Do measures of investor sentiment predict returns? J. Financ. Quant. Anal. 33, 523-547.

Rosenthal, R., 1981. Games of perfect information, predatory pricing, and the chain-store paradox. J. Econ. Theory 25, 92-100.

Schmeling, M., 2009. Investor sentiment and stock returns: Some international evidence. J. Emp. Fin.. 16, 394-408.

Smith, V., Suchanek, G., Williams, A., 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. Econometrica 56, 1119-1151.

Stoll, H. 2000. Friction. J. Financ. 55, 1479-1514.

Temin, P., Voth, H.J., 2004. Riding the South Sea bubble. Am. Econ. Rev. 94, 1654-1668.

Xiong, W., Yu, J., 2011. The Chinese warrants bubble. Am. Econ. Rev. 101, 2723-2753.

Table 1
Portfolio return summary statistics.

Portfolio	Mean	Median	Standard Deviation	N
Mkt	0.431	0.730	4.612	545
σ_{low}	0.472	0.718	3.011	545
σ_{high}	3.694	2.848	11.039	545
$\sigma_{high-low}$	3.222	2.170	9.758	545
Age_{old}	0.424	0.608	4.100	545
Age_{young}	0.532	1.186	6.974	545
$Age_{young-old}$	0.108	0.242	4.959	545
$Size_{large}$	0.384	0.709	4.452	545
$Size_{small}$	1.824	1.340	8.213	545
$Size_{small-large}$	1.441	0.544	7.003	545
$Spread_{small}$	0.507	0.563	3.805	545
$Spread_{large}$	0.901	1.187	8.101	545
$Spread_{large-small}$	0.395	0.043	6.548	545

This table presents summary statistics for monthly portfolio excess returns from August 1965 through December 2010. Value-weighted excess returns are presented for the market, volatility, age, size, and spread portfolios. The excess market return, *Mkt*, and the riskless rate are obtained from Kenneth French's data library. The volatility portfolio return data are from CRSP volatility sorted portfolios. *Age* is defined as the number of months since the firm's first appearance in the CRSP database. *Size* is defined as the number of shares outstanding multiplied by the closing stock price, both measured during month t-1. *Spread* is defined using the Corwin and Schultz's (2012) estimate of average daily spread within a given month, and averaged over months t-6 through t-1. For all characteristics, firms are assigned to ten deciles, and we report results for the first and tenth decile portfolios. Finally, for each characteristic, we create returns for a representative long-short portfolio.

Table 2
Sentiment variable summary statistics.

	$Sum_{t-1,\Delta sent+}$	$Count_{t-1,\Delta sent+}$
Mean	0.681	0.980
Median	0	0
Standard Deviation	1.140	1.350
P_{10^+}	0.180	1
P_{25^+}	0.420	1
P_{50^+}	0.983	1
P_{75^+}	1.833	3
P_{90^+}	3.089	4
P_{95^+}	3.915	5

This table presents summary statistics for the sentiment variables. We calculate the sum, $Sum_{t-1,\Delta sent+}$, and count, $Count_{t-1,\Delta sent+}$, of consecutive sentiment increases based on the Baker and Wurgler monthly orthogonalized sentiment changes index. For month *t*, $Sum_{t-1,\Delta sent+}$ represents the sum of all consecutive sentiment increases through month *t*-1, and $Count_{t-1,\Delta sent+}$ represents the number of consecutive months in which sentiment has increased through month *t*-1. Both variables take the value of zero following a negative sentiment change in month *t*-1. We denote the i^{th} percentile of strictly positive realizations for the underlying variables with P_{i^+}.

Table 3
Conditional returns following increases and decreases in investor sentiment.

Portfolio	(1) $I^{-}_{ST,t-1}$	(2) $I^{-}_{Med,t-1}$	(3) $I^{-}_{LT,t-1}$	(4) $I^{+}_{ST,t-1}$	(5) $I^{+}_{Med,t-1}$	(6) $I^{+}_{LT,t-1}$	(7) Equal across all conditions	(8) Equal across pos. conditions	(9) Equal across neg. conditions
Mkt	0.315	0.144	1.504	0.525	0.777	-2.081	0.743	1.294	0.529
σ_{low}	0.379	0.795	1.017	0.441	0.630	-1.356	0.832	1.685	0.572
σ_{high}	2.541	3.382	2.546	3.968	7.999	-3.734	3.049**	5.550**	0.131
$\sigma_{high-low}$	2.162	2.587	1.529	3.526	7.369	-2.378	3.393**	5.328**	0.088
Age_{old}	0.429	0.161	1.306	0.413	0.701	-1.638	0.604	1.043	0.480
Age_{young}	-0.013	0.032	2.441	0.956	1.612	-5.854	2.183	4.159*	0.833
$Age_{young-old}$	-0.442	-0.129	1.135	0.542	0.911	-4.217	2.379*	4.414*	0.650
$Size_{large}$	0.312	0.100	1.570	0.456	0.565	-1.562	0.582	0.760	0.671
$Size_{small}$	0.765	1.348	0.145	2.064	5.999	-3.556	4.784**	9.910**	0.152
$Size_{small-large}$	0.453	1.249	-1.425	1.608	5.434	-1.994	5.919**	10.066**	0.877
$Spread_{small}$	0.483	0.494	1.556	0.481	0.651	-1.614	0.697	1.113	0.597
$Spread_{large}$	0.732	0.054	1.354	0.891	2.914	-5.418	1.774	4.256*	0.212
$Spread_{large-small}$	0.249	-0.440	-0.202	0.410	2.262	-3.805	1.820	3.869*	0.253

This table presents mean excess returns during month *t* conditional on sentiment dynamics through month *t*-1. We define indicator variables for short-, medium-, and long-term sentiment dynamics, $I_{ST,t-1}$, $I_{Med,t-1}$, and $I_{LT,t-1}$ representing one to two, three through five, or six or more months of consecutive positive or negative realizations in the Baker and Wurlger orthogonalized sentiment changes index, respectively. The superscripts "+" and "-" denote consecutive increases and decreases in the sentiment changes index. Portfolios are defined in Table 1, and identified in the initial column. The initial six data columns present conditional mean excess returns. The final three columns report *F*-statistics testing equality of conditional means across all six indicator conditions, all positive sentiment change conditions, and all negative sentiment change conditions, with * and ** denote significance at the 5% and 1% levels, respectively.

Table 4
Sentiment and portfolio returns.

Portfolio	(1) $Intercept$	(2) $Sum_{t-1,\Delta sent+}$	(3) $Sum^2_{t-1,\Delta sent+}$	(4) $Sent_{t-1}$
Panel A: $R_{j,t} = \alpha_j + \theta_j Sum_{t-1,\Delta sent+} + \varphi_j Sum^2_{t-1,\Delta sent+} + e_{j,t}$				
Mkt	0.261	0.880**	-0.244**	-
	(1.01)	(2.83)	(-3.81)	
σ_{low}	0.395*	0.416*	-0.117**	-
	(2.19)	(2.08)	(-3.17)	
σ_{high}	2.319**	4.093**	-0.801**	-
	(3.91)	(4.77)	(-5.32)	
$\sigma_{high-low}$	1.923**	3.677**	-0.684**	-
	(3.81)	(4.75)	(-5.15)	
Age_{old}	0.307	0.690*	-0.200**	-
	(1.36)	(2.55)	(-3.60)	
Age_{young}	0.183	1.719**	-0.466**	-
	(0.46)	(3.04)	(-3.59)	
$Age_{young-old}$	-0.124	1.029*	-0.266**	-
	(-0.44)	(2.45)	(-2.92)	
$Size_{large}$	0.262	0.723*	-0.210**	-
	(1.06)	(2.45)	(-3.52)	
$Size_{small}$	0.525	3.411**	-0.580**	-
	(1.13)	(5.83)	(-5.60)	
$Size_{small-large}$	0.263	2.687**	-0.370**	-
	(0.73)	(5.49)	(-4.45)	
$Spread_{small}$	0.445*	0.515*	-0.164**	-
	(2.09)	(2.04)	(-3.36)	
$Spread_{large}$	0.375	2.107**	-0.516**	-
	(0.82)	(3.49)	(-4.51)	
$Spread_{large-small}$	-0.070	1.593**	-0.351**	-
	(-0.20)	(3.11)	(-4.08)	

Portfolio	(1) $Intercept$	(2) $Sum_{t-1,\Delta sent+}$	(3) $Sum^2_{t-1,\Delta sent+}$	(4) $Sent_{t-1}$
Panel B: $R_{j,t} = \alpha_j + \theta_j Sum_{t-1,\Delta sent+} + \varphi_j Sum^2_{t-1,\Delta sent+} + \gamma_j Sent_{t-1} + e_{j,t}$				
Mkt	0.289	0.828**	-0.239**	-0.315
	(1.12)	(2.68)	(-3.88)	(-1.46)
σ_{low}	0.395*	0.416*	-0.117**	-0.001
	(2.19)	(2.09)	(-3.18)	(-0.01)
σ_{high}	2.470**	3.806**	-0.776**	-1.753**
	(4.19)	(4.62)	(-5.53)	(-3.31)
$\sigma_{high-low}$	2.075**	3.391**	-0.659**	-1.751**
	(4.15)	(4.57)	(-5.36)	(-4.03)
Age_{old}	0.321	0.663*	-0.198**	-0.164
	(1.43)	(2.46)	(-3.63)	(-0.89)
Age_{young}	0.251	1.591**	-0.455**	-0.780*
	(0.64)	(2.88)	(-3.71)	(-2.44)
$Age_{young-old}$	-0.071	0.928*	-0.257**	-0.617**
	(-0.26)	(2.27)	(-3.03)	(-2.80)
$Size_{large}$	0.283	0.683*	-0.207**	-0.247
	(1.16)	(2.32)	(-3.56)	(-1.21)
$Size_{small}$	0.607	3.255**	-0.567**	-0.950*
	(1.33)	(5.74)	(-5.68)	(-2.40)
$Size_{small-large}$	0.324	2.572**	-0.360**	-0.703*
	(0.91)	(5.39)	(-4.33)	(-2.18)
$Spread_{small}$	0.442*	0.521*	-0.165**	0.040
	(2.08)	(2.08	(-3.37)	(0.22)
$Spread_{large}$	0.479	1.911**	-0.499**	-1.201**
	(1.07)	(3.26)	(-4.68)	(-3.21)
$Spread_{large-small}$	0.037	1.389**	-0.334**	-1.241**
	(0.11)	(2.82)	(-4.18)	(4.52)

This table reports regression results for the models described in each panel. $R_{j,t}$ represents the excess return to portfolio *j* during month *t* for portfolios identified in the initial column and described in Table 1. $Sum_{t-1,\Delta sent+}$ represents the sum of consecutive increases in the orthogonalized Baker and Wurgler sentiment changes index, $Sum^2_{t-1,\Delta sent+}$ is the squared sum of consecutive changes, and $Sent_{t-1}$ represents the Baker and Wurgler orthogonalized sentiment level index. The table reports *t*-statistics based on Newey-West standard errors using one lag, where * and ** denote significance at the 5% and 1% levels, respectively.

Table 5
Robustness analyses.

	(1) Condition	(2) Parameter	(3) Mkt	(4) σ_{high}	(5) Age_{young}	(6) $Size_{small}$	(7) $Spread_{large}$
(1)	The empirical model includes the Excess Market, Size, Value, and Momentum factors as regressors.	$Sum_{t-1,\Delta sent+}$	-	1.818**	0.295	1.972**	0.333
				(3.81)	(1.40)	(5.45)	(1.21)
		$Sum^2_{t-1,\Delta sent+}$	-	-0.264**	-0.080	-0.228**	-0.070
				(-3.37)	(-1.65)	(-3.32)	(-1.60)
		$Sent_{t-1}$	-	-0.947**	-0.166	-0.333	-0.556**
				(-3.58)	(-1.47)	(-1.59)	(-3.82)
(2)	$Sum_{t-1,\Delta sent+}$ is further defined conditional on $Sent_{t-1} > 0$. For any month *t* in which $Sent_{t-1}$ is less than zero, $Sum_{t-1,\Delta sent+}$ is set equal to zero.	$Sum_{t-1,\Delta sent+}$	1.396**	2.473**	2.262**	2.618**	1.579*
			(3.46)	(2.90)	(3.23)	(3.72)	(2.13)
		$Sum^2_{t-1,\Delta sent+}$	-0.349**	-0.617**	-0.649**	-0.491**	-0.505**
			(-5.46)	(-4.06)	(-6.07)	(-3.55)	(-4.27)
		$Sent_{t-1}$	-0.410	-2.070**	-0.898**	-1.376**	-1.281**
			(-1.84)	(-3.61)	(-2.68)	(-3.14)	(-3.29)
(3)	$Count_{t-1,\Delta sent+}$ represents the number of consecutive months in which the previous change in sentiment has been positive.	$Count_{t-1,\Delta sent+}$	0.376	2.408**	1.007*	2.123**	1.092
			(1.15)	(2.89)	(2.00)	(3.63)	(1.83)
		$Count^2_{t-1,\Delta sent+}$	-0.097	-0.461**	-0.243*	-0.342**	-0.255*
			(-1.49)	(-2.99)	(-2.36)	(-3.03)	(-2.09)
		$Sent_{t-1}$	-0.319	-1.748**	-0.776*	-0.913*	-1.208**
			(-1.45)	(-3.17)	(-2.41)	(-2.23)	(-3.18)
(4)	Observations in which sentiment has increased for six or more consecutive months are excluded from the sample.	$Sum_{t-1,\Delta sent+}$	0.882	3.886**	2.198**	2.644**	1.946*
			(01.85)	(3.03)	(2.93)	(3.00)	(2.21)
		$Sum^2_{t-1,\Delta sent+}$	-0.271*	-0.786*	-0.664**	-0.324	-0.510*
			(-2.05)	(-2.34)	(-3.28)	(-1.30)	(-2.10)
		$Sent_{t-1}$	-0.301	-1.721**	-0.718*	-0.965*	-1.174**
			(-1.38)	(-3.23)	(-2.22)	(-2.43)	(-3.11)

This table presents regression results for variants of the primary empirical model:

$$R_{j,t} = \alpha_j + \theta_j Sum_{t-1,\Delta sent+} + \varphi_j Sum^2_{t-1,\Delta sent+} + \gamma_j Sent_{t-1} + e_{j,t},$$

where $R_{j,t}$ represents the excess return to portfolio *j* during month *t* for portfolios identified in Columns 3 through 7 and described in Table 1. Regressors include an intercept (unreported); the sum of consecutive increases in the orthogonalized Baker and Wurgler sentiment changes index through month *t*-1, $Sum_{t-1,\Delta sent+}$; its square, $Sum^2_{t-1,\Delta sent+}$; the Baker and Wurgler orthogonalized sentiment level index, $Sent_{t-1}$; the number of consecutive sentiment increases, $Count_{t-1,\Delta sent+}$; and its square, $Count^2_{t-1,\Delta sent+}$. Column 1 details the variation considered in each panel. All *t*-statistics are based on Newey-West standard errors using one lag, and we denote significance at the 5% and 1% levels with * and **, respectively.

Table 6
Sentiment changes and price corrections.

Portfolio	(1) $Intercept$	(2) $I^{+}_{ST,t-1}Sum_{t-1,\Delta sent+}$	(3) $I^{+}_{Med,t-1}Sum_{t-1,\Delta sent+}$	(4) $I^{+}_{LT,t-1}Sum_{t-1,\Delta sent+}$	(5) $Sent_{t-1}$
Mkt	0.454	0.109	-0.056	-0.704*	-0.357
	(1.80)	(0.39)	(-0.35)	(-2.10)	(-1.62)
σ_{low}	0.461**	0.089	0.036	-0.440**	-0.023
	(2.64)	(0.56)	(0.28)	(-2.61)	(-0.14)
σ_{high}	2.934**	1.554*	1.252*	-1.693*	-1.891**
	(5.04)	(2.30)	(2.32)	(-2.29)	(-3.46)
$\sigma_{high-low}$	2.473**	1.465*	1.216*	-1.253*	-1.868**
	(4.96)	(2.46)	(2.33)	(-2.04)	(-4.16)
Age_{old}	0.462*	0.036	-0.033	-0.620*	-0.196
	(2.09)	(0.14)	(-0.23)	(-2.02)	(-1.04)
Age_{young}	0.569	0.133	0.049	-1.425*	-0.853**
	(1.47)	(0.27)	(0.19)	(-2.24)	(-2.61)
$Age_{young-old}$	0.107	0.098	0.082	-0.805*	-0.657**
	(0.38)	(0.21)	(0.45)	(-1.97)	(-2.95)
$Size_{large}$	0.431	0.060	-0.110	-0.599	-0.284
	(1.79)	(0.22)	(-0.69)	(-1.93)	(-1.36)
$Size_{small}$	0.922*	1.552**	1.651**	-1.072*	-1.044*
	(2.05)	(2.94)	(4.97)	(-2.04)	(-2.57)
$Size_{small-large}$	0.491	1.492**	1.761**	-0.473	-0.760*
	(1.36)	(2.85)	(5.37)	(-1.32)	(-2.33)
$Spread_{small}$	0.558**	0.004	-0.059	-0.550*	0.013
	(2.67)	(0.02)	(-0.45)	(-2.17)	(0.07)
$Spread_{large}$	0.811	0.320	0.314	-1.530**	-1.279**
	(1.85)	(0.60)	(0.87)	(-2.59)	(-3.35)
$Spread_{large-small}$	0.254	0.316	0.373	-0.980**	-1.292**
	(0.75)	(0.67)	(1.09)	(-2.61)	(-4.64)

This table presents parameter estimates for the following correction model:

$$R_{j,t} = \alpha_j + \theta_{j,ST} I^{+}_{ST,t-1} Sum_{t-1,\Delta sent+} + \theta_{j,Med} I^{+}_{Med,t-1} Sum_{t-1,\Delta sent+} + \theta_{j,LT} I^{+}_{LT,t-1} Sum_{t-1,\Delta sent+} + \gamma_j Sent_{t-1} + e_{j,t},$$

where $R_{j,t}$ is the excess return to portfolio *j* during month *t* for portfolios identified in the initial column. Indicator variables $I^{+}_{ST,t-1}$, $I^{+}_{Med,t-1}$, and $I^{+}_{LT,t-1}$ take the value of one following one to two, three through five, or six or more consecutive increases in sentiment, respectively, and take the value of zero otherwise. $Sum_{t-1,\Delta sent+}$ is the sum of consecutive increases in the orthogonalized Baker and Wurgler sentiment changes index through month *t*-1, and $Sent_{t-1}$ is the Baker and Wurgler orthogonalized sentiment level index. We report coefficient estimates with associated *t*-statistics based on Newey-West standard errors using one lag. We denote significance at the 5% and 1% levels with * and **, respectively.

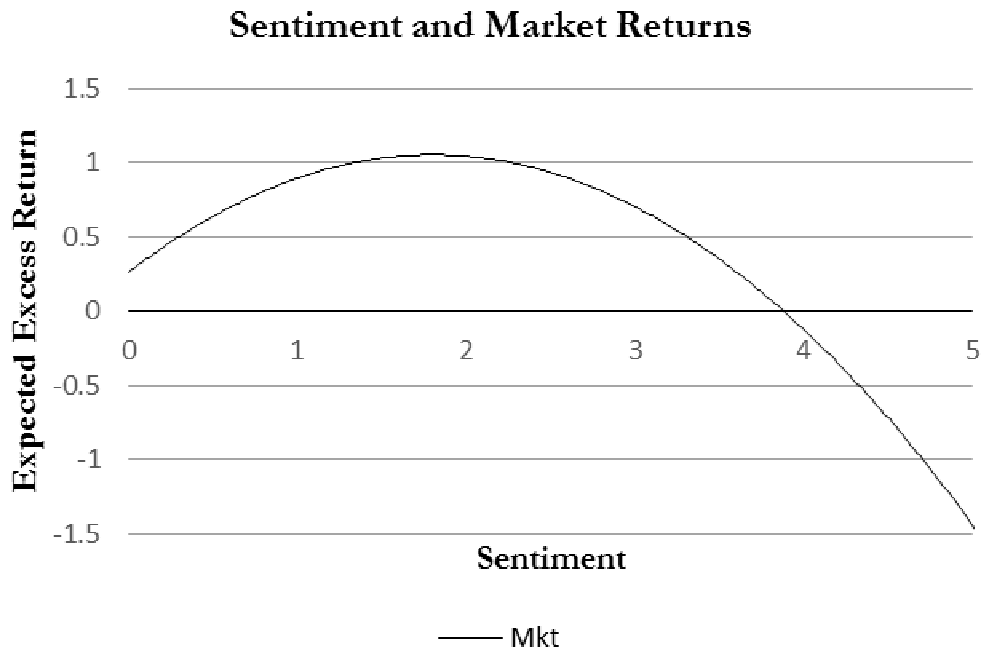

Figure 1. Sentiment and market returns.

This figure shows fitted values of excess market returns as a function of $Sum_{t-1,\Delta sent+}$. Fitted values are based on parameter estimates from Panel A of Table 4:

$$R_{mkt,t} = \alpha_{mkt} + \theta_{mkt} Sum_{t-1,\Delta sent+} + \varphi_{mkt} Sum^2_{t-1,\Delta sent+} + e_{mkt,t}.$$

The expected excess market return is plotted on the y-axis, and the sentiment variable is plotted on the x-axis.

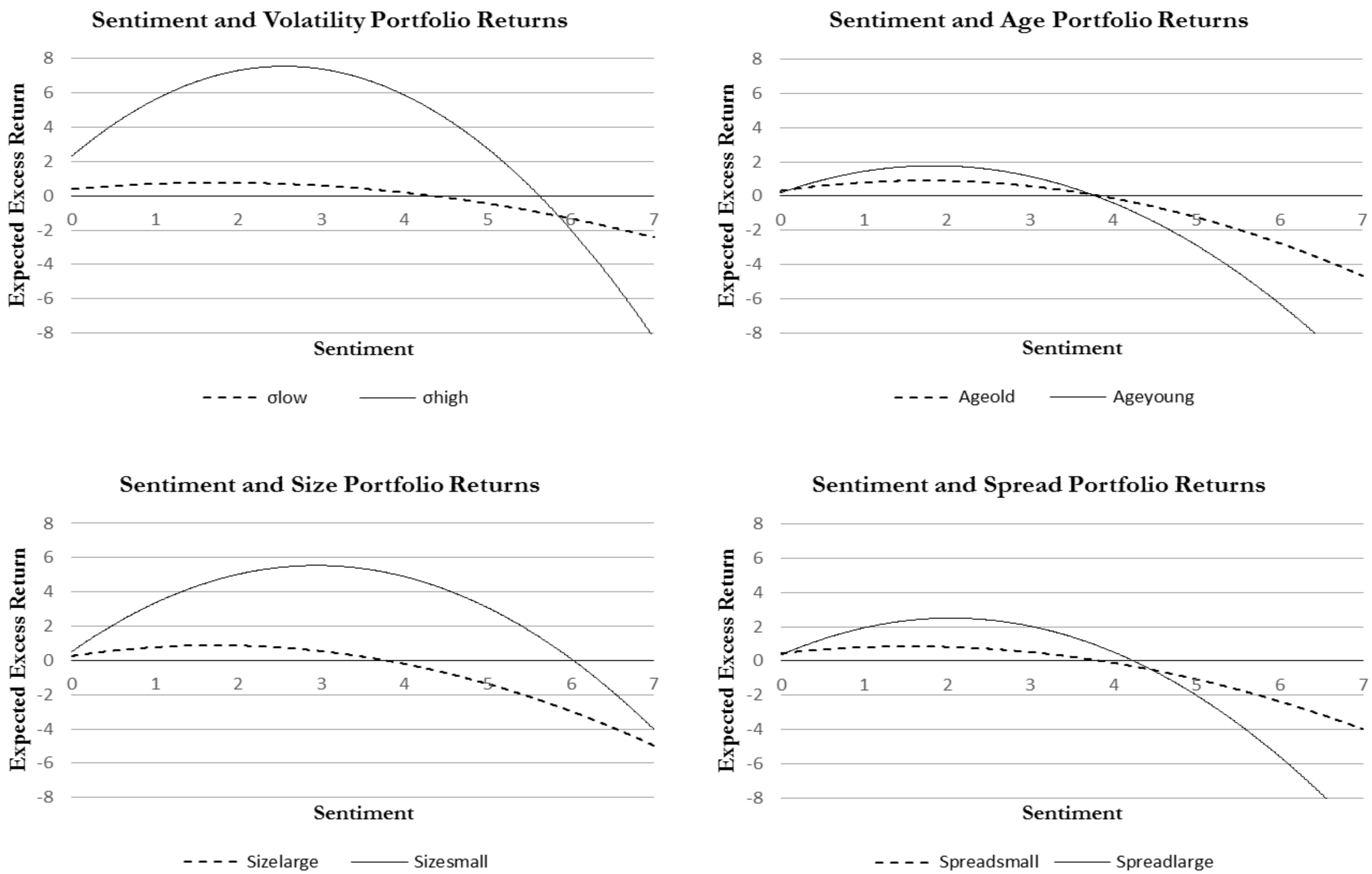

Figure 2. Sentiment and portfolio returns.

This figure shows fitted values of excess portfolio returns as a function of $Sum_{t-1,\Delta sent+}$. Fitted values are based on parameter estimates from Panel A of Table 4:

$$R_{j,t} = \alpha_j + \theta_j Sum_{t-1,\Delta sent+} + \varphi_j Sum^2_{t-1,\Delta sent+} + e_{j,t}.$$

The expected excess portfolio return is plotted on the y-axis, and the sentiment variable is plotted on the x-axis.