Investor Sentiment and Feedback Trading: Evidence from the Exchange-Traded Fund Markets

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Abstract:

This paper extends the standard feedback trading model of Sentana and Wadhwani (1992) by allowing the demand for shares by feedback traders to depend on sentiment. Our empirical analysis of three largest Exchange-Traded Fund (ETF) contracts in the U.S. suggests that there is a significant positive feedback trading in these markets and the intensity of which is generally linked to investor sentiment. Specifically, the level of feedback trading tends to increase when investors are optimistic. In addition, we find that the influence of sentiment on feedback trading varies across market regimes. These results are consistent with the view that feedback trading activity is largely caused by the presence of sentiment-driven noise trading. Overall, the findings are important in understanding the role of sentiment in investment behaviour and market dynamics and are of direct relevance to the regulators and investors in ETF markets.

JEL classification: G14; C22

Keywords: Investor sentiment; feedback trading; exchange-traded fund

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1. Introduction

The question of whether investor sentiment affects financial asset prices has received a considerable attention in the academic literature, especially after the dramatic rises and falls of the stock market in recent years. A growing number of empirical studies have found evidence of a relationship between investor sentiment and market returns.[1] This in turn has motivated many researchers to explore the explanatory power of sentiment for various well-documented anomalies including the size effect (Baker and Wurgler, 2006), value effect (Frazzini and Lamont, 2008), and momentum effect (Antoniou *et al*., 2010). The general finding from this literature is that sentiment-related overpricing is at least a partial explanation for these asset-pricing anomalies.[2]

Nevertheless, despite the growing importance and interest, there has been little research on the direct impact of sentiment on the trading behaviour of investors, and in particular we can identify only a limited number of studies on the potential link between investor sentiment and positive feedback trading (trend-chasing) behaviour.[3] This is somewhat surprising given that sentiment has been strongly linked with herding activity (Blasco *et al*., 2011), speculative trading (Lemmon and Ni, 2010), and the profitability of momentum strategy (Antoniou *et al*., 2010), and that the momentum trading is often referred to as positive feedback trading in the literature. Furthermore, it is well known that many market watchers and finance practitioners believe in "sentiment" and treat it as an indicator for future market movement.[4]

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[1] See, for example, Lee et al. (2002), Brown and Cliff (2005), Baker and Wurgler (2006, 2007) for the findings on both cross-sectional and time-series relationships between sentiment and stock returns.
[2] Alternative rational explanations such as time-varying expected returns, market microstructure bias, macroeconomic conditions have also been proposed as the possible causes of these anomalies.
[3] In a study directly related to this paper, Kurov (2008) examines feedback trading in the E-mini index futures markets in microstructure setting. He shows that traders in index futures markets are positive feedback traders and that feedback trading tends to be more active in period of high investor sentiment.
[4] See, among others, Solt and Statman (1988) and Shefrin (2002).

Against this backdrop, we aim to present one of the first attempts to fill in this gap by examining whether, and to what extent, investor sentiment influences the level of feedback trading in three largest Exchange-traded Fund (ETF) contracts in the U.S., and whether there is any variation in such relationship across the market regimes.[5]

ETFs were first introduced in the U.S. in January 1993 and since then the demand for ETFs has grown markedly, making ETF trading one of the world's largest businesses with an estimated net asset value of US$531 billion and an annual growth rate of around 6%.[6] Given the significance of these instruments, there has been a surging academic interest in the area with an increasing number of studies investigating various topics relating to ETF markets (see Deville, 2008 for an excellent review). Despite these developments, scarce evidence exists in the current literature on the trading and investment behaviour (rational or irrational) of ETF investors.[7] Intuitively, because of their ease and low cost of trading, ETFs may be appealing to individual (unsophisticated, uninformed) investors who are more likely to chase trends, raising a concern over the impact of their introduction on the overall market efficiency (Kallinterakis and Kaur, 2010). In this paper, we contribute to bridge the gap by examining this important issue on the premises of three largest U.S. ETF contracts.

More specifically, we test for the hypothesis that ETFs attract noise traders in general and positive feedback traders in particular.[8] This paper contends that the emergence of

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[5] ETFs are baskets of securities that are traded, like individual stocks, on an exchange. Unlike regular open-end mutual funds, ETFs can be bought and sold throughout the trading day like any stock.
[6] From the U.S. Investment Company Institute (ICI)'s Yearly Fact book 2009, www.ici.org.
[7] A notable exception is the recent work of Kallinterakis and Khurana (2009) which, using the SW model, reports no evidence of significant feedback trading in a relatively new ETF market in India. Goetzmann and Massa (2002), however, identifies momentum behaviour of index funds investors.
[8] It is worth noting that, however, while this issue is somewhat important in itself, the central goal of the current paper is to examine the influence of investor sentiment on feedback trading behaviour.

ETFs has provided a unique and natural laboratory to test feedback trading theories. There are several types of feedback trading models in the literature carrying different implications for the autocorrelation pattern of returns (Shiller, 1984; Cutler *et al.*, 1990; Sentana and Wadhwani, 1992; hereafter SW).[9] Nonetheless, the prior literature has generally restricted itself to testing the presence of feedback trading on stock market indices which are not directly tradable. Such a restricted testing framework is overly limiting and, thus, may lead to inappropriate policy responses. But in the case of ETFs, we can directly observe the investor trading behaviour and, therefore, we can be ascertain that our empirical results are not driven by factors other than the existence of feedback traders, e.g., the non-synchronous trading.

Using the SW model and a data set of U.S. ETFs from 2000 to 2007, this paper attempts to address the issues raised above by estimating the feedback trading behaviour of index fund investors and studying how their activity can be related to the changes in investor sentiment. In particular, unlike previous studies, this paper uses a unique framework that allows the behaviour of feedback traders to be determined by both market prices and investor sentiment in order to address the following questions.

- Do ETF investors exhibit positive feedback trading activity?
- Whether, and to what extent, investor sentiment affects the feedback trading?
- Are there any differences in the relationship between investor sentiment and the level of feedback trading across market regimes?

[9] It should be noted that the feedback trader argument is only one of many arguments proposed for the presence of autocorrelation. Alternative explanations such as the presence of time-varying risk premia (Fama and French, 1988), non-synchronous trading (Lo and MacKinlay, 1990), and other market microstructure bias (Mech, 1993) have been largely dismissed in the literature.

Taken together, the present study adds to the existing literature in a number of ways. First, we extend the work of Goetzmann and Massa (2002) and Kallinterakis and Khurana (2009), by performing a detailed analysis of the trading behaviour of index fund investors in the fast growing ETF markets in the U.S. In particular, using the original SW model, we examine whether ETF traders use positive feedback strategies. The result of such investigation may provide additional insights into the potential determinants of stock return autocorrelation.[10] In a series of papers, McKenzie and Faff (2003), McKenzie and Faff (2005), and McKenzie and Kim (2007) investigate what characteristics drive the nature of autocorrelation pattern. Their results suggest that the observed autocorrelation are too large to be explained by the time-varying expected returns and non-synchronous trading. They then examine the role of feedback trading strategies and conclude that autocorrelation is, at least in part, induced by traders systematically follow trend-chasing strategies. Our paper addresses this issue using a framework that directly links autocorrelation and feedback trading.

Secondly, our study also contributes to a growing literature studying the role of investor sentiment in asset pricing and investor behaviour. We extend the standard model of SW by allowing the demand of feedback traders to be determined not solely by prices but also by sentiment. The result obtained may be particularly relevant in providing a deeper understanding of question *why* feedback trading might take place. Although a number of reasons (both rational or irrational) have been put forward in explaining the presence of feedback trading, such strategies are usually associated with noise / uninformed traders whose demand are likely to be driven by sentiment.[11]

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[10] The behaviour (and the determinants) of stock return serial correlation has been a long-standing interest to economists. See McKenzie and Faff (2005) for a survey.

[11] Positive feedback trading can also be the result of many 'rational' motivations such as trading on extrapolative expectations, activation of stop-loss orders, and portfolio insurance strategies.

Thirdly, we repeat our analyses using data from different market conditions (bull and bear markets) in order to provide a comparison of findings on up-market with that of down-market. This appears to be another novelty in the literature on the subject. Assuming that sentiment is an important factor in inducing noise trading activity, the sentiment-driven feedback trading is likely to be more pronounced in the bull market with higher sentiment state. Consistent with this notion, Cooper *et al.* (2004) finds that momentum trading activity by noise traders increases in the up-market periods.

Finally, a number of previous investigations have yielded results suggesting that the predictability of stock returns varies over time (e.g., Pesaran and Timmermann, 2000). Our extension of SW model to allow feedback traders to react to the sentiment predicts a link between autocorrelation and the investor sentiment, and may provide another possible explanation for the phenomenon of time-varying predictability.[12]

The major findings of our investigation can be summarized as follows. First, our empirical results suggest that, consistent with the existence of positive feedback traders in the markets, there is a negative relationship between autocorrelation and volatility of ETF returns. Moreover, we find that the level of positive feedback trading is generally related to investor sentiment. Specifically, when investors are optimistic (pessimistic), they are more (less) likely to follow trend-chasing investment strategies. The influence of sentiment also appears to be stronger during the bullish market. These results survive an array of robustness checks and are consistent with the view that feedback trading consists, at least partly, of sentiment-driven noise trading.

[12] McKenzie and Faff (2003, 2005) investigate the determinants of conditional autocorrelation and find that return volatility, trading volume and market returns are important determinants. However, to our knowledge, there has been no investigation of the potential link between sentiment and autocorrelation.

The remainder of the paper is organized as follows. Section 2 briefly reviews the related literature and section 3 outlines the alternative feedback trading models used in our investigation. The data and descriptive statistics are provided in Section 4. Section 5 presents and discusses the main empirical results and robustness checks. Finally, section 6 concludes the paper.

2. Investor Sentiment and Feedback Trading

Sentiment in an investment context may be broadly defined as '*fluctuations in risk tolerance or to overly optimistic or pessimistic cash flow forecasts. In either case, sentiment should have an impact on asset pricing that is distinct from the impact of fundamentals...*' (Edelen *et al*., 2010, p.20).[13] Accordingly, over the last few decades, there has been a growing interest in researching the implications of investor sentiment in financial asset pricing, especially in regards to how and when the sentiment-induced bias may impact on (or distort) stock prices. The attention of literature thus far, however, has been focused on the cross-sectional and the time-series relationship between sentiment and market returns (Wang *et al*., 2006; Baker and Wurgler, 2006) and how sentiment affects corporate financing decisions (Lamont and Stein, 2005).[14] The central question of whether investor sentiment affects investors' trading strategies has received a much less attention in the extant literature, and in particular we can identify only a limited number of studies on the potential link between investor sentiment and positive feedback trading (trend-chasing) strategies.

[13] However, another possible definition of investor sentiment is the propensity/likelihood to speculate. Under this definition, sentiment drives the relative demand for speculative investments, causing cross-sectional effects in stock prices even in the presence of rational arbitrage (Baker and Wurgler, 2006).

[14] While considerable evidence exists that investor sentiment affects the cross-section of stock returns, empirical findings on the time-series relationship appear much less clear and diverges substantially in terms of the direction and magnitude of the effects. See, for example, Wang *et al*., (2006).

Many studies have considered the role of feedback trading on market dynamics and show that such behaviour may be destabilizing on stock prices (DeLong *et al*., 1990). Consistent with the existence of positive feedback traders, a number of studies have found significant links between autocorrelation and the volatility of stock returns (LeBaron, 1992; Koutmos, 1997). Cutler *et al*. (1990) even argues that the autocorrelation properties of a large number of assets can be explained by a simple model which allows for the existence of both rational investors and feedback traders.

This has attracted an enormous attention devoted to asset pricing models that rely on the existence of heterogeneous investors. For instance, building on the work of Cutler *et al*. (1990), SW develops a theoretical model consisting of two groups of investors: (i) rational investors whose demand for shares depends on the risk-adjusted expected return, and (ii) feedback traders whose demand depends on the previous stock return. This model implies that actual returns are generated as a simple autoregressive process in which the parameter on lagged returns is a function of the conditional variance, i.e., the existence of a relationship between autocorrelation and volatility. SW finds strong statistical support for their model using a century of daily data on the U.S. stock market. Moreover, they find that returns switch from being positively autocorrelated to negatively autocorrelated as volatility increases. SW interprets this result as an indication that positive feedback trading is higher in the periods of high volatility, but negative feedback trading dominates in the period of low volatility.[15]

[15] Dean and Faff (2008) test this hypothesis directly using a regime-switching model for changing variance of daily Australian market returns, and find that positive feedback traders are responsible for the observed increase in the negative autocorrelation during the period of high and increasing volatility.

We extend the logic of SW analysis to consider the potential links between investor sentiment and the behaviour of feedback traders. Several papers have explored the links between sentiment and stock returns (Brown and Cliff, 2005; Baker and Wurgler, 2006), and there have been a number of empirical investigations concerned with the behaviour of feedback traders in mature and emerging stock markets (Bohl and Siklos, 2008) as well as stock index futures markets (Salm and Schuppli, 2010). However, there has been scarce empirical investigation of feedback trading that allows for time-varying investor behaviour over different sentiment states.[16]

Since it is widely recognised in the recent literature that investor sentiment has significant predictive power for stock returns (Baker and Wurgler, 2006, 2007) and that stock market fluctuations are also to some extent related to investor sentiment (Lee et al., 2002; Wang et al., 2006), it seems overly restrictive to assume that the behaviour of feedback traders is unaffected by their sentiment. Intuitively, to the extent that feedback traders believe in non-fundamental signals emerging from technical analysis or heuristic rules (e.g., trend extrapolation) and trade upon the sentiment-driven expectation (i.e., excessively optimism or pessimism), their investment decisions / activities are expected to be influenced by sentiment. Indeed, several recent papers show that investor sentiment affects the trading behaviour of both individual and institutional investors (Edelen *et al*., 2010). As shown by Basu *et al*. (2006), sentiment improves the performance of dynamically managed portfolio strategies, both for standard market-timers as well as for momentum-type investors.

[16] As mentioned earlier, a notable exception is the recent work of Kurov (2008) which find that the intensity of positive feedback trading increases (declines) in periods of bullish (bearish) sentiment.

Motivated by these arguments and empirical findings, in this paper we make several extensions to SW model to allow the behaviour of feedback traders to vary depending on whether they are feeling optimistic or pessimistic about the future market. This not only provides a robustness check to the previous empirical results that rely on the assumption of fixed behaviour over different sentiment states but also is relevant in our understanding of the central question of *why* feedback trading might take place.

3. Feedback Trading Models

There are several types of feedback trading models proposed in the literature carrying different implications for the autocorrelation pattern of returns. For instance, the feedback models by Shiller (1984) and Cutler *et al*. (1990) both imply *positive* autocorrelation of stock returns. However, Shiller (1989) point out that positive feedback trading can give rise to negligible (or even negative) return autocorrelation. On the contrary, the heterogeneous trader model developed by SW predicts that the interaction between positive feedback traders and rational investors tend to induce *negative* first-order autocorrelation, especially so during the high volatility periods[17].

3.1 Feedback Trading in SW's Framework

Before incorporating the effect of sentiment into feedback trading, we first briefly outline the model of feedback trading developed by Sentana and Wadhwani (1992). SW model assumes that there are two distinct groups of investors: one is a group of rational 'smart-money' investors who responds rationally to expected returns subject to their wealth limitations; the other is a group of feedback traders who do not base their investment decisions on fundamentals but rather react to previous price changes.

[17] However, more recent research suggests that the autocorrelation pattern of stock returns is more complex than commonly believed. For further discussion on the nature and causes of autocorrelation, see McKenzie and Faff (2003, 2005).

The demand for shares by the first group (rational or 'smart-money') investors in period t, S_t, is consistent with the maximization of expected mean-variance utility:

$$S_t = [E_{t-1}(R_t) - \omega] / \theta(\sigma_t^2) \tag{1}$$

where $E_{t-1}R_t$ is the expected return in the period t-1, ω is the risk-free return, σ^2_t is the conditional variance (risk) in period t and θ is the fixed coefficient of risk aversion. As θ is positive, the product $\theta(\sigma^2_t)$ is the required risk premium.

The second group 'feedback traders' whose demand for shares, F_t, depends solely on the previous period's return:

$$F_t = \gamma R_{t-1} \tag{2}$$

where R_{t-1} denotes the actual return in the previous period. The value of the parameter γ allows us to discriminate between two types of feedback traders: $\gamma > 0$ refers to the case of positive feedback traders who buy (sell) after a price rise (fall),[18] while $\gamma < 0$ indicates the case of negative feedback traders, who exhibit the opposite investment behaviour by adhering to a 'buy low, sell high' investment strategy.

Equilibrium in the stock market requires that all shares are held, thus:

$$S_t + F_t = 1 \tag{3}$$

If all investors are rational 'smart-money' investors (i.e., $F_t = 0$), market equilibrium ($S_t = 1$) yields the standard capital asset pricing model (CAPM):

$$E_{t-1}(R_t) - \omega = \theta(\sigma_t^2) \tag{4}$$

[18] Evidence of this type of behaviour for both individual investors and institutions can be found in Nofsinger and Sias (1999). It should be noted that positive feedback trading needs *not* be irrational or noise trading. It is consistent with, for example, portfolio insurance strategies and the stop-loss orders. Nonetheless, as Shleifer (2000) point out, this trading behaviour has the potential detrimental effect of moving prices away from their fundamental value.

However, allowing the existence of both types of traders, substituting (1) and (2) into (3) and rearranging gives:

$$E_{t-1}(R_t) - \omega = \theta(\sigma_t^2) - \gamma[\theta(\sigma_t^2)]R_{t-1} \tag{5}$$

Compared to the standard CAPM of (4), equation (5) has an extra term $-\gamma[\theta(\sigma_t^2)]R_{t-1}$ implying that in a market with rational investors as well as feedback traders the resulting returns exhibit autocorrelation; and the degree of autocorrelation depends on (i) the dominant type of feedback traders (i.e., that determined by the sign of γ), and (ii) the conditional volatility of returns, σ_t^2. In particular, as volatility rises, the demand for shares by feedback traders increases relative to the demand for shares by smart-money investors and consequently autocorrelation in returns becomes stronger. The pattern of autocorrelation, however, depends on the type of feedback traders. Positive feedback trading, $\gamma>0$, implies negatively autocorrelated returns, vice versa.[19]

Then, assuming the rational expectation, i.e., $R_t = E_{t-1}(R_t) + \varepsilon_t$, substituting it into (5) and rearranging gives:

$$R_t = \omega + \theta(\sigma_t^2) - \gamma[\theta(\sigma_t^2)]R_{t-1} + \varepsilon_t \tag{6}$$

where ε_t is an independently and identically distributed error term. And in order to investigate the presence and the role of feedback traders, SW convert equation (6) into an empirical version of their model:

$$R_t = \omega + \theta(\sigma_t^2) + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \varepsilon_t \tag{7}$$

[19] It has been argued that the higher predictability that arises because of feedback trading will not necessarily be exploited by the first group of investors as the risk is also higher. By contrast, in anticipation of the responses of positive feedback investors, rational speculators tend to 'jump on the bandwagon' and therefore, instead of stabilising prices, they move them further away from their fundamental values. Thus, the interaction of positive feedback traders and rational investors could lead to price movements that are not warranted by their fundamental value (Shleifer, 2000).

where $\varphi_1 = -\gamma\theta$. Thus, the presence of positive (negative) feedback trading implies that φ_1 must be negative (positive) and statistically significant. The coefficient φ_0 is added to capture the autocorrelation induced by the potential market frictions / inefficiency.

In their empirical work, SW assumes that the conditional variance σ^2_t can be modelled as a generalised autoregressive conditional heteroscedastic (GARCH) process.[20] Using a comprehensive U.S. data set and estimating all the parameters of the model simultaneously by maximum likelihood, SW find that $\hat{\varphi}_0 = 0.111$ and $\hat{\varphi}_1 = -0.019$, and that both parameters are statistically significant. Taken together with the estimated conditional variance, the parameter values reveal an interesting result, i.e., returns are positively autocorrelated during low volatility period, but during high volatility period they tend to become negatively autocorrelated. This sign reversal is consistent with the notion that positive feedback trading is higher in the period of high volatility, but that negative feedback trading dominates in the period of low volatility. In subsequent investigations a negative relationship between autocorrelation and volatility has also been found to be a feature of returns for mature and emerging stock markets (Bohl and Silkos, 2008), foreign exchange markets (Laopodis, 2005), as well as stock index futures markets (Salm and Schuppli, 2010).[21]

3.2 Feedback Trading with Sentiment

The feedback traders' demand function used in the studies mentioned above assumes that their demand for shares depends only on the previous period's return and is invariant across different level of investor sentiment (as given by the equation (2)).

[20] Numerous studies have shown that the stock returns are heteroscedastic. Teräsvirta (2009) provides a recent survey of studies modelling stock returns as conditionally heteroscedastic process.
[21] For more recent applications of the SW model, see Chau *et al*. (2008) and Schuppli and Bohl (2010).

However, recent literature has seen a rise of studies investigating the link between investor sentiment and stock returns and finds that investors' demand for stocks are to some extent driven by sentiment, particularly for those noise / uninformed traders. Kurov (2008) has showed that, in a microstructure setting, the positive feedback trading in the E-mini index futures markets increases when investors are optimistic. This suggests that positive feedback activity is, at least in part, driven by the existence of noise traders who are more likely to follow trend-chasing strategies; and that the degree of this positive feedback trading intensifies in high-sentiment periods.

Motivated by the above literature, we extend the feedback trading model to allow for the investor sentiment to exert an additional influence on feedback trading. Specifically, following the SW framework, this paper assumes the existence of a group of investors who does not explicitly take risk into account, however, their decision of buying or selling is more complex than the naïve feedback traders who simply react to the previous price changes. Instead, when deciding whether to invest, their decision making process is to some extent dependent on how they feel about the future performance of stock market i.e., whether they are optimistic or pessimistic.

More formally, we assume there are two distinct groups of investors: smart-money investors and feedback traders, and the relative demand by smart-money investors are given by equation (1). Consider first extending SW model so that the demand for shares by feedback traders depends on their sentiment state in an *additive* way:

$$F_t = \gamma R_{t-1} + \lambda D_t \tag{8}$$

where D_t is a dummy variable that is equal to 1 in a period of high investor sentiment (i.e., optimistic) and 0 in a period of low investor sentiment (i.e., pessimistic), allowing the demand function of feedback traders to be somewhat sentiment-driven. In order to identify whether a particular period is optimistic or pessimistic, we follow Antoniou *et al*. (2010) to calculate a rolling average of the sentiment level for three months prior to the time period under consideration. In particular, a particular period is classified as 'optimistic' if the current investor sentiment indicator is greater than its previous 3 month average; otherwise the period is classified as a 'pessimistic' state.[22]

Substituting (1) and (8) into (3), and assuming the rational expectation produces:

$$R_t = \omega + \theta(\sigma_t^2) - \gamma[\theta(\sigma_t^2)]R_{t-1} - \lambda D_t[\theta(\sigma_t^2)] + \varepsilon_t \qquad (9)$$

Thus the return in period t depends additively on the sentiment indicator D_t and the extent of this dependence varies with conditional volatility σ^2_t. If we assume a linear form for $\theta\sigma^2_t$ such that $\theta\sigma_t^2 = \varphi_0 + \varphi_1\sigma_t^2$, then (9) can be re-parameterised as:

$$R_t = \omega_H D_t + \omega_L(1-D_t) + \theta_H D_t\sigma_t^2 + \theta_L(1-D_t)\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \varepsilon_t \qquad (10)$$

giving a non-linear model similar to the model estimated by SW, but here both the constant ω and parameter on the conditional variance θ are allowed to vary across the different investor sentiment states (ω_H vs. ω_L ; θ_H vs. θ_L).

Note that in the extended feedback trading model associated with equations (8)-(10), the reaction of feedback traders to price changes is not dependent on the sentiment, although their overall demand for share is. As an alternative we consider feedback traders demand function that is affected by sentiment in a *multiplicative* way:

$$F_t = [\gamma D_t + \lambda(1-D_t)]R_{t-1} \qquad (11)$$

[22] We use the most renowned sentiment measures constructed by baker and Wurgler (2006, 2007) for the main analysis in this paper. However, as a robustness tests, we also checked the sensitivity of our results to an alternative measure based on the Michigan Consumer Confidence Index.

where D_t is defined as before. In this case the reaction of feedback traders to individual price rises and price falls varies over the sentiment state if $\gamma \neq \lambda$. Substituting (1), (11) into (3) and assuming the rational expectation gives:

$$R_t = \omega + \theta(\sigma_t^2) - [\gamma D_t + \lambda(1 - D_t)]\theta(\sigma_t^2)R_{t-1} + \varepsilon_t \tag{12}$$

As in the original feedback trader model of SW, a relationship between autocorrelation and volatility exists, but in this augmented model the strength of that relationship differs over the sentiment state if $\gamma \neq \lambda$. Again, if we assume a linear form for $\theta\sigma^2_t$ so that $\theta\sigma_t^2 = \varphi_0 + \varphi_1\sigma_t^2$, then (12) can be re-parameterised as:

$$R_t = \omega + \theta\sigma_t^2 + D_t(\varphi_{0H} + \varphi_{1H}\sigma_t^2)R_{t-1} + (1 - D_t)(\varphi_{0L} + \varphi_{1L}\sigma_t^2)R_{t-1} + \varepsilon_t \tag{13}$$

3.3 Empirical Model Specifications

In our empirical analysis we estimate a number of positive feedback trading models. The first is the original specification of SW (1992):

$$R_t = \omega + \theta(\sigma_t^2) + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \varepsilon_t \tag{14}$$

It is clear from equation (14) that, to complete the model, it is necessary to specify the conditional variance equation. Since it is now well established in the literature that stock returns are characterised by conditional heteroscedasticity, a GARCH type specification is used for the conditional volatility.[23] In the subsequent analysis we assume a GJR-GARCH (1,1) specification for the conditional variance of returns:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2 \tag{15}$$

where σ^2_t is the conditional volatility in period t, ε_{t-1} is the innovation in period t-1 and I_{t-1} is an indicator which assumes a value of one in response to bad news ($\varepsilon_{t-1} < 0$)

[23] Extensive tests were conducted to see which form of the conditional volatility equation seems to fit our return data the best. On the basis of the log-likelihood, AIC and SBC, the asymmetric models tend to fit the data better than the symmetric model, with GJR-GARCH performing better than EGARCH. The results of these specification tests are not reported here, but are available on request.

and zero otherwise. If δ is positive and statistically significant, it would indicate that a negative shock has a greater impact on future volatility than a positive shock of the same size. α_1 is the news coefficient capturing the impact of the most recent innovation, β is a measure of persistence, and α_0 represents unconditional volatility.[24] The model given by equations (14) and (15) is referred to as the 'baseline' Model I.

The first modification to this baseline model (Model II) is to incorporate the impact of investor sentiment on the demand of feedback traders in the manner of equation (8). The actual model we estimate is a re-parameterised version of (9):

$$R_t = \omega_H D_t + \omega_L(1-D_t) + \theta_H D_t\sigma_t^2 + \theta_L(1-D_t)\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \varepsilon_t \tag{16}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2 \tag{17}$$

where $D_t = 1$ in a period of high sentiment and $D_t = 0$ in a period of low sentiment. The third model (Model III) assumes the demand by feedback traders depends on the sentiment as in (11). The actual specification is re-parameterised version of (12):

$$R_t = \omega + \theta\sigma_t^2 + D_t(\varphi_{0H} + \varphi_{1H}\sigma_t^2)R_{t-1} + (1-D_t)(\varphi_{0L} + \varphi_{1L}\sigma_t^2)R_{t-1} + \varepsilon_t \tag{18}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2 \tag{19}$$

The fourth model considered (Model IV) is the augmented model which allows *all* parameters in the conditional mean to shift over the sentiment state:

$$\begin{aligned} R_t = {} & \omega_H D_t + \omega_L(1-D_t) + \theta_H D_t\sigma_t^2 + \theta_L(1-D_t)\sigma_t^2 \\ & + D_t(\varphi_{0H} + \varphi_{1H}\sigma_t^2)R_{t-1} + (1-D_t)(\varphi_{0L} + \varphi_{1L}\sigma_t^2)R_{t-1} + \varepsilon_t \end{aligned} \tag{20}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2 \tag{21}$$

[24] Most studies dealing with stock returns use the normal density function; however the standardised residuals obtained from GARCH models that assume normality tend to be leptokurtic thereby rendering standard t-tests unreliable. To overcome this problem, we employ the density function with ticker tails such as the Generalised Error Distribution (GED).

Given the initial values for ε_t and σ^2_t, the parameters of each model's mean and variance equations can be estimated simultaneously by maximum likelihood method. The WinRATS 7.2 software was used and for numerical optimisation the Newton-Raphson and Berndt-Hall-Hall-Hausman (BHHH) algorithms were employed.[25]

4. Data and Descriptive Statistics

Given its growing significance in global financial market and its unique characteristics, ETF markets provide a key opportunity to investigate further the impact of feedback trading on stock returns, and to examine the fluctuations (if any) in the intensity of feedback trading over investor sentiment states. As mentioned above, since ETFs are directly tradable just like any other stocks, it is expected that the sentiment-driven noise trading will be easier to identify and the potential non-synchronous trading issue inherent in many previous studies relying on market indices can be overcome. Hence, conclusion drawn here can be considered to be more robust. Therefore, for the empirical analysis we investigate returns on the three largest Exchange-traded funds (ETFs) in the US i.e., (i) S&P500 SPDR the 'Spider' which was launched in January 1993, ticket symbol SPY; (ii) Dow Jones Industrial Average (DJIA) ETF the 'Diamond' that was listed in January 1998, ticker symbol DIA; and (iii) Nasdaq-100 ETF the 'Cubes' launched in March 1999, ticker symbol QQQQ.[26]

Daily closing prices on these ETFs were collected from Datastream for the period of 01/01/2000–31/10/2007 and returns were calculated as the first-difference of the

[25] Due to the increased complexity caused by allowing the parameters to vary over time, one might encounter convergence difficulties in some cases. Broyden–Fletcher–Goldfarb–Shanno (BFGS) method was used instead for situation in which convergence cannot be reached within 50 iterations.

[26] The overall trading in these three index funds accounted for almost one-third of the assets invested in the U.S. passive ETFs (Alexander and Barbosa, 2008). This helps to ensure that our empirical results are not driven by potential problems of thin trading or illiquidity.

natural logarithm of prices. The full sample covers both upward and downward market trends (as shown in Figure 1a). To accommodate the possibility that the behaviour of feedback traders may vary across different market conditions / regimes, we divide the full sample into two sub-periods: (i) the 'Bear market' period from 01/01/2000 to 31/10/2002, and (ii) the 'Bull market' period from 01/11/2002 to 31/10/2007. Our sample period ends in October 2007 in an attempt to mitigate the potential impact of the recent 2008-09 financial crisis on our empirical results.[27]

[FIGURE 1 ABOUT HERE]

To test the linkage between intensity of feedback trading and investor sentiment, we need a proxy for the investor sentiment. A number of proxies have been proposed in the literature to capture the variation of investor sentiment or expectation. These measures can generally be classified as the market-based measures (e.g., Baker and Wurgler sentiment index) and the survey-based measures (see Qiu and Welch, 2006). This paper uses the monthly investor sentiment measures constructed by Baker and Wurgler (2006, 2007). These sentiment measures were constructed using six market-based variables that relate to investors' tendency to purchase stocks. Since these variables are partly related to economic fundamentals, they regress each of these sentiment proxies on a set of macroeconomic variables and use the residuals from this regression as the sentiment proxies to extract an 'orthogonalized' sentiment index. The overall index is the first principal component of these six sentiment proxies.[28]

[27] It is worth noting that our choice of sample period is also restricted by the availability of Baker and Wurgler's sentiment measures.

[28] This index is available from Jeffrey Wurgler's website (http://pages.stern.nyu.edu/~jwurgler/) on both monthly and annual basis from 1966 to 2007. We would like to thank Jeffrey Wurgler and Malcolm Baker for making their sentiment indices publicly available. For more details on the construction of this index, see Baker and Wurgler (2006, 2007).

The descriptive statistics for ETF returns as well as two sentiment indices are provided in Panel A of Table 1. The table shows a clear evidence of departures from normality (as implied by significant JB statistics) and significant ARCH (1) effects. The Ljung-Box (LB) statistics show temporal dependencies in the first moment of ETF return distribution, and for squared returns in all cases. The JOINT test of Engle and Ng (1993) for potential asymmetries in conditional volatility suggests that significant asymmetries exist in all ETF returns. Also shown in this Panel, the sentiment index (SENT) has a mean of 0.267 and standard deviation of 0.779, whilst the statistics for the orthogonalized index (SENT^) are 0.234 and 0.793 respectively. Furthermore, both the raw and orthogonal versions of sentiment indices display a skewed and leptokurtic pattern. And as shown in Figure 1b, they fall sharply during the bursting of dot-com bubbles in 2000-2002 and rise steadily thereafter. Interestingly, similar pattern can also be seen in ETF price movements in Figure 1a.[29]

[TABLE 1 ABOUT HERE]

To gauge the initial idea on the intensity of feedback trading in ETF markets we estimate an autoregressive model.[30] The results reported in Panel C of Table 1 show that there are significant autocorrelations and the coefficients are mostly negative. Nonetheless, as shown in Section 3, the interaction of feedback traders and rational investors will give rise to autocorrelation patterns that are more complex than a simple autoregressive model can capture. It is, therefore, interesting and informative to further investigate the extent to which feedback trading affect the link between autocorrelation and volatility, and whether this change over different sentiment states.

[29] This is perhaps not very surprising given the relatively high correlations between the sentiment indices and ETF return series as shown in Panel B of Table 1.
[30] The common perception is that the positive (negative) feedback trading leads to positive (negative) autocorrelation of stock returns. To investigate this possibility we estimate a simple autoregressive model of order five, AR(5).

5. Empirical Results

Tables 2 and 3 summarise the results of maximum likelihood estimates for the original and three extended versions of SW feedback trader models as specified in Section 3.3 allowing for the possible influence of sentiment on feedback trading behaviour. In Tables 4 and 5, we present some robustness checks of our results by implementing alternative sentiment measures, econometric specifications and data set.

5.1 Evidence on the Feedback Trading in ETF Markets

Consider first the results for the 'baseline' Model I (equations (14) and (15)) given in the first three columns of Table 2. It can be seen that the coefficients describing the conditional variance process, α_0, α_1, β, and δ are not unusual. Specifically, they are all highly significant (except α_1) for ETF returns. In all cases, the moving average parameters α_1 are close to 0 and autoregressive parameter β tend to be 1, suggesting that the conditional variance is a highly persistent process. The significance of δ means that conditional variance is an asymmetric function of past squared residuals.

The parameters testing the presence of feedback trading are those governing the autocorrelation of returns (φ_0 and φ_1). Consistent to results reported in Table 1, Panel C, the constant components of autocorrelation (φ_0) are all negative although significant in only QQQQ market. Interestingly, as in SW and Koutmos (1997), the parameter of interest φ_1 is negative and statistically significant in all instances, suggesting that positive feedback trading is present in ETF markets and their influence tend to be greater in periods of high volatility. Moreover, in all cases, the estimated parameter ν is well below 2, the value required for normality, and varies close to unity suggesting that the distributions of returns are similar to the Laplace.

This confirms that the departures from normality observed in raw returns series cannot be entirely attributed to temporal first and second moment dependencies. Finally, an array of diagnostics performed on the standardized residuals shows no serious misspecification of the 'baseline' Model I.

For completeness, we repeat our analysis using the national stock market indices in order to provide a comparison of our findings based on ETF data with that of the underlying indices.[31] The results are reported in the last three columns of Table 2. Interestingly, whilst the parameters governing the behaviour of conditional variance remains almost the same, it turns out that the coefficient capturing the presence of feedback trading (i.e., φ_1) becomes statistically insignificant in DJIA and NASDAQ. The differences allow us to suggest that relying on the data for 'non-investable' assets (e.g. stock market indices) may underestimate the actual extent of feedback trading.

[TABLE 2 ABOUT HERE]

5.2 The Effect of Sentiment on Feedback Trading

Turing our attention to the focus of this paper and consider the impact of investor sentiment on the behaviour and intensity of positive feedback trading in ETF markets. As a useful starting point to our analysis, we extract the conditional autocorrelation from the baseline Model I, $\rho_t^{implied} = \hat{\varphi}_0 + \hat{\varphi}_1 \sigma_t^2$; and compare that to the evolution of Baker and Wurgler's orthogonal sentiment index (SENT^). As can be seen from Figure 2, the time series resemble to each other and, in particularly, downward spikes in autocorrelation during 2001-02 coincide with pronounced drops in the sentiment.[32]

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[31] We thank the referee for suggesting this additional analysis.
[32] Salm and Schuppli (2010) present similar figures for the conditional autocorrelation of 19 international stock index futures and show that autocorrelation drops during the recent financial crisis.

[FIGURE 2 ABOUT HERE]

Consider next the results for Model II, which are given in the first three columns of Table 3. In this case, we allow the investor sentiment dummy to *additively* affect the demand for shares by feedback traders. This leads to the equations (16) and (17) in which the constant and the parameter on the conditional variance in (16) are allowed to shift with sentiment states. We find that as one might expect, in high-sentiment state and investors are optimistic, the average return (ω_H) is more positive than in the low-sentiment periods (ω_L). The parameter on conditional variance is also more positive in optimistic state (θ_H) than in pessimistic state (θ_L). This is however inconsistent with the recent findings of Yu and Yuan (2011) who shows that the correlation between the markets expected return and its conditional volatility is positive during low-sentiment periods and nearly flat during high-sentiment periods. They argue that the market is less rational during high-sentiment periods, due to higher participation by noise traders in such periods.[33] Nonetheless, using a likelihood ratio test we test the restrictions: $H_0 : \omega_H = \omega_L, \theta_H = \theta_L$, $H_{01} : \omega_H = \omega_L$, $H_{02} : \theta_H = \theta_L$ and find that these hypotheses cannot be rejected (see the LR statistics in Panel C). Thus while allowing for this type of parameter change over sentiment state yields parameter values that have their expected signs, the statistical support for Model II is weak.

[TABLE 3 ABOUT HERE]

The results for Model III as specified in the equations (18) and (19) are presented in the second three columns of Table 3. Recall that this model allows the reaction of feedback traders to previous price changes to vary across investor sentiment states

[33] Examination of why such differences exist is worthy of a study, but is beyond the scope of this paper.

(the sentiment dummy enters the conditional mean equation (18) *multiplicatively*). Across both optimistic and pessimistic sentiment states, we still find a negative relationship between autocorrelation and volatility (see the parameters $\varphi_{1H};\varphi_{1L}$), which is consistent with notion that positive feedback traders exist in both periods. However, such relationship is much stronger in high-sentiment state than in low-sentiment state in SPY (φ_{1H} = -0.0376 vs. φ_{1L} = -0.0043), DIA (φ_{1H} = -0.0501 vs. φ_{1L} = -0.0097), and QQQQ (φ_{1H} = -0.0094 vs. φ_{1L} = -0.0071). To formally test the hypothesis that changes of the feedback trading parameter (φ_{1H}, φ_{1L}) are statistically significant, again we use a likelihood ratio test to directly test the following hypotheses: H_0: $\varphi_{0H} = \varphi_{0L}$, $\varphi_{1H} = \varphi_{1L}$, H_{01}: $\varphi_{0H} = \varphi_{0L}$, H_{02}: $\varphi_{1H} = \varphi_{1L}$. The LR statistics reported in Table 3, Panel C, reject H_{02}: $\varphi_{1H} = \varphi_{1L}$ in SPY and DIA cases, suggesting that the changes of the feedback trading parameter are statistically significant.

This finding is consistent with the recent evidence of Kurov (2008) who also documents that the level of positive feedback trading increases when investors are optimistic. In addition, McKenzie and Kim (2007) argues that '*the restrictions which apply to short selling will curtail the ability of an investor to engage in positive feedback trading following an increase in volatility caused by a fall in prices.' (p.23).* This argument could be used to explain our finding that positive feedback trading is less intense during low-sentiment periods because the short-selling restrictions make it much more difficult and less profitable for investors to engage feedback trading when market is falling. From Model III we also find that there is a higher base level of positive autocorrelation (see the parameters $\varphi_{0H};\varphi_{0L}$), consistent with the view that market is less rational / efficient during high-sentiment periods as more noise traders likely to trade in such periods. Also note that in contrast for Model II, in the case of

SPY at least, the null hypothesis of parameter stability across sentiment states (H_0: $\varphi_{0H} = \varphi_{0L}, \varphi_{1H} = \varphi_{1L}$) is rejected by likelihood ratio test at the 1% significance level. This indicates that a model, such as the 'baseline' Model I, which assumes parameter constancy for this data is mis-specified.

The results for Model IV (equations (20) and (21)) are reported in the final three columns of Table 3. In this case we find similar results to our previous models; the constant (ω_H) is relatively higher in high-sentiment state (when investors are optimistic) as one would expect, and we find a stronger negative relationship between autocorrelation and volatility in the high-sentiment state than in low-sentiment state. Note that the null hypothesis of parameter stability over sentiment state ($H_0 : \omega_H = \omega_L, \theta_H = \theta_L, \varphi_{0H} = \varphi_{0L}, \varphi_{1H} = \varphi_{1L}$) is rejected by the likelihood ratio test at the 5% significance level, in SPY case at least. In addition, we also test the hypothesis $H_{01} : \omega_H = \omega_L, \theta_H = \theta_L$ in Model IV; i.e. the null hypothesis that only the parameters on the lagged return vary over sentiment states as in Model III, against the alternative hypothesis that all parameters vary over sentiment state as in Model IV. This null hypothesis cannot be rejected by a likelihood ratio test in all three cases. Overall, from those feedback traders models considered in this paper, Model III appears to be the preferred model for capturing the variability of feedback trading over different investor sentiment states. Furthermore, in all four models, the diagnostics on standardised residuals show no serious evidence of misspecification.[34] The use of GED distribution is also found to be appropriate given that estimated values of ν are well below 2 (i.e., the value required for normality).

[34] Although the standardized residuals are showing asymmetric responses in many cases (as indicated by the significance of JOINT tests), this is perhaps not surprising as many studies have linked the presence of asymmetric volatility to the activities of feedback traders. See, e.g., Antoniou *et al*. (2005).

5.3 Robustness and Alternative Measures

To summarize the results so far, the evidence presented above suggests that there is there is a significant positive feedback trading in the U.S. ETF markets, and the intensity of which tends to increase when investors are optimistic. These results are consistent with the view that the market is less rational during high-sentiment periods, due to higher participation by noise traders in such periods. In this section, we examine the robustness of our results by implementing different econometric specifications, data set and frequency as well as alternative sentiment measures.

5.3.1 Robustness Tests

First we estimate the 'best' feedback traders Model III in equations (18) and (19) assuming the student-t distribution for standardized residuals instead of the GED distribution we used previously (note however that both distributions have a fatter tail than the normal distribution). Next, we estimate the same specification removing observations around the holidays to test the potential influence of non-synchronous or / infrequent trading on the main findings. Compared to the national stock market indices, the ETF markets are less prone to these problems; they may not be completely free of thin-trading bias as they might not be traded every day.[35] Overall, the findings (reported in Table 4) are qualitatively similar to the results presented in Table 3 and confirm that our main conclusions from the best-fit Model III hold for these alternative specifications. In addition, consideration is also given to the possible changes of our results when data with different frequency was used. In general, the results for the daily return do not carry over to the weekly returns and, in particular,

[35] The authors are grateful to the referee for pointing out this possibility.

there was no evidence of positive feedback trading (either base or sentiment-induced) suggesting that feedback trading affect return dynamics only in the short term.

[TABLE 4 ABOUT HERE]

5.3.2 Alternative Measures of Investor Sentiment

In this section, we check the sensitivity of our results to an alternative ‘survey-based’ index for investor sentiment using measures based on University of Michigan’s (MCG) consumer confidence surveys conducted in the U.S. for which we extracted directly from the Euromonitor International’s Economic Observer database. Again, we follow previous procedure to calculate a moving average of the sentiment level for three months prior to the time period under consideration to determine whether a particular period is optimistic or pessimistic. Specifically, a particular period is classified as ‘optimistic’ if the current investor sentiment indicator is greater than its previous 3 month average; otherwise the period is classified as a ‘pessimistic’ state.[36]

[TABLE 5 ABOUT HERE]

Table 5 reports the best model (i.e., Model III) results for using this alternative MCG index as well as the ‘unorthogonal’ version of Baker and Wurgler’s measure. Consistent with our earlier findings, the new evidence confirms the stronger negative relationship between autocorrelation and volatility (which is consistent with the presence of positive feedback trading) in high-sentiment state in all instances, except for QQQQ using MCG index. This supports the notion that our previous results are not driven by the choice of sentiment index. Taken these additional sets of tests together, the general conclusions discussed earlier appear to be robust to different model specifications, data set / frequency, and alternative sentiment measures.

[36] We also examine the robustness of our main results to average sentiment calculated as the average of the six-months prior to the time period concerned. The results (not being reported here) confirm that our main conclusions from the best-fit Model III hold for this alternative sentiment specification.

5.4 The Effect of Sentiment on Feedback Trading across Market Regimes

The analysis presented thus far for the entire period has revealed evidence of significant feedback trading in the U.S. ETF markets, and the extent of positive feedback trading rises with investor sentiment. However, it is plausible that the relation between investor sentiment and trading behaviour may vary across market regimes. We explore this possibility by dividing the full sample into two sub-periods: (i) the 'Bear market' period from 01/01/2000 to 31/10/2002 and (ii) the 'Bull market' period from 01/11/2002 to 31/10/2007.[37] For each sub-period, we run the Model III following the same GJR-GARCH specification and estimation procedure as before.

[TABLE 6 ABOUT HERE]

To keep the discussion compact, we will concentrate on the interpretation of the values for the feedback parameters φ_{1H} and φ_{1L}, which indicate the level of feedback trading and the influence of investor sentiment, respectively. An inspection of the sub-period results in Table 6 shows that the impact of sentiment on positive feedback trading tends to be stronger in bullish periods. More specifically, all the feedback trading parameters (φ_{1H}, φ_{1L}) increase during the Bull market periods. Likelihood ratio test for the equality of φ_{1H} and φ_{1L} across market regimes is rejected in many cases. The fact that investor sentiment is more influential in the bullish market is consistent with (i) the conjecture of Shiller (1984) noise trader model and notion that sentiment-driven noise trading tends to be more significant when markets are bullish, and (ii) evidence that sentiment improves the performance of dynamically managed portfolio strategies for momentum-based investors uncovered by Basu *et al*. (2006).

[37] The rationale for partitioning of the whole sample period in such a way is based on the time-trend shown in Figure 1 which clearly indicates that the market slumped down during the bursting of dot-com bubble 2000-2002 and then steadily rises thereafter.

6. Conclusion

In this we has developed and estimated several feedback trader models in which the demand for shares by feedback traders is conditional not only on the previous price changes, but also on the investor sentiment state. Given the recent literature on the impact of investor sentiment on stock return predictability, it seems overly restrictive to assume that feedback traders would not affect by their sentiment when deciding whether to invest. Using the data on three largest ETF contracts in the U.S. and the investor sentiment measures constructed by Baker and Wurgler (2006, 2007), we find statistically significant evidence suggesting that the negative relationship between autocorrelation and volatility, first uncovered by Sentana and Wadhwani (1992), varies over the investor sentiment states. Specifically, we find this relationship (due to the presence of positive feedback traders) to be stronger when investors are optimistic. This finding is in line with the recent results of Kurov (2008) who documents that the intensity of positive feedback trading tends to increase in the high-sentiment state. This in turn suggests that positive feedback trading is driven, at least in part, by expectations of sentiment-driven noise traders. In addition, we also find that the influence of sentiment seems to be much stronger during the bullish market.

Overall, the findings provide new evidence of the direct impact of investor sentiment on the momentum-style feedback trading strategies. We deem our results very important in contributing to the current debate on the role of investor sentiment in asset pricing and investment behaviour, and are of great significance to the financial market regulators and many finance practitioners who continue to believe in ‘sentiment’ and treat it as a useful predictor for future market movement.

However, as with any empirical investigation, the results in this paper must be taken in context. We investigate relatively simple extensions of SW model and applied them to the data from three US ETF markets. Also, we classify the investor sentiment level into just two states, while it may be more practical to allow for three different categories: optimistic, pessimistic, and a 'mild' sentiment category. Further research might seek to resolve these issues should provide additional insights into the link between sentiment and investor trading behaviour. Furthermore, the recent findings of Edelen *et al.* (2010) suggest that fluctuations in the individual retail investors' sentiment relative to that of institutional investors was the primary driver of equity valuations for reasons unrelated to fundamentals. Exploration of similar 'relative' sentiment measures to this issue would seem to an interesting area for future research.

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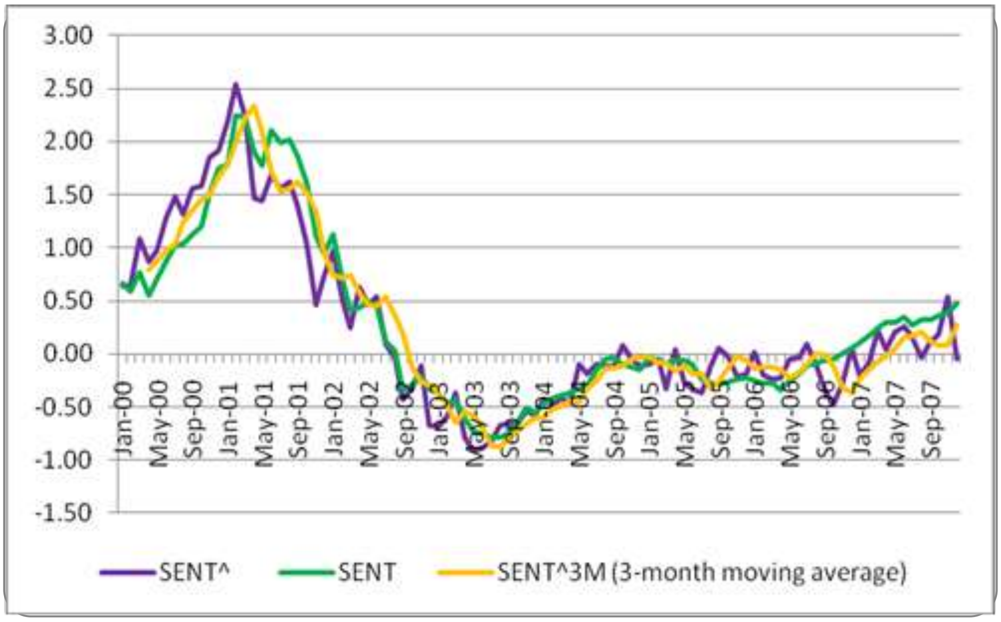
Figure 1: ETF Prices and Investor Sentiment Indices from 2000-2007

a. ETF Prices

b. Investor Sentiment Indices



Notes:
SPY represents the S&P500 SPDR the 'Spider', DIA denotes the Dow Jones Industrial Average (DJIA) ETF the 'Diamond', and QQQQ is Nasdaq-100 ETF the 'Cubes'. SENT is the index for investor sentiment constructed by Baker and Wurgler (2006, 2007) and SENT^ is the same sentiment index, orthogonal to macroeconomic variables. The third series, SENT^3M, is the 3-month moving average of SENT^.

Table 1: Descriptive Statistics of ETF Returns and Investor Sentiment Indices

	ETF Returns						Investor Sentiment			
	SPY		DIA		QQQQ		SENT		SENT^	
Panel A: Summary Statistics										
μ	0.023		0.010		-0.015		0.267		0.234	
σ	1.109		1.066		2.152		0.779		0.793	
S	0.074		-0.122		0.220		1.044		1.019	
K	2.734		4.557		4.773		0.226		0.266	
JB	638.057	***	1,772.955	***	1,955.554	***	17.655	***	16.890	***
LB(12)	22.804	***	15.312	*	34.124	***	732.929	***	718.115	***
LB²(12)	938.415	***	609.861	***	1,065.612	***	430.750	***	393.627	***
ARCH(1)	39.892	***	26.290	***	97.651	***	86.189	***	80.344	***
JOINT	24.141	***	15.038	***	45.527	***	244.576	***	137.665	***
Panel B: Correlation Coefficients										
SPY	1									
DIA	0.892	***	1							
QQQQ	0.722	***	0.371	***	1					
SENT	0.398	***	0.186	**	0.467	***	1			
SENT^	0.455	***	0.177	**	0.604	***	0.953	***	1	
Panel C: Autocorrelation										
b_0	0.024		0.011		-0.016		0.007		-0.002	
b_1	-0.077	***	-0.091	***	-0.137	***	1.220	***	0.904	***
b_2	-0.071	***	-0.070	***	-0.085	***	-0.295	*	-0.107	
b_3	-0.012		0.020		-0.057	***	0.201		0.110	
b_4	-0.016		-0.022		0.040	*	0.072		0.239	
b_5	-0.025	*	0.001		0.002		-0.231	**	-0.191	*
F-test	9.256	***	8.077	***	13.178	***	619.100	***	191.200	***

Notes:
SPY represents the S&P500 SPDR the 'Spider', DIA denotes the Dow Jones Industrial Average (DJIA) ETF the 'Diamond', and QQQQ is Nasdaq-100 ETF the 'Cubes'. SENT is the index for investor sentiment constructed by Baker and Wurgler (2006, 2007) and SENT^ is the same sentiment index, orthogonal to macroeconomic variables. μ = sample mean; σ = standard deviation; S = skewness; K = Excess Kurtosis; JB = Jarque-Bera test for normality LB(n) & LB²(n) are the Ljung-Box Q test of serial correlation for the level & squared ETF returns and sentiment indices, respectively; the test statistics are distributed as χ^2 with n degree of freedom where n is the number of lags. ARCH(N) is the Lagrange Multiplier LM test for ARCH effects and distributed as a χ^2 with N degree of freedom. The test results for JOINT are Engle and Ng's (1993) test for the potential asymmetries in conditional volatility. The test statistic is a F-statistic for the null hypothesis of b1=b2=b3=0 of the following regression:

$$Z_t^2 = a + b_1 S_t^- + b_2 S_t^- \varepsilon_{t-1} + b_3 S_t^+ \varepsilon_{t-1} + v_t$$

where Z_t^2 is the square standardized residuals, $(\varepsilon_{t-1}/\sigma_t)^2$, St^- is a dummy variable that takes a value of unity if $\varepsilon_{t-1} < 0$ and zero otherwise; and St^+ is a dummy variable that takes a value of unity if $\varepsilon_{t-1} > 0$ and zero otherwise.
The unconditional autocorrelation (b_i) estimates are obtained using the following autoregressive equation:

$$R_t = b_0 + \sum_{i=1}^{5} b_i R_{t-i} + u_t$$

*, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table 2: Evidence on the Feedback Trading in ETFs and Underlying Indices

	Baseline Model I					
	ETFs			INDICES		
	SPY	DIA	QQQQ	S&P500	DJIA	NASDAQ
Panel A: Mean Equation						
ω	0.0371 ***	0.0344 **	0.0148	0.0342 ***	0.0260 *	0.0070
	(2.834)	(2.004)	(0.772)	(3.204)	(1.777)	(0.374)
θ	0.0104	-0.0043	0.0031	0.0010	-0.0041	0.0011
	(0.984)	(-0.324)	(0.244)	(0.095)	(-0.282)	(0.064)
φ_0	-0.0258	-0.0148	-0.0500 **	-0.0071	-0.0288	-0.0534 **
	(-1.562)	(-0.719)	(-2.260)	(-0.878)	(-1.634)	(-2.094)
φ_1	-0.0069 ***	-0.0112 **	-0.0073 ***	-0.0103 **	-0.0093	-0.0021
	(-3.291)	(-2.015)	(-2.970)	(-2.257)	(-1.574)	(-0.298)
Panel B: Variance Equation						
α_0	0.0103 ***	0.0082 **	0.0141 ***	0.0084 ***	0.0082 ***	0.0132 ***
	(3.398)	(2.370)	(3.340)	(3.136)	(2.587)	(3.555)
α_1	-0.0023	-0.0015	-0.0059	-0.0048	-0.0065	-0.0158
	(-0.274)	(-0.183)	(-0.582)	(-0.656)	(-0.896)	(-1.519)
β	0.9289 ***	0.9338 ***	0.9195 ***	0.9352 ***	0.9400 ***	0.9226 ***
	(88.793)	(85.588)	(77.815)	(92.465)	(103.534)	(65.888)
δ	0.1254 ***	0.1244 ***	0.1406 ***	0.1214 ***	0.1195 ***	0.1565 ***
	(5.760)	(6.073)	(6.703)	(5.683)	(6.737)	(7.393)
ν	1.2891 ***	1.3609 ***	1.4002 ***	1.3261 ***	1.3726 ***	1.6059 ***
	(25.599)	(23.591)	(21.666)	(25.253)	(20.574)	(19.906)
Panel C: Diagnostic Tests						
$E(Z_t)$	-0.027	-0.024	-0.038	-0.022	-0.029	-0.035
$E(Z^2_t)$	0.998	0.998	0.998	0.997	0.982	0.983
LB(12)	11.544	4.324	13.302	16.358	8.571	14.781
$LB^2(12)$	7.822	9.882	16.851	10.391	21.910 **	19.221 *
ARCH(5)	7.785	5.325	3.705	7.220	10.815 *	10.640 *
JOINT	7.485 ***	4.825 ***	1.352	7.936 ***	5.768 ***	4.145 ***

Notes:
This table presents maximum likelihood estimates for the Sentana and Wadhwani (1992) feedback trading model [i.e., baseline model 1 given by equations (14) and (15)] from 01/01/2000 to 31/10/2007 for the three most popular ETFs in U.S. and their underlying market indices. In particular, the estimated mean equation is

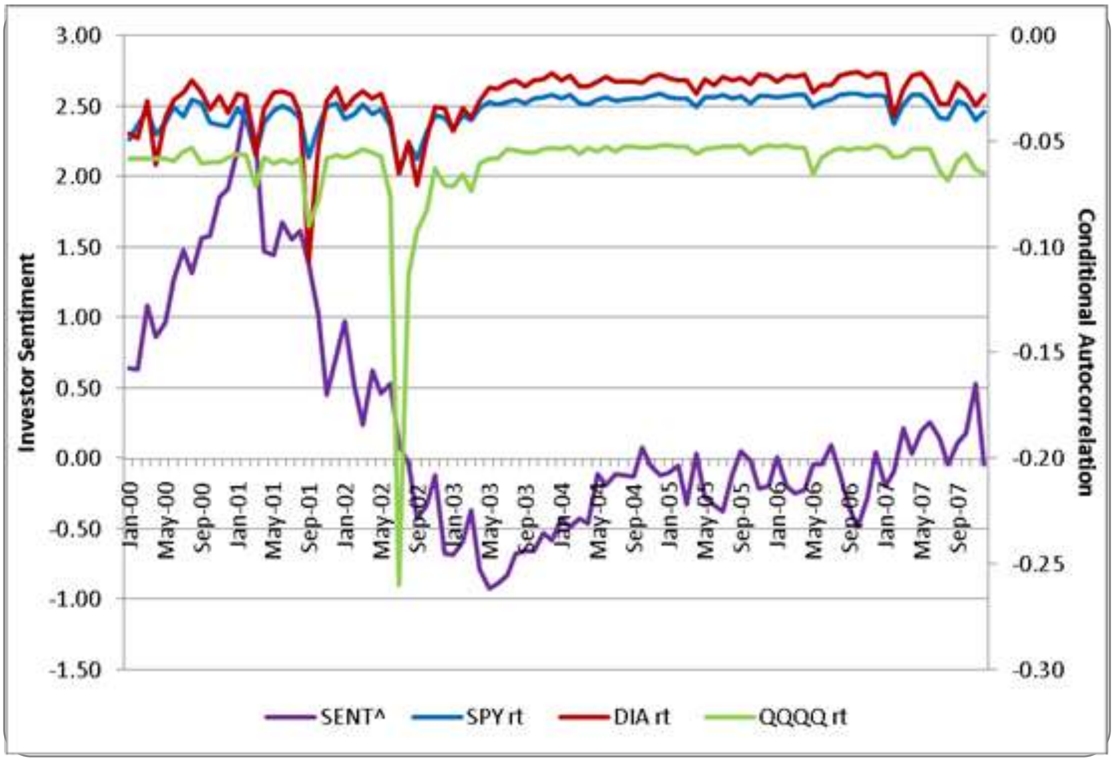
$$R_t = \omega + \theta(\sigma_t^2) + (\varphi_0 + \varphi_1\sigma_t^2)R_{t-1} + \varepsilon_t$$

The variance equation is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

Errors are assumed to follow the Generalised Error Distribution (GED) distribution that nests the normal (for ν=2) and the Laplace (for ν=1) distributions; ν is a scale parameter estimated endogenously. The estimated t-statistics (shown in parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Wooldridge (1992) standard errors. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Also see the notes given in Table 1.

Figure 2: Investor Sentiment and Conditional Return Autocorrelation



Notes:

SENT^ represents the investor sentiment index constructed by Baker and Wurgler (2006, 2007) which is orthogonal to macroeconomic variables. SPYρt, DIAρt, QQQQρt, are the conditional return autocorrelation, $\rho_t^{implied} = \hat{\varphi}_0 + \hat{\varphi}_1 \sigma_t^2$ implied by the Sentana and Wadhwani's (1992) feedback trading model [i.e., baseline model I given by equations (14) and (15)] for (i) SPY: S&P500 SPDR the 'Spider', (ii) DIA: Dow Jones Industrial Average (DJIA) ETF the 'Diamond', and (iii) QQQQ: Nasdaq-100 ETF the 'Cubes'.

Table 3: The Effect of Sentiment on Feedback Trading

	Model II			Model III			Model IV		
	SPY	**DIA**	**QQQQ**	**SPY**	**DIA**	**QQQQ**	**SPY**	**DIA**	**QQQQ**
Panel A: Mean Equation									
ω				0.0362 ***	0.0329 **	0.0150			
				(3.103)	(2.311)	(0.837)			
ω_H	0.0407 *	0.0326	0.0162				0.0368	0.0292	0.0178
	(1.848)	(1.536)	(0.533)				(1.628)	(1.291)	(0.602)
ω_L	0.0245	0.0247	0.0111				0.0247 **	0.0245	0.0110
	(1.587)	(1.153)	(0.598)				(2.163)	(1.079)	(0.608)
θ				0.0088	-0.0040	0.0027			
				(0.808)	(-0.300)	(0.202)			
θ_H	0.0329	0.0195	0.0097				0.0337	0.0204	0.0081
	(1.347)	(0.667)	(0.334)				(1.392)	(0.804)	(0.267)
θ_L	0.0029	-0.0079	0.0016				0.0036	-0.0078	0.0015
	(0.266)	(-0.503)	(0.118)				(0.444)	(-0.517)	(0.187)
φ_0	-0.0248 *	-0.0134	-0.0501 **						
	(-1.744)	(-0.677)	(-2.054)						
φ_1	-0.0072 *	-0.0117 **	-0.0072 ***						
	(-1.648)	(-2.057)	(-2.616)						
φ_{0H}				0.0194	0.0313	-0.0510 *	0.0104	0.0316	-0.0538
				(0.878)	(0.766)	(-1.906)	(0.424)	(0.696)	(-1.639)
φ_{1H}				-0.0376 ***	-0.0501 *	-0.0094 **	-0.0328 ***	-0.0502 **	-0.0084 ***
				(-5.927)	(-1.843)	(-1.974)	(-3.703)	(-2.068)	(-3.462)
φ_{0L}				-0.0358 *	-0.0156	-0.0471	-0.0305	-0.0134	-0.0465 *
				(-1.649)	(-0.650)	(-1.528)	(-1.603)	(-0.658)	(-1.683)
φ_{1L}				-0.0043 ***	-0.0097 *	-0.0071	-0.0050 ***	-0.0101 ***	-0.0072
				(-4.257)	(-1.713)	(-1.503)	(-3.199)	(-3.124)	(-1.000)
Panel B: Variance Equation									
α_0	0.0103 ***	0.0082 **	0.0142 ***	0.0103 ***	0.0082 ***	0.0141 ***	0.0103 ***	0.0082 ***	0.0142 ***
	(3.674)	(2.568)	(3.503)	(3.910)	(2.601)	(3.621)	(3.642)	(2.618)	(3.454)
α_1	-0.0041	-0.0036	-0.0062	-0.0024	-0.0007	-0.0061	-0.0039	-0.0028	-0.0062
	(-0.603)	(-0.464)	(-0.525)	(-0.393)	(-0.093)	(-0.566)	(-0.453)	(-0.367)	(-0.502)
β	0.9299 ***	0.9349 ***	0.9194 ***	0.9283 ***	0.9328 ***	0.9196 ***	0.9294 ***	0.9342 ***	0.9196 ***
	(92.025)	(92.828)	(65.858)	(96.092)	(93.581)	(70.985)	(83.629)	(101.214)	(69.002)
δ	0.1269 ***	0.1259 ***	0.1410 ***	0.1272 ***	0.1251 ***	0.1407 ***	0.1275 ***	0.1260 ***	0.1410 ***
	(7.093)	(7.429)	(6.393)	(7.386)	(6.736)	(6.360)	(6.758)	(6.996)	(5.834)
ν	1.2906 ***	1.3648 ***	1.4009 ***	1.2900 ***	1.3613 ***	1.4003 ***	1.2912 ***	1.3635 ***	1.4011 ***
	(27.113)	(19.783)	(23.691)	(40.792)	(24.657)	(20.816)	(35.446)	(21.351)	(26.988)

Table 3: The Effect of Sentiment on Feedback Trading (Cont'd)

	Model II			Model III			Model IV		
	SPY	**DIA**	**QQQQ**	**SPY**	**DIA**	**QQQQ**	**SPY**	**DIA**	**QQQQ**
Panel C : Likelihood Ratio Tests									
LR	3.98	1.52	0.20	25.16 ***	2.16	0.12	12.83 **	4.34	0.26
LR1	0.37	0.08	0.02	2.85	1.05	0.01	3.13	1.62	0.19
LR2	1.25	0.69	0.07	25.07 ***	2.74 *	0.10	9.28 ***	2.95	0.06
Panel D : Diagnostic Tests									
$E(Z_t)$	-0.028	-0.025	-0.038	-0.026	-0.024	-0.037	-0.028	-0.026	-0.037
$E(Z^2_t)$	0.999	0.999	0.998	0.998	0.998	0.998	0.999	0.999	0.998
LB(12)	15.247	4.254	13.269	15.055	4.450	13.327	14.856	4.335	13.326
$LB^2(12)$	12.687	9.856	16.706	13.279	10.062	16.859	13.113	9.981	16.739
ARCH(5)	7.637	5.176	3.694	8.346	5.748	3.672	8.037	5.520	3.671
JOINT	7.823 ***	5.011 ***	1.357	7.216 ***	5.351 ***	1.328	7.847 ***	5.072 ***	1.407

Notes:

This table presents maximum likelihood estimates for all three "augmented" Sentana and Wadhwani (1992) feedback trading models [i.e., models II-IV given by equations (16) to (21)] from 01/01/2000 to 31/10/2007 for the three most popular ETFs in U.S. In particular, the estimated mean equations are

$$R_t = \omega_H D_t + \omega_L (1-D_t) + \theta_H D_t \sigma_t^2 + \theta_L (1-D_t)\sigma_t^2 + (\varphi_0 + \varphi_1 \sigma_t^2) R_{t-1} + \varepsilon_t \qquad \text{(Model II)}$$

$$R_t = \omega + \theta\sigma_t^2 + D_t(\varphi_{0H} + \varphi_{1H}\sigma_t^2) R_{t-1} + (1-D_t)(\varphi_{0L} + \varphi_{1L}\sigma_t^2) R_{t-1} + \varepsilon_t \qquad \text{(Model III)}$$

$$R_t = \omega_H D_t + \omega_L (1-D_t) + \theta_H D_t \sigma_t^2 + \theta_L (1-D_t)\sigma_t^2 + D_t(\varphi_{0H} + \varphi_{1H}\sigma_t^2) R_{t-1} + (1-D_t)(\varphi_{0L} + \varphi_{1L}\sigma_t^2) R_{t-1} + \varepsilon_t \qquad \text{(Model IV)}$$

The variance equation is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2 \qquad \text{(All Models)}$$

Errors are assumed to follow the Generalised Error Distribution (GED) distribution that nests the normal (for ν=2) and the Laplace (for ν=1) distributions; ν is a scale parameter estimated endogenously. The estimated t-statistics (shown in parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Wooldridge (1992) standard errors. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Also see the notes given in Table 1.

Dt is a dummy variable that is equal to 1 in a period of high investor sentiment (i.e., optimistic) and 0 in a period of low investor sentiment (i.e., pessimistic).
LR is the likelihood ratio statistic for testing the following restrictions:

- In Model II, H_0: $\omega_H = \omega_L$, $\theta_H = \theta_L$ (LR), $H_{01}\omega_H = \omega_L$ (LR1), H_{02}: ,$\theta_H = \theta_L$ (LR2)
- In Model III, H_0: $\varphi_{0H} = \varphi_{0L}$,$\varphi_{1H} = \varphi_{1L}$ (LR), H_{01}: $\varphi_{0H} = \varphi_{0L}$ (LR1), H_{02}: $\varphi_{1H} = \varphi_{1L}$ (LR2)
- In Model IV, H_0: $\omega_H = \omega_L$, $\theta_H = \theta_L$, $\varphi_{0H} = \varphi_{0L}$, $\varphi_{1H} = \varphi_{1L}$ (LR), H_{01}: $\omega_H = \omega_L$, $\theta_H = \theta_L$ (LR1), H_{02}: $\varphi_{0H} = \varphi_{0L}$, $\varphi_{1H} = \varphi_{1L}$ (LR2)

Table 4: The Effect of Sentiment on Feedback Trading – Robustness Tests

	Model III								
	Student-t Distribution			**Excluding Holiday/Infrequent Trading**			**Weekly Data**		
	SPY	**DIA**	**QQQQ**	**SPY**	**DIA**	**QQQQ**	**SPY**	**DIA**	**QQQQ**
Panel A: Mean Equation									
ω	0.0444***	0.0380**	0.0147	0.0476***	0.0404***	0.0109	0.2339***	0.1113	0.1654*
	(3.518)	(2.240)	(0.783)	(5.413)	(2.630)	(0.538)	(2.909)	(0.909)	(1.670)
θ	0.0070	-0.0125	0.0049	0.0067	-0.0066	-0.0022	-0.0047	0.0042	-0.0291
	(0.409)	(-0.679)	(0.294)	(0.779)	(-0.541)	(-0.163)	(-0.363)	(0.244)	(-1.454)
φ_{0H}	0.0192	0.0293	-0.0771**	0.0246	0.0229	-0.0975**	-0.2060***	-0.1170	-0.2102***
	(0.963)	(0.694)	(-2.185)	(1.186)	(0.536)	(-2.144)	(-2.782)	(-0.873)	(-3.004)
φ_{1H}	-0.0617***	-0.0709**	-0.0093**	-0.0399***	-0.0525**	-0.0065***	0.0101	0.0102	0.0154***
	(-5.374)	(-2.192)	(-2.466)	(-3.715)	(-2.404)	(-2.747)	(0.933)	(0.428)	(2.961)
φ_{0L}	-0.0232	-0.0111	-0.0569**	-0.0323	-0.0245	-0.0712***	-0.0729	-0.0701	-0.0369
	(-1.101)	(-0.479)	(-2.100)	(-1.561)	(-1.003)	(-3.296)	(-1.315)	(-1.209)	(-0.646)
φ_{1L}	-0.0079	-0.0136***	-0.0082	-0.0048*	-0.0091***	-0.0052	-0.0011	-0.0008	0.0003
	(-1.614)	(-3.238)	(-0.454)	(-1.729)	(-2.737)	(-0.314)	(-0.847)	(-1.035)	(0.107)
Panel B: Variance Equation									
α_0	0.0064***	0.0050**	0.0104***	0.0112***	0.0093**	0.0147***	0.1484*	0.4640*	0.1489***
	(3.554)	(2.462)	(3.089)	(3.417)	(2.262)	(3.643)	(1.954)	(1.901)	(3.200)
α_1	-0.0028	-0.0004	-0.0077	-0.0018	0.0015	-0.0015	0.0360	-0.0082	-0.1645***
	(-0.564)	(-0.067)	(-0.783)	(-0.239)	(0.168)	(-0.124)	(1.421)	(-0.286)	(-8.916)
β	0.9295***	0.9350***	0.9222***	0.9260***	0.9283***	0.9134***	0.8522***	0.7762***	0.9636***
	(98.757)	(105.064)	(60.168)	(89.875)	(75.634)	(68.263)	(19.751)	(9.619)	(48.725)
δ	0.0909***	0.0930***	0.1092***	0.1269***	0.1272***	0.1470***	0.1620**	0.2955***	0.3078***
	(6.933)	(6.630)	(5.872)	(7.009)	(6.082)	(6.452)	(2.279)	(2.589)	(8.186)
ν	6.5253***	8.0913***	8.3109***	1.4508***	1.5251***	1.7647***	1.5033***	1.4493***	1.4305***
	(9.502)	(5.745)	(6.476)	(25.178)	(20.902)	(28.005)	(14.741)	(12.857)	(16.946)

Table 4: The Effect of Sentiment on Feedback Trading - Robustness Tests (Cont'd)

	Model III								
	Student-t Distribution			Excluding Holiday/Infrequent Trading			Weekly Data		
	SPY	DIA	QQQQ	SPY	DIA	QQQQ	SPY	DIA	QQQQ
Panel C : Likelihood Ratio Test									
LR	20.16 ***	3.19	0.21	10.57 ***	4.06	0.28	2.01	0.22	6.70 **
LR1	2.32	0.73	0.20	4.27 **	0.94	0.26	2.01	0.12	3.52 *
LR2	19.83 ***	3.10 *	0.01	10.46 ***	3.92 *	0.01	1.02	0.21	6.50 **
Panel D : Diagnostic Tests									
E(Z_t)	-0.038	-0.028	-0.046	-0.035	-0.027	-0.025	-0.050	-0.077	-0.080
E(Z^2_t)	1.432	1.331	1.305	1.002	1.001	1.002	0.997	1.002	1.082
LB(12)	15.933	4.670	12.440	16.416	5.844	5.868	13.225	14.948	16.268
LB²(12)	12.746	9.656	15.944	10.914	12.069	10.552	10.424	14.780	8.861
ARCH(5)	7.831	5.365	5.938	9.022	6.876	6.364	5.728	9.428 *	4.113
JOINT	7.327 ***	4.818 ***	1.759	7.431 ***	4.639 ***	0.416	1.832	2.330 *	2.955 **

Notes:
This table presents maximum likelihood estimates for the best "augmented" Sentana and Wadhwani (1992) feedback trading model [i.e., model III given by equations (18) and (19)] from 01/01/2000 to 31/10/2007 for the three most popular ETFs in U.S. In particular, the estimated mean equation is

$$R_t = \omega + \theta\sigma_t^2 + D_t(\varphi_{0H} + \varphi_{1H}\sigma_t^2)R_{t-1} + (1-D_t)(\varphi_{0L} + \varphi_{1L}\sigma_t^2)R_{t-1} + \varepsilon_t$$

The variance equation is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

Errors are assumed to follow either the Student-t distribution or the Generalised Error Distribution (GED) distribution that nests the normal (for ν=2) and the Laplace (for ν=1) distributions; ν is a scale parameter estimated endogenously. The estimated t-statistics (shown in parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Wooldridge (1992) standard errors. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Also see the notes given in Table 1.

Dt is a dummy variable that is equal to 1 in a period of high investor sentiment (i.e., optimistic) and 0 in a period of low investor sentiment (i.e., pessimistic).
LR is the likelihood ratio statistic for testing the restrictions, H_0: $\varphi_{0H} = \varphi_{0L}, \varphi_{1H} = \varphi_{1L}$ (LR), H_{01}: $\varphi_{0H} = \varphi_{0L}$ (LR1), H_{02}: $\varphi_{1H} = \varphi_{1L}$ (LR2).

Table 5: The Effect of Sentiment on Feedback Trading – Alternative Sentiment Measures

	Model III					
	SENT			**MCG Sentiment Index**		
	SPY	**DIA**	**QQQQ**	**SPY**	**DIA**	**QQQQ**
Panel A: Mean Equation						
ω	0.0363 ***	0.0328 ***	0.0154	0.0269 ***	0.0290 **	0.0437 *
	(3.064)	(3.086)	(0.900)	(3.398)	(2.193)	(1.859)
θ	0.0088	-0.0039	0.0027	0.0296 **	0.0124	-0.0130
	(0.8577)	(-0.319)	(0.216)	(2.230)	(0.683)	(-0.673)
φ_{0H}	0.0175	0.0172	-0.0643 *	-0.0141	-0.0100	-0.0112
	(0.803)	(0.464)	(-1.782)	(-0.632)	(-0.362)	(-0.312)
φ_{1H}	-0.0373 ***	-0.0435 *	-0.0081 **	-0.0230 **	-0.0252 **	0.0000
	(-9.364)	(-1.781)	(-2.080)	(-2.280)	(-2.571)	(0.002)
φ_{0L}	-0.0345 *	-0.0103	-0.0392 *	-0.0083	-0.0103	-0.0806
	(-1.678)	(-0.511)	(-1.899)	(-0.330)	(-0.297)	(-1.584)
φ_{1L}	-0.0044 **	-0.0103 **	-0.0075 ***	-0.0156	-0.0022	-0.0057
	(-2.458)	(-2.092)	(-3.035)	(-1.229)	(-0.240)	(-0.441)
Panel B: Variance Equation						
α_0	0.0104 ***	0.0083 **	0.0104 ***	0.0111 ***	0.0082 **	0.0106 **
	(3.461)	(2.424)	(2.776)	(2.991)	(2.188)	(2.539)
α_1	-0.0024	-0.0010	-0.0066	-0.0025	0.0018	-0.0102
	(-0.314)	(-0.130)	(-0.476)	(-0.331)	(0.247)	(-0.711)
β	0.9282 ***	0.9329 ***	0.9197 ***	0.9282 ***	0.9349 ***	0.9176 ***
	(92.130)	(83.622)	(61.954)	(76.673)	(81.286)	(55.540)
δ	0.1273 ***	0.1255 ***	0.1416 ***	0.1215 ***	0.1115 ***	0.1633 ***
	(6.573)	(6.963)	(6.259)	(5.754)	(5.197)	(5.164)
ν	1.2898 ***	1.3610 ***	1.4012 ***	1.2935 ***	1.3574 ***	1.4825 ***
	(23.739)	(27.511)	(21.503)	(24.351)	(18.871)	(17.211)
Panel C : Likelihood Ratio Test						
LR	124.71 ***	3.01	1.11	0.77	6.13 **	2.51
LR1	4.13 **	0.43	0.37	0.04	0.00	1.34
LR2	122.05 ***	2.79 *	0.03	0.36	3.98 **	0.13
Panel D : Diagnostic Tests						
$E(Z_t)$	-0.026	-0.031	-0.043	-0.026	-0.025	-0.027
$E(Z^2_t)$	0.998	0.980	0.976	1.001	1.002	0.989
LB(12)	15.010	9.615	13.619	14.685	4.027	10.984
$LB^2(12)$	13.295	19.742 *	18.141	9.874	7.225	6.598
ARCH(5)	8.351	8.902	8.307	6.764	4.226	4.031
JOINT	7.221 ***	6.173 ***	3.401 **	7.482 ***	4.643 ***	0.896

Notes:
This table presents maximum likelihood estimates for the best "augmented" Sentana and Wadhwani (1992) feedback trading model [i.e., model III given by equations (18) and (19)] from 01/01/2000 to 31/10/2007 for the three most popular ETFs in U.S. In particular, the estimated mean equation is

$$R_t = \omega + \theta\sigma_t^2 + D_t(\varphi_{0H} + \varphi_{1H}\sigma_t^2)R_{t-1} + (1-D_t)(\varphi_{0L} + \varphi_{1L}\sigma_t^2)R_{t-1} + \varepsilon_t$$

The variance equation is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

Errors are assumed to follow the Generalised Error Distribution (GED) distribution that nests the normal (for ν=2) and the Laplace (for ν=1) distributions; ν is a scale parameter estimated endogenously. The estimated t-statistics (shown in parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Wooldridge (1992) standard errors. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Also see the notes given in Table 1.
Dt is a dummy variable that is equal to 1 in a period of high investor sentiment (i.e., optimistic) and 0 in a period of low investor sentiment (i.e., pessimistic).
LR is the likelihood ratio statistic for testing the restrictions, H_0: $\varphi_{0H} = \varphi_{0L}, \varphi_{1H} = \varphi_{1L}$ (LR), H_{01}: $\varphi_{0H} = \varphi_{0L}$ (LR1), H_{02}: $\varphi_{1H} = \varphi_{1L}$ (LR2).
SENT is the investor sentiment index constructed by Baker and Wurgler (2006, 2007) which is 'unorthogonal' to macroeconomic variables.
MCG Sentiment Index is an alternative measure based on University of Michigan's consumer confidence surveys.

Table 6: The Effects of Sentiment on Feedback Trading across Market Regimes

	Model III					
	Bear Market			Bull Market		
	SPY	DIA	QQQQ	SPY	DIA	QQQQ
Panel A: Mean Equation						
ω	-0.0558	-0.0611	-0.1176	-0.0150	-0.0081	-0.0021
	(-0.524)	(-0.620)	(-0.961)	(-0.524)	(-0.543)	(-0.064)
θ	0.0035	-0.0055	0.0109	0.1478 ***	0.1429 ***	0.0979 *
	(0.141)	(-0.167)	(0.268)	(8.816)	(2.936)	(1.805)
φ_{0H}	0.0171	0.0165	0.0092	0.1174 ***	0.1315 **	-0.0567
	(0.209)	(0.109)	(0.085)	(4.879)	(1.978)	(-0.929)
φ_{1H}	-0.0359 ***	-0.0515	-0.0214	-0.2268 ***	-0.2230 ***	-0.0856
	(-3.030)	(-1.168)	(-0.612)	(-7.636)	(-4.383)	(-1.413)
φ_{0L}	-0.0136	0.0033	-0.1016 *	-0.0094	0.0020	-0.0223
	(-0.218)	(0.050)	(-1.785)	(-0.154)	(0.032)	(-0.451)
φ_{1L}	-0.0051	-0.0120 **	0.0061	-0.0727	-0.0407	-0.0268
	(-1.217)	(-1.993)	(0.386)	(-1.413)	(-0.553)	(-0.512)
Panel B: Variance Equation						
α_0	0.0540	0.0455	0.1042	0.0135 ***	0.0116 *	0.0201 **
	(1.402)	(1.261)	(1.311)	(5.392)	(1.949)	(2.467)
α_1	-0.0090	-0.0161	-0.0440 *	-0.0185 ***	-0.0091	0.0016
	(-0.346)	(-0.646)	(-1.958)	(-3.029)	(-0.705)	(0.121)
β	0.9134 ***	0.9128 ***	0.9072 ***	0.9302 ***	0.9310 ***	0.8944 ***
	(32.986)	(31.223)	(24.797)	(29.486)	(42.396)	(33.680)
δ	0.1567 ***	0.1816 ***	0.2172 ***	0.1177 ***	0.1033 ***	0.1305 ***
	(4.186)	(4.671)	(4.256)	(14.118)	(3.335)	(3.651)
ν	1.3407 ***	1.44154 ***	1.3025 ***	1.2427 ***	1.2597 ***	1.5924 ***
	(8.498)	(7.734)	(8.957)	(7.327)	(13.777)	(16.484)
Panel C : Likelihood Ratio Tests						
LR	9.50 ***	2.00	1.36	8.81 **	4.81 *	2.03
LR1	0.08	0.01	1.16	7.63 ***	2.29	0.19
LR2	4.99 **	0.78	0.63	8.71 ***	4.76 **	0.53
LR'				82.24 ***	11.36 ***	1.12
LR''				2.69 *	0.15	0.39
Panel D : Diagnostic Tests						
$E(Z_t)$	-0.046	-0.027	-0.025	-0.047	-0.045	-0.031
$E(Z^2_t)$	0.976	0.976	0.972	1.009	1.014	1.014
LB(12)	5.822	7.033	9.035	5.718	7.675	10.695
$LB^2(12)$	18.269	12.513	14.558	8.182	6.805	5.002
ARCH(5)	8.357	8.817	11.683 **	2.430	2.479	1.124
JOINT	2.183 *	3.617 **	0.838	2.399 *	2.171 *	0.877

Notes:
This table presents maximum likelihood estimates for the best "augmented" Sentana and Wadhwani (1992) feedback trading model [i.e., model III given by equations (18) and (19)] from 01/01/2000 to 31/10/2002 (Bear market); and from 01/11/2002 to 31/10/2007 (Bull market) for the three most popular ETFs in U.S. In particular, the estimated mean equation is

$$R_t = \omega + \theta\sigma_t^2 + D_t(\varphi_{0H} + \varphi_{1H}\sigma_t^2)R_{t-1} + (1-D_t)(\varphi_{0L} + \varphi_{1L}\sigma_t^2)R_{t-1} + \varepsilon_t$$

The variance equation is given by

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

Errors are assumed to follow the Generalised Error Distribution (GED) distribution that nests the normal (for ν=2) and the Laplace (for ν=1) distributions; ν is a scale parameter estimated endogenously. The estimated t-statistics (shown in parentheses) are robust to autocorrelation and heteroscedasticity using Bollerslev and Wooldridge (1992) standard errors. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Also see the notes given in Table 1.

Dt is a dummy variable that is equal to 1 in a period of high investor sentiment (i.e., optimistic) and 0 in a period of low investor sentiment (i.e., pessimistic). LR is the likelihood ratio statistic for testing the restrictions, H_0: $\varphi_{0H} = \varphi_{0L}, \varphi_{1H} = \varphi_{1L}$ (LR), H_{01}: $\varphi_{0H} = \varphi_{0L}$ (LR1), H_{02}: $\varphi_{1H} = \varphi_{1L}$ (LR2). LR' is the same statistic for testing H_{01}: φ_{1H} (Bear) = φ_{1H} (Bull), LR'' is the statistic for testing H_{02}: φ_{1L} (Bear) = φ_{1L} (Bull).