The Cost of Credit and Positive Feedback Trading: Title Evidence from the U.K. Stock Market

Antonios Antoniou¹ and Gregory Koutmos²

Abstract
The manipulation of credit in the conduct of monetary policy is receiving increasing attention in regards to the impact it exerts on asset prices and accompanied volatility. Several authors have claimed that relaxed monetary conditions can induce asset bubbles thereby distorting investment decisions on the part of economic actors, be they corporate managers or, investors. This paper explores the impact of the cost of credit on stock return dynamics in the United Kingdom. More specifically it tests the hypothesis that cheap credit (loose monetary conditions) makes it easier for investors to follow trend chasing strategies, or equivalently positive feedback trading. Such strategies can lead to runaway prices or, devastating crashes. The model employed is based on the assumption that investors are not homogeneous in the sense that some of them follow expected utility maximizing behavior, whereas others follow positive feedback trading strategies. The evidence from the U.K. market suggests that there is positive feedback trading linked to the cost of credit. Specifically, the lowering of the cost of credit in the pursuit of easy monetary policies leads to positive feedback trading and possibly to unsustainable price bubbles.

JEL classification numbers: G12
Keywords: Feedback trading, heterogeneous investors, Cost of credit.

1 Introduction
The role of monetary policy in countering the business cycle has been praised by policy makers, market participants and academic researchers in the last decade or so. Following the technology bubble burst in the U.S. in the spring of 2001 and suspected real estate bubbles in several countries, concerns have been raised on the side effect of

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such policies on asset price dynamics. Conventional finance theory predicts that a change in the rate of interest will induce revaluation of all assets whose price is the present value of future cash streams. At the macroeconomic level, real effects will likely emerge through the so-called “wealth effect” whereby higher asset prices boost personal consumption expenditures. As such, it is argued that monetary policy should factor in the likely response of asset prices (e.g. Lansing2003). On the volatility front, Bomfim (2000) finds that unanticipated rate changes tend to increase volatility in stock market returns.

Several studies have considered the role of positive feedback trading on stock returns and the possibility that such behavior may destabilize stock prices (see DeLong et all 1990 and Antoniou, Koutmos and Pericli 2005). However, there has been no investigation of the impact (if any) of monetary policy on feedback trading through the cost of borrowing. The main tool monetary authorities are using is the cost of borrowing (especially in recent years). Thus the possibility of impacting on stock prices is real assuming that lowering the cost of credit makes it less costly for feedback traders to leverage their stock purchases or, short sales. This in turn may cause prices to deviate from fundamental values for prolonged periods of time.

Positive feedback trading can be the result of many different motivations. For example, such commonly followed strategies as, trading on the basis of extrapolative expectations, using stop-loss orders, or, engaging in certain types of portfolio insurance, are essentially positive feedback trading strategies. Such behavior can be destabilizing because it implies that investors buy overpriced securities and sell underpriced securities thus, moving prices away from fundamentals and possibly causing asset bubbles and crashes.

Sentana and Wadhwani (1992) investigate the presence of positive feedback trading in the U.S. stock market assuming that some traders are risk-averse expected utility maximizers, along the lines of the CAPM, and some traders adopt positive feedback trading strategies. Such a model predicts negative autocorrelation in stock returns, especially during high volatility periods. Sentana and Wadhwani (1992) report evidence consistent with the presence of positive feedback traders in the U.S. markets whereas Koutmos (1997) reports similar findings for several developed stock markets.

Despite the evidence on positive feedback trading in several developed stock market and the growing debate on the role of monetary policy on asset prices there has been no investigation of the potential link between the cost of credit (easy money) and positive feedback trading. This paper explores the impact of credit availability on stock return dynamics in the United Kingdom. More specifically it tests the hypothesis that cheap credit (loose monetary conditions) makes it easier for investors to follow trend chasing strategies, or equivalently positive feedback trading. Such strategies can lead to runaway prices or, devastating crashes. The model employed is based on the assumption that investors are not homogeneous in the sense that some of them follow expected utility maximizing behavior whereas others follow positive feedback trading strategies.

The evidence from the U.K. market suggests that there is positive feedback trading linked to the cost of credit. Specifically, the lowering of the cost of credit in the pursuit of easy monetary policies leads to positive feedback trading and possibly to unsustainable price bubbles. This pattern is detected on daily stock returns but not in lower frequency data such as weekly or monthly. This in turn suggests that the cost of credit may induce short term noise rather than longer term deviations from fundamentals. The rest of this paper is organized as follows. The next section outlines the positive feedback trading model. Section 3 discusses the data used and the empirical findings. Section 4 concludes this paper.
2 Positive Feedback Trading Model

There are several types of feedback trading models in the literature carrying different implications for the autocorrelation pattern of stock returns. For example, the feedback models used by Cutler, Poterba and Summers (1990), and Shiller (1984) imply positive autocorrelation of short term returns. Given that very little positive autocorrelation is found in stock returns, it would appear that feedback trading models are not credible alternatives to the traditional martingale models for stock prices. Shiller (1989) however, points out, positive feedback trading can give rise to negligible, even negative autocorrelation. More recent research suggests that the autocorrelation pattern of stock returns is more complex than commonly believed. LeBaron (1992) uses a GARCH model with an exponential time varying first order autocorrelation to describe the short run dynamics of several U.S. index stock returns, as well as individual stock returns. He reports significant non-linear first moment dependencies in the sense that autocorrelation and volatility are inversely related. Stating it differently, first order autocorrelations of stock price changes are higher during tranquil periods and lower during volatile periods. Campbell et al. (1993) find that trading volume and stock return autocorrelation are inversely related for U.S. stock returns. During high volume days autocorrelations turn negative. Such a relationship is consistent with their model where risk averse market makers accommodate buying or selling pressure from liquidity or, non-informed investors.

The approach adopted by Sentana and Wadhwani (1992) is based on the existence of two types of investors: rational expected utility maximizers and positive feedback (trend chasing) investors. Based on U.S. stock market data they find evidence that during low volatility periods daily stock returns are positively autocorrelated, but during high volatility periods they tend to be negatively autocorrelated. This sign reversal in stock return autocorrelation is consistent with the hypothesis that some traders follow feedback strategies i.e., they buy (sell) when the price rises (falls). The model used in this paper is an extension of Shiller (1984), Sentana and Wadhwani (1992) and Antoniou, Koutmos and Pericli (2005). Specifically, it is assumed that traders consist of two heterogeneous groups. The demand for shares by the first group (smart money or rational speculators) is consistent with expected utility maximization. This group is therefore assumed to hold a fraction of shares of the market portfolio given by

\[
Y_{1,t-1} = \frac{\left( E_{t-1}(R_t) - r_t \right)}{\vartheta \sigma_t^2}
\]

(1)

where, \(Y_{1,t-1}\) is the fraction of shares demanded by this group at time \(t-1\); \(R_t\) is the ex-post stock return at \(t\); \(E_{t-1}\) is the expectation as of time \(t-1\); \(r_t\) the rate of return on a risk-free asset; \(\sigma_t^2\) is the conditional variance (risk) at \(t\); and \(\vartheta\) is the coefficient of risk aversion.
Assuming $\vartheta$ is positive, the product $\vartheta \sigma^2_t$ is the required risk premium.\(^3\)

The second group of investors follow a positive feedback strategy i.e., they buy (sell) after price increases (decreases). The feedback function used in most of the studies mentioned above assumes that demand on the part of positive feedback traders is simply proportional to the past price changes of the asset. This study extends the feedback function to allow for the cost of credit to exert additional influence on feedback trading. Consequently the demand function postulated for the second group is given by

$$Y_{2,t-1} = \{\rho_1 + \rho_2 (\bar{r} - r_{t-1})\} R_{t-1}$$

where, $\rho_1$ is the base feedback parameter and $\rho_2$ is the incremental feedback effect induced by the cost of credit. $\bar{r}$ is the long term or, equilibrium level of the cost of credit proxied by the sample average short-term interest rate and $r_{t-1}$ is the short term rate at $t-1$. When $\bar{r} - r_{t-1} > 0$ the short term rate, or cost of credit is below its long-term average, implying that monetary policy is accommodative. The model predicts that $\rho_1$ will be positive and significant if positive feedback trading is present. If in addition, $\rho_2$ is also positive and statistically significant then it can be concluded that positive feedback trading is encouraged by expansive monetary policies and discouraged by restrictive ones. $R_{t-1}$ is defined as $(P_{t-1} - P_{t-2})$ where, $P_{t-1}$ and $P_{t-2}$ are the natural logarithms of stock prices at times $t-1$ and $t-2$ respectively.

In equilibrium all shares must be held i.e., $Y_{1,t} + Y_{2,t} = 1$. It follows from (1) and (2) that

$$E_{t-1}(R_t) - r_{t-1} = \vartheta \sigma^2_t - \vartheta \{\rho_1 + \rho_2 (\bar{r} - r_{t-1})\} \sigma^2_t R_{t-1}$$

Equation (3) implies that the presence of positive feedback trading will induce negative autocorrelation in returns which will become more negative during low cost-of-credit periods. Moreover, the higher the volatility the more negative the autocorrelation. The higher (absolute) autocorrelation or, predictability that arises because of feedback trading will not necessarily be exploited by the first group of investors because the risk is higher. Thus, the interaction of positive feedback traders and rational speculators could lead to price movements that are not warranted by their fundamental value.

It is easy to convert (3) into a regression equation with a stochastic error term by setting $R_t = E_{t-1}(R_t) + \varepsilon_t$ and substituting into (3) to get:

$$R_t - r_{t-1} = \vartheta \sigma^2_t - \vartheta \{\rho_1 + \rho_2 (\bar{r} - r_{t-1})\} \sigma^2_t R_{t-1} + \varepsilon_t$$

The empirical version used to estimate the parameters is given by equation (5)

\(^3\)Note that if all investors had the same demand function given by (1) then in equilibrium $E_{t-1}(R_t) - r_t = \vartheta \sigma^2_t$, which is the dynamic or Intertemporal Capital Asset Pricing Model proposed by Merton (1973).
\[ R_t - r_{t-1} = c + \theta \sigma_t^2 + \{ \varphi_1 + \varphi_2 (R - r_{t-1}) \} \sigma_t^2 R_{t-1} + \varepsilon_t \]  

(5)

where, \( \varphi_1 = -9 \rho_1 \), \( \varphi_2 = -9 \rho_2 \) and \( c \) is the regression intercept. Thus, the presence of positive feedback trading implies that \( \varphi_1 \) is negative and statistically significant. If in addition \( \varphi_2 \) is negative and statistically significant then lower cost of borrowing reinforces positive feedback trading.

Completion of the model requires that the conditional variance be specified. Numerous studies have shown that stock returns are conditionally heteroskedastic. \(^4\) Consequently, the conditional variance of the returns is modelled as an asymmetric GARCH(1,1) process given by

\[ \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta S_{t-1} \varepsilon_{t-1}^2 \]  

(6)

where, \( \sigma_t^2 \) is the conditional variance of the returns at time \( t \), \( \varepsilon_t \) is the innovation at time \( t \) and \( \alpha_0, \alpha_1, \beta \) and \( \delta \) are nonnegative fixed parameters. \( \delta \) captures the sign effect, i.e., the asymmetric impact of positive and negative innovations. \( S_t \) takes the value of unity if the innovation at time \( t \) is negative and zero otherwise. If \( \delta \) is positive and statistically significant then negative innovations increase volatility more than positive innovations.

Several parametric specifications have been used in the literature for stock returns, the most common being the standard normal distribution. More often than not the standardised residuals obtained from GARCH models that assume normality appear to be leptokurtic thereby rendering standard t-tests unreliable. As such, distributions with flatter tails such as the student's \( t \) and the Generalised Error Distribution (GED) have been suggested. In this paper we employ the GED. Its density function is given by

\[ f(\mu, \sigma, \nu) = \frac{1}{2} \left[ \Gamma(3/\nu) \right]^{1/2} \left[ \Gamma(1/\nu) \right]^{3/2} (1/ \sigma_t) \exp(-[\Gamma(3/\nu)/\Gamma(1/\nu)] \nu/2) \mid \varepsilon_t \mid/ \sigma_t \]  

(7)

where, \( \Gamma(.) \) is the gamma function and \( \nu \) is a scale parameter, or degrees of freedom to be estimated endogenously. For \( \nu = 2 \), the GED yields the normal distribution, while for \( \nu = 1 \) it yields the Laplace or, double exponential distribution.

Given initial values for \( \varepsilon_t \) and \( \sigma_t^2 \), the fixed parameters of the system of equations (1) - (7) can be estimated by maximising the log-likelihood over the sample period, which can be expressed as,

\[ L(\theta) = \sum_{t=1}^{T} \log f(\mu, \sigma, \nu) \]  

(8)

where, \( \mu_t \) and \( \sigma_t \) are the conditional mean and the conditional standard deviation respectively. Since the log-likelihood function is highly non-linear in the parameters, numerical maximisation techniques are used to obtain estimates of the parameter vector. The method of estimation used in this paper is based on the Berndt et al. (1974) algorithm.

\(^4\)For an excellent survey of studies modeling stock returns as conditionally heteroskedastic processes see Bollerslev et al. (1992).
3 Data and Main Results

The stock price index used in this paper is the FTSE-100 price index and the proxy for the cost of credit used is the 3 month Treasury bill rate, obtained from Datastream. Both time series are daily and cover the period 9/14/90 – 9/16/10. Daily and weekly stock returns are calculated as the percent logarithmic differences in the stock prices index. Similarly, the annualized 3 month interest rate is converted into daily and weekly rates. Descriptive statistics for the returns are provided in Table 1. The statistics reported are the mean, the standard deviation, measures for skewness and kurtosis and the Ljung-Box (LB) statistic for 5 lags. Both daily and weekly stock returns are significantly negatively skewed and highly leptokurtic. These two measures provide evidence that the return series are not normally distributed. The same applies to the annualized 3-month interest rate. Rejection of normality can be partially attributed to temporal dependencies in the moments of the series. It is common to test for such dependencies using the Ljung and Box portmanteau test (LB) e.g., Bollerslev et al. (1994). The LB statistic is significant for daily and weekly stock return. This provides evidence of temporal dependencies in the first moment of the distribution of returns. Evidence on higher order temporal dependencies is provided by the LB statistic when applied to the squared returns. The size of LB for the squared returns is much larger suggesting that higher moment temporal dependencies are more pronounced. This of course is an empirical regularity encountered in almost all financial time series, especially in high frequencies. What is not clear from these statistics is the extent to which the two types

<table>
<thead>
<tr>
<th></th>
<th>Daily Returns</th>
<th>Excess</th>
<th>Weekly Returns</th>
<th>Excess</th>
<th>3-Month Annualized Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0242</td>
<td>0.1255</td>
<td>6.3443</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>1.0226</td>
<td>2.1093</td>
<td>2.3413</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.1070*</td>
<td>-0.1479*</td>
<td>1.5112*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>3.3576*</td>
<td>1.9135*</td>
<td>2.0763*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LB(5)</td>
<td>29.5723*</td>
<td>7.0537*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LB²(50)</td>
<td>1263.0273*</td>
<td>47.1928*</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: * Denotes significance at the 5% level at least. Excess returns are calculated as stock returns over and above the 3 month rate converted to daily and weekly frequencies respectively.

5 The Ljung-Box statistic for N lags is calculated as LB(N)=T(T+2)Σj=1N (ρj²/T-j) where ρj is the sample autocorrelation for j lags and T is the sample size.

6 For uniformity, the five percent level of significance is used throughout.
of dependencies are linked i.e., whether volatility and autocorrelation are linked because of the presence of positive feedback trading. The common perception is that positive feedback trading will lead to positive autocorrelation of stock returns. To investigate that possibility a simple autoregressive model of order one AR(1) is estimated. The results reported on Table 2 show no evidence of positive autocorrelation suggesting that feedback trading, if present, gives rise to more complex return dynamics that cannot be captured by a simple AR(1) model.\textsuperscript{7}

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|}
\hline
 & \textbf{Daily Returns} & \textbf{Weekly Returns} \\
\hline
\textbf{b}_0 & 0.0239 & 0.1352 \\
 & (1.465) & (1.791) \\
\hline
\textbf{b}_1 & 0.0106 & -0.0726 \\
 & (0.664) & (-2.033)* \\
\hline
\textbf{R}^2 & 0.0001 & 0.0040 \\
\hline
\textbf{DW} & 1.9986 & 1.9936 \\
\hline
\end{tabular}
\caption{AR(1) Model.}
\end{table}

Note: * Denotes significance at the 5\% level at least.

Table 3, Panel A, reports the maximum likelihood estimates of a restricted version of the feedback model. Specifically, the restriction sets parameter $\varphi_2 = 0$. Such restriction implies that the cost of credit plays no role on positive feedback trading. First, it can be seen that the coefficients describing the conditional variance process, $\alpha_0$, $\alpha_1$, $\beta$ and $\delta$ are highly significant for both daily and weekly returns. This in turn implies that current volatility is a function of last period's squared innovation and last period's volatility. The significance of $\delta$ means that the conditional variance is an asymmetric function of past squared residuals. Specifically past negative innovations increase volatility more than past positive

\textsuperscript{7}In fact the autoregressive parameter for the weekly series is negative and significant.
Table 3: Restricted Feedback Model.

**Panel A: Parameter Estimates**

\[
R_t - r_{t-1} = c + \delta \sigma_t^2 + \{ \varphi_1 + \varphi_2 (\bar{r} - r_{t-1}) \} \sigma_t^2 + \varepsilon_t
\]

\[
\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta S_{t-1} \varepsilon_{t-1}^2
\]

<table>
<thead>
<tr>
<th></th>
<th>Daily Excess Returns</th>
<th>Weekly Excess Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha_0)</td>
<td>0.0099 (4.362)*</td>
<td>0.1494 (2.353)*</td>
</tr>
<tr>
<td>(\alpha_1)</td>
<td>0.0165 (2.365)*</td>
<td>0.0172 (0.684)</td>
</tr>
<tr>
<td>(\beta)</td>
<td>0.9323 (120.261)*</td>
<td>0.8765 (28.154)</td>
</tr>
<tr>
<td>(\delta)</td>
<td>0.0782 (7.143)*</td>
<td>0.1381 (3.840)*</td>
</tr>
<tr>
<td>(\mathbf{c})</td>
<td>1.5790 (40.302)</td>
<td>1.6571 (15.196)</td>
</tr>
<tr>
<td>(\alpha_1 + \delta) / \alpha_1)</td>
<td>5.7394 (40.302)</td>
<td>9.0290 (15.196)</td>
</tr>
</tbody>
</table>

Note: * Denotes significance at the 5% level at least. Numbers in parentheses are the estimated t-statistics. This version of the model restricts \(\varphi_2\) to be zero.

innovations. The contribution of a positive innovation is equal to \(\alpha_1\), whereas the contribution of a negative innovation is \(\alpha_1 + \delta\). The ratio \((\alpha_1 + \delta) / \alpha_1\) can be used as an intuitive measure of asymmetry. On the basis of this measure it can be seen that weekly returns exhibit higher volatility asymmetry than daily returns. On average, volatility is 9 times higher following market declines compared to market advances. The corresponding asymmetry measure for daily returns is less than 6.

Interestingly, the parameter of interest \(\varphi_1\) is insignificant suggesting that without accounting for the cost of credit, no positive feedback trading is present in the U.K. market. Moreover, an array of diagnostics performed on the standardized
Table 3: Restricted Feedback Model Continued.

<table>
<thead>
<tr>
<th></th>
<th>Daily Excess Returns</th>
<th>Weekly Excess Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0098</td>
<td>-0.0146</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>1.0014</td>
<td>0.9951</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.1401*</td>
<td>-0.1900</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>1.2384*</td>
<td>0.8142*</td>
</tr>
<tr>
<td>LB(5)</td>
<td>9.4760</td>
<td>1.9978</td>
</tr>
<tr>
<td>LB(5)</td>
<td>2.9705</td>
<td>1.9515</td>
</tr>
<tr>
<td>Sign Bias Test</td>
<td>0.4208</td>
<td>0.4731</td>
</tr>
<tr>
<td>Negative Size Bias Test</td>
<td>-0.1851</td>
<td>-0.6097</td>
</tr>
<tr>
<td>Positive Size Bias Test</td>
<td>-0.683</td>
<td>-0.61763</td>
</tr>
<tr>
<td>Joint Test</td>
<td>0.1571</td>
<td>0.1857</td>
</tr>
</tbody>
</table>

residuals show no serious misspecification of the model. Specifically, the parameters of skewness and kurtosis are substantially reduced (compared to those of the return) and the LB statistics show no autocorrelation up to 5 lags. Additional variance specification tests are also reported in Table 3, Panel B. These tests were proposed by Engle and Ng (1993) and they are designed to investigate how well the particular model used captures the volatility dynamics. The tests are applied on the estimated squared standardized residuals. If the model is successful the squared standardized returns should nor be predictable on the basis of observed variables. The Engle-Ng tests are i) the Sign Bias Test, ii) the Negative Size Bias Test iii) the Positive Size Bias Test and iv) the Joint Test. The first test examines the asymmetric impact of positive and negative innovations on volatility not predicted by the model. The squared standardized returns are regressed against a constant and a dummy S that takes the value of unity if $\varepsilon_{t-1}$ is negative and zero otherwise. The test is based on the t-statistic for S. The Negative Size Bias Test examines how well the model captures the impact of large and small negative innovations. It is based on the regression of the squared standardized returns against a constant and $S\varepsilon_{t-1}$. The calculated t-statistic for $S\varepsilon_{t-1}$ is used in this test. The Positive Size Bias Test examines possible biases associated with large and small positive innovations. Here, the squared standardized returns are regressed against a constant and $(1-S)\varepsilon_{t-1}$. Again, the t-statistic for $(1-S)\varepsilon_{t-1}$ is used to test for possible biases. Finally a joint test can be based on the F-statistic of a regression involving all three explanatory variables, i.e., S, $S\varepsilon_{t-1}$ and $(1-S)\varepsilon_{t-1}$. It is interesting to see that the individual tests as well as the joint test are insignificant in all instances. This provides evidence that the conditional variance model used successfully captures the time variation in the second
moments of stock returns. The absence of base feedback trading however does not preclude the possibility of positive feedback trading conditional on the cost of credit. Empirical evidence on this issue is reported in Table 4, Panel A. The estimated parameters for volatility are similar to those of the restricted model. Likewise, the base feedback parameter \( \phi_1 \) remains insignificant. However, the cost-of-credit related feedback parameter, \( \phi_2 \) is clearly significant at the 5% level at least. Moreover, it is negative as predicted by the model suggesting that during low interest rate periods i.e., when \( \bar{r} - r_{t-1} > 0 \), positive feedback trading increases as the cost of credit moves below its long-term average. Positive feedback trading strategies are reduced and eventually eliminated as the cost of credit approaches its long term average. Interestingly, when monetary policy becomes restrictive, i.e., when \( \bar{r} - r_{t-1} < 0 \), feedback trading becomes negative. Negative feedback traders tend to sell when prices move up and buy when prices move down. Such behavior obviously has a stabilising impact on stock prices, whereas, positive feedback trading can lead to

### Table 4: Unrestricted Feedback Model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Daily Excess Returns</th>
<th>Weekly Excess Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>0.0123 (0.655)</td>
<td>0.1675 (1.397)</td>
</tr>
<tr>
<td>( \theta )</td>
<td>0.0219 (0.954)</td>
<td>-0.0047 (-0.150)</td>
</tr>
<tr>
<td>( \phi_1 )</td>
<td>0.0114 (1.030)</td>
<td>-0.0083 (-1.348)</td>
</tr>
<tr>
<td>( \phi_2 )</td>
<td>-0.01175 (-2.422)*</td>
<td>-0.0014 (-0.434)</td>
</tr>
<tr>
<td>( \alpha_0 )</td>
<td>0.0098 (4.390)*</td>
<td>0.1516 (2.367)*</td>
</tr>
<tr>
<td>( \alpha_1 )</td>
<td>0.0156 (2.198)*</td>
<td>0.0173 (0.677)</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.9328 (121.257)*</td>
<td>0.8754 (27.989)*</td>
</tr>
<tr>
<td>( \delta )</td>
<td>0.0791 (7.183)*</td>
<td>0.1388 (3.849)*</td>
</tr>
<tr>
<td>( (\alpha_1 + \delta) / \alpha_1 )</td>
<td>6.0705</td>
<td>9.0231</td>
</tr>
</tbody>
</table>

Note: * Denotes significance at the 5% level at least. Numbers in parentheses are the estimated t-statistics.
could lead to emergence and bursting of bubbles.
The results for the daily returns do not carry over to the weekly returns meaning that positive feedback trading affects return dynamics in the very short term, one day in this case.

Table 4: Unrestricted Feedback Model Continued.

Panel B. Diagnostics on Model Standardized Residuals.

<table>
<thead>
<tr>
<th></th>
<th>Daily Excess Returns</th>
<th>Weekly Excess Returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.0097</td>
<td>-0.0146</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>1.0013</td>
<td>0.9951</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.1454</td>
<td>-0.1933</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>1.2142</td>
<td>0.8015</td>
</tr>
<tr>
<td>LB(5)</td>
<td>6.9287</td>
<td>2.1247</td>
</tr>
<tr>
<td>LB(5)</td>
<td>3.5036</td>
<td>2.0931</td>
</tr>
<tr>
<td>Sign Bias Test</td>
<td>0.5964</td>
<td>0.5194</td>
</tr>
<tr>
<td>Negative Size Bias Test</td>
<td>-0.1690</td>
<td>-0.6237</td>
</tr>
<tr>
<td>Positive Size Bias Test</td>
<td>-0.7296</td>
<td>-0.6401</td>
</tr>
<tr>
<td>Joint Test</td>
<td>0.2039</td>
<td>0.1939</td>
</tr>
</tbody>
</table>

The diagnostics on the standardized residuals of the unrestricted model show no serious evidence of misspecification. The use of the GED distribution is more appropriate given that the estimated values of $\nu$ are well below 2, the value required for normality, for both the restricted and the unrestricted models.

5 Conclusion

This paper has tested the hypothesis that positive feedback trading is linked to the cost of credit in the sense that lower interest rates can induce higher positive feedback trading in the U.K. stock market. Such trading can lead to runaway prices or, devastating crashes. The model employed is based on the assumption that investors are not homogeneous in the sense that some of them follow expected utility maximizing behavior whereas others

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8The model was estimated also using monthly returns. There was no evidence of positive feedback trading either base or, cost-of-credit induced.
follow positive feedback trading strategies. The evidence from the U.K. market suggests that there is positive feedback trading linked to the cost of credit. Specifically, the lowering of the cost of credit in the pursuit of easy monetary policies leads to positive feedback trading. This pattern is detected on daily stock returns but not in lower frequency data such as weekly or monthly. This in turn suggests that the cost of credit may induce short term noise rather than longer term deviations from fundamentals.

References


