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

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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 polices 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

$$Y_{1,t-1} = \frac{(E_{t-1}(R_t) - r_t)}{\vartheta\sigma_t^2} \tag{1}$$

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; σ^2_t is the conditional variance (risk) at t; and ϑ is the coefficient of risk aversion.

Assuming ϑ 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

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

where, ρ_1 is the base feedback parameter and ρ_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 ρ_1 will be positive and significant if positive feedback trading is present. If in addition, ρ_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

$$E_{t-1}(R_t) - r_{t-1} = \vartheta\sigma_t^2 - \vartheta\{\rho_1 + \rho_2(\bar{r} - r_{t-1})\}\sigma_t^2 R_{t-1} \tag{3}$$

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:

$$R_t - r_{t-1} = \vartheta\sigma_t^2 - \vartheta\{\rho_1 + \rho_2(\bar{r} - r_{t-1})\}\sigma_t^2 R_{t-1} + \varepsilon_t \tag{4}$$

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

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

$$R_t - r_{t-1} = c + \vartheta\sigma_t^2 + \{\varphi_1 + \varphi_2(\bar{r} - r_{t-1})\}\sigma_t^2 R_{t-1} + \varepsilon_t \quad (5)$$

where, φ_1 = $-\vartheta\rho_1$, φ_2 = $-\vartheta\rho_2$ and c is the regression intercept. Thus, the presence of positive feedback trading implies that φ_1 is negative and statistically significant. If in addition φ_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

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2 \quad (6)$$

where, σ_t^2 is the conditional variance of the returns at time t, ε_t is the innovation at time t and α_0, α_1, β and δ are nonnegative fixed parameters. δ 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 δ is positive and statistically significant then negative innovations increase volatility more that 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

$$f(\mu_t, \sigma_t, v) = \frac{v}{2}\,[\,\Gamma(3/v)\,]^{1/2}\,[\,\Gamma(1/v)\,]^{-3/2}\,(1/\,\sigma_t\,)\exp(-[\,\Gamma(3/v)/\Gamma(1/v)\,]^{v/2}\,|\,\varepsilon_t\,/\,\sigma_t\,|) \quad (7)$$

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

Given initial values for ε_t, and σ_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,

$$L(\theta) = \textstyle\sum_{t=1}^{T} \log f(\mu_t, \sigma_t, v) \quad (8)$$

where, μ_t and σ_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.

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[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.[5] Both daily and weekly stock returns are significantly negatively skewed and highly leptokurtic. These two measures

Table 1: Preliminary Statistics

	Daily Excess Returns	Weekly Excess Returns	3-Month Annualized Rate
Mean	0.0242	0.1255	6.3443
Standard Deviation	1.0226	2.1093	2.3413
Skewness	-0.1070*	-0.1479*	1.5112*
Excess Kurtosis	3.3576*	1.9135*	2.0763*
LB(5)	29.5723*	7.0537*	
$LB^2(50)$	1263.0273*	47.1928*	

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.

provide evidence that the return series are not normally distributed.[6] 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

[5]The Ljung-Box statistic for N lags is calculated as $LB(N)=T(T+2)\Sigma^{N}_{j=1} (\rho_j^2/T-j)$ where ρ_j 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.[7]

Table 2: AR(1) Model.

$R_t = b_0 + b_1 R_{t-1} + u_t$

	Daily Returns	Weekly Returns
b_0	0.0239 (1.465)	0.1352 (1.791)
b_1	0.0106 (0.664)	-0.0726 (-2.033)*
R^2	0.0001	0.0040
DW	1.9986	1.9936

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, α_0, α_1, β and δ 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 δ means that the conditional variance is an asymmetric function of past squared residuals. Specifically past negative innovations increase volatility more than past positive

[7]In fact the autoregressive parameter for the weekly series is negative and significant.

Table 3: Restricted Feedback Model.

Panel A: Parameter Estimates

$$R_t - r_{t-1} = c + \vartheta\sigma_t^2 + \{\varphi_1 + \varphi_2(\bar{r} - r_{t-1})\}\sigma_t^2 R_{t-1} + \varepsilon_t$$

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

	Daily Excess Returns	Weekly Excess Returns
α	0.0123 (0.653)	0.1696 (1.
ϑ	0.0227 (0.990)	-0.0048 (-0.153)
φ_1	-0.0044 (-0.451)	-0.0101 (-1.649)
φ_2	———	———
α_0	0.0099 (4.362)*	0.1494 (2.353)*
α_1	0.0165 (2.365)*	0.0172 (0.684)
β	0.9323 (120.261)*	0.8765 (28.154)
δ	0.0782 (7.143)*	0.1381 (3.840)*
□	1.5790 (40.302)	1.6571 (15.196)
$(\alpha_1+\delta)/\alpha_1$	5.7394	9.0290

Note: * Denotes significance at the 5% level at least. Numbers in parentheses are the estimated t-statistics. This version of the model restricts φ_2 to be zero.

innovations. The contribution of a positive innovation is equal to α_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 φ_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.

Panel B. Diagnostics on Model Standardized Residuals.

	Daily Excess Returns	Weekly Excess Returns
Mean	00.0098	-0.0146
Standard Deviation	1.0014	0.9951
Skewness	-0.1401*	-0.1900
Excess Kurtosis	1.2384*	0.8142*
LB(5)	9.4760	1.9978
LB(5)	2.9705	1.9515
Sign Bias Test	0.4208	0.4731
Negative Size Bias Test	-0.1851	-0.6097
Positive Size Bias Test	-0.683	-0.61763
Joint Test	0.1571	0.1857

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 ε_{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 φ_1 remains insignificant. However, the cost-of-credit related feedback parameter, φ_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.

Panel A: Parameter Estimates

$$R_t - r_{t-1} = c + \vartheta\sigma_t^2 + \{\varphi_1 + \varphi_2(\bar{r} - r_{t-1})\}\sigma_t^2 R_{t-1} + \varepsilon_t$$

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

	Daily Excess Returns	Weekly Excess Returns
α	0.0123 (0.655)	0.1675 (1.397)
ϑ	0.0219 (0.954)	-0.0047 (-0.150)
φ_1	0.0114 (1.030)	-0.0083 (-1.348)
φ_2	-0.01175 (-2.422)*	-0.0014 (-0.434)
α_0	0.0098 (4.390)*	0.1516 (2.367)*
α_1	0.0156 (2.198)*	0.0173 (0.677)
β	0.9328 (121.257)*	0.8754 (27.989)*
δ	0.0791 (7.183)*	0.1388 (3.849)*
□	1.5865 (40.153)	1.6647 (15.225)*
$(\alpha_1 + \delta)/\alpha_1$	6.0705	9.0231

Note: * Denotes significance at the 5% level at least. Numbers in parentheses are the estimated t-statistics.

bubbles and higher volatility. In that sense it can be argued that prolonged periods of low interest rates have the potential to encourage positive feedback trading which in turn 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[8]

Table 4: Unrestricted Feedback Model Continued.

Panel B. Diagnostics on Model Standardized Residuals.

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

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 v 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

[8]The 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 fundaments.

References

[1] Antoniou, A., Koutmos G. and Pericli A., 2005, Index Futures and Positive Feedback Trading: Evidence from Major Stock Exchanges, *Journal of Empirical Finance*, **12**, 2005, 219-238.

[2] Berndt, E.K., H.B. Hall, R.E. Hall and J.A. Hausman, 1974, Estimation and Inference in Nonlinear Structural Models, *Annals of Economic and Social Measurement* **4**, 653-666.

[3] Bollerslev, T., R.Y. Chou and K.F. Kroner, 1992, ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence, *Journal of Econometrics* **52**, 5-59.

[4] Bollerslev, T., R.F Engle and D. Nelson, 1994, *ARCH Models*, in R.F. Engle and D.L.

[5] McFadden, eds, *Handbook of Econometrics*, Vol IV (Elsevier Science B.V.) Ch 49.

[6] Bomfim Antulo N., 2000, Pre-Announcement Effects, News and Volatility: Monetary Policy and the Stock Market, *Working paper*.

[7] Campbell, J.Y., S.J Grossman and J. Wang, 1993, Trading Volume and Serial Correlation in Stock Returns, *Quarterly Journal of Economics* CVIII, 905-939.

[8] Cutler, D.M., J.M Poterba and L.H. Summers, 1990, Speculative Dynamics and the Role of Feedback Traders, *American Economic Review*, AEA Papers and Proceedings, 63-68.

[9] De Long B.J., A. Shleifer, L.H Summers and R.J Waldman, 1990, Positive Feedback Investment Strategies and Destabilizing Rational Speculation, *Journal of Finance* **45**, 379-395.

[10] Engle, R.F., and Ng., V.K. (1993), Measuring and Testing the Impact of News on Volatility, *Journal of Finance*, **48**, pp. 1749-1778.

[11] Koutmos G., 1997, "Feedback Trading and the Autocorrelation Pattern of Stock Returns: Further Empirical Evidence", *Journal of International Money and Finance*, **16**, 4, 625-636.

[12] Lansing, Kelvin J., 2003, Should the Fed React to the Stock Market?, *FRBSF* November 14, no. 2003-34.

[13] LeBaron, B., 1992, Some Relations Between Volatility and Serial Correlations in Stock Market Returns, *The Journal of Business* **65**, 199-219.

[14] Merton, R.C., 1973, An Intertemporal Capital Asset Pricing Model, *Econometrica* **41**, 867-888.

[15] Sentana, E. and S. Wadhwani, 1992, Feedback Traders and Stock Return Autocorrelations: Evidence from a Century of Daily Data, *The Economic Journal* **102**, 415-425.

[16] Shiller, R.J., 1984, Stock Prices and Social Dynamics, *Brookings Papers on Economic Activity* **2**, 457-498.

[17] Shiller, R.J., 1989, Market Volatility, p. 375, (MIT Press: Cambridge).