Business Cycle Variation in Positive Feedback Trading: Evidence from the G-7 Economies

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Abstract

Using the business cycle indicators and the aggregate stock market data, this paper examines the degree of positive feedback trading in the G-7 economies and the extent to which such behaviour varies across business cycle. The evidence suggests that there is a significant positive feedback trading in the major stock exchanges of G-7 countries and its intensity is linked to the overall macroeconomic conditions. Specifically, our investigation reveals that in expansions there is more active positive feedback trading than in recessions. Overall, our results yield an important insight into the effect of business cycle on investors' behaviour and market dynamics and bear important implications for the investment professions and market regulators.

JEL classification: G14, C22

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1. Introduction

It is well known that stock return displays time-varying serial correlation.[1] However, less is known about the dynamics and economic sources of its variations. Starting with the seminal work of Fama (1971), a large number of studies have analysed this issue using a wide range of variables and techniques (see, e.g., Lo and MacKinlay, 1990; McKenzie and Faff, 2003, 2005). In spite of the growing research, empirical evidence suggests that fundamental factors such as time-varying risk premia and nonsynchronous trading are not sufficiently large to explain autocorrelation observed in stock returns. Recent research has taken a different approach and argued that return autocorrelation can be, at least in part, attributed to the existence of 'feedback' traders who base their investment decisions on past price movements.[2]

For instance, building on the 'fads' model of Shiller (1984), Sentana and Wadhwani (1992; hereafter, SW) develops a heterogeneous trader model carrying important implications for the serial correlation properties of stock index returns. Specifically, SW extends the intertemporal capital asset pricing model (ICAPM) to integrate the heterogeneous trading behaviour of two groups of investors, i) rational utility maximizers whose demand for shares depends on the risk-adjusted expected return, and ii) positive feedback traders whose demand for shares depends on the previous price movements. Within this model setting, it can be argued that the level and sign of autocorrelation may reflect the relative market dominance of these two groups of investors, and that the return itself can be characterized as an autoregressive process in which the parameter on lagged returns is a function of the conditional variance, i.e., the existence of a relationship between volatility and serial correlation.

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[1] See, for example, Atchison et al. (1987), Ogden (1997), and Säfvenblad (2000). The terms autocorrelation and serial correlation are used interchangeably in the paper.
[2] These so-called 'feedback' or 'trend-following' traders pursue a positive (negative) feedback trading strategy of buying (selling) after price rises and of selling (buying) following price falls.

Using the U.S. stock market data, SW finds some statistical support for their model. Moreover, they find an interesting result 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 periods of high volatility, but negative feedback trading dominates in periods of low volatility.[3]

However, previous investigations have assumed that the behaviour of feedback traders is invariant to the business cycle regime. In this paper, we relax this assumption and consider the behaviour of feedback traders over business cycle. Numerous studies have investigated links between macroeconomic variables and stock market returns (Fama and French, 1989; Ferson and Harvey, 1993; Pesaran and Timmermann, 2000),[4] and there have been a number of empirical investigations concerned with the behaviour of feedback traders (Kurov, 2008; Salm and Schuppli, 2010). Nevertheless, to our knowledge there has been no investigation of feedback trading that allows for time-varying behaviour over the business cycle.[5] As it is widely recognised that business cycle indicators have a predictive power for stock returns (Paye, 2012) and that stock market fluctuations to some extent lead business cycle turning-points (Hamilton and Lin, 1996), it seems overly restrictive to assume that the behaviour of feedback traders is unaffected by macroeconomic conditions.[6,7].

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

[4] In general, these papers find a significant relationship between stock market returns and changes in macroeconomic variables, such as inflation, interest rates, industrial production and the yield curve. It is also found that the economic factors explain stock market volatility e.g., Binder and Merges (2001).

[5] In a study directly related to this paper, Chau et al. (2011) examine whether positive feedback trading is related to investor sentiment in the U.S. exchange-traded fund (ETF) markets, and find that feedback trading increases in periods of optimistic market sentiment. Antoniou et al. (2007) investigate whether business cycle variables can explain the profitability of momentum trading, and find momentum profits can be largely attributable to asset mispricing that systematically varies with business conditions.

[6] If such an assumption is made but is not true, then econometric results may be subject to bias. Thus relaxing the assumption of fixed behaviour over the business cycle is warranted.

[7] A noticeable exception is the work of Antoniou and Koutmos (2014) which examines the impact of monetary policy on stock return dynamics in the U.K. and finds that there is a linkage between the cost of credit and positive feedback trading. Given the important role of monetary policy in countering the

Furthermore, a number of previous studies have yielded results that suggest the predictability of stock returns varies over time (Pesaran and Timmermann, 2000; McMillan and Wohar, 2013). Extending the standard feedback trading model to allow feedback traders to react to business cycle indicators can predict a link between serial correlation and the business cycle, and thus provide a plausible explanation for the time-varying predictability.[8]

Motivated by the above arguments and findings, in this paper we make several extensions to SW model to allow the behaviour of feedback traders to vary depending on whether the economy is in recession or expansion. This not only provides a robustness check to the previous studies that rely on the assumption of fixed behaviour over different stages of business cycle but also is relevant to our understanding of the question why feedback trading might take place.[9] We investigate the statistical support for our 'augmented' models using the aggregate stock market data of seven industrialised nations (G-7) and the Economic Cycle Research Institute (ECRI) business cycle indicators. Our results show that, consistent with the existence of positive feedback traders, there is a negative relationship between volatility and autocorrelation in G-7 stock markets (with the only exception of France). More importantly, we also find that in expansions there is a stronger negative relationship between volatility and autocorrelation than in recessions, suggesting that positive feedback trading is stronger during the economic upturns. Our investigation also

business cycle, it seems natural for this paper to further investigate the influence (if any) of business cycle on feedback trading strategies.

[8] McMillan and Wohar (2013) investigate the predictive power of six business cycle variables for the U.K. stock market. Their empirical findings suggest that dividend yield, price-earnings ratio and bond-equity yield ratio all have significant in-sample predictive power. Moreover, they also uncover an interesting evidence of time variation within predictive power for all variables and such time variation is directly linked to the state of the macroeconomy.

[9] Although a number of reasons (both rational and irrational) have been put forward in explaining the presence of feedback trading, such strategies are usually associated with noise or uninformed traders. However, positive feedback trading may well be the result of 'rational' motivations such as trading on extrapolative expectations, activation of stop-loss orders, and portfolio insurance strategies. These strategies are very likely to be influenced by the macroeconomic conditions.

reveals that the base level of autocorrelation is higher during the expansion cycle. These results survive an array of robustness checks and are consistent with the view that positive feedback trading is linked, at least partly, to macroeconomic conditions.

The rest of this paper is organised as follows. In the next section we briefly discuss the Sentana and Wadhwani (1992) model of feedback trading and introduce our extended versions of this model incorporating the impact of business cycle. Section 3 presents our data and the empirical results. Section 4 concludes the paper.

2. Feedback Trading Models

A growing number of academic studies have found significant evidence on the link between autocorrelation and the volatility of stock returns (LeBaron, 1992). There has also been an increased attention devoted to asset pricing models that recognise the existence of heterogeneous investors (Koutmos, 2012). For instance, Cutler et al. (1990) argue that the autocorrelation properties of a large number of assets can be explained by simple models which allow for the existence of both rational investors and feedback traders. A noticeable example is the model developed by SW (1992) which predicts that the existence and interaction of positive feedback traders and rational 'smart-money' investors may cause negative autocorrelation, especially so during the high volatility periods.[10]

2.1 Feedback trading in SW's framework

[10] For a critical review of the theoretical and empirical literature on positive feedback trading, the reader is referred to Koutmos (2014). He presents an excellent overview of the existing work in this area, especially the literature related to the SW model, and points out some important issues in the extant literature that warrant further research.

SW model assumes there are two heterogeneous groups of investors: one is a group of rational 'smart-money' investors whose demand for shares in period t, Q_t, is consistent with utility maximization theory and can be given as follows:

$$Q_t = \frac{E(R_t/\Omega_{t-1}) - \alpha}{\mu_t} \tag{1}$$

where Q_t is the fraction of shares demanded by this group in period t, E is the expectation operator, R_t is the return from investing in shares, Ω_{t-1} is the information set available to the investor in period t, α is the risk-free rate of return, and μ_t is a measure of risk positively related to the conditional variance of returns, h_t; $\mu_t = \mu(h_t)$. The other is a group of 'feedback traders' whose demand for shares F_t depends only 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. Within this model setting, it can be argued that the sign and strength of parameter γ reflect the relative market dominance of one type of feedback traders over another. If $\gamma > 0$ then positive feedback traders outweigh and outnumber negative feedback traders and vice versa.[11] Equilibrium in the stock market requires that all shares are held:[12]

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

Then, assuming that the smart-money investors have rational expectations, i.e., $R_t = E(R_t / \Omega_{t-1}) + \varepsilon_t$ substituting (1) and (2) into (3) and rearranging gives:

$$R_t = \alpha + \mu(h_t) - \gamma\mu(h_t)R_{t-1} + \varepsilon_t \tag{4}$$

[11] Positive (negative) feedback traders systematically follow the strategy of buying (selling) after price rises and selling (buying) after price falls. It is important also to note that, within this feedback trading model setting, one might be unable to uncover their presence and relative market dominance should both types of feedback traders are equally active in the market and fully offsetting each other's actions. The authors are extremely grateful to the referee for pointing out this possibility.

[12] Note that if all investors are rational 'smart-money' investors (i.e., Q_t = 1), then equation (1) would yield the familiar ICAPM in market equilibrium i.e., $E(R_t/\Omega_{t-1}) - \alpha = \mu_t$

where ε_t is an independently and identically distributed error term. The term $-\gamma\mu(h_t)R_{t-1}$ in equation (4) implies that in a market with rational investors as well as feedback traders the resulting returns exhibit autocorrelation and the degree of autocorrelation depends on volatility, h_t.[13] 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. Note that the positive feedback trading induces negative autocorrelation, while negative feedback trading induces positive autocorrelation in returns.[14]

In their empirical work, SW assumes a linear form for $\mu(h_t)$): $\mu(h_t) = \gamma_0 + \gamma_1 h_t$ and that the conditional variance h_t can be modelled as an E-GARCH (1,1) process. Using a century of daily data on the U.S. stock market and estimating all the parameters of the model simultaneously, SW finds that $\hat{\gamma}_0 = 0.11$ and $\hat{\gamma}_1 = -0.019$, and that both parameters are statistically significant. When taken together with the estimated conditional variance, these parameter values reveal an intriguing result, i.e., when volatility is low returns exhibit positive serial correlation, but as volatility increases a sign reversal occurs and returns exhibit negative serial correlation. Interpreted within the context of the feedback trading model this result suggests that positive feedback trading is higher in the period of high volatility, but that negative feedback trading dominates in the period of low volatility.[15]

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[13] Note that as the conditional variance appears in the conditional mean, equation (4) is a type of ARCH-in-mean model.

[14] Antoniou et al. (2005) argue that the predictability that arises because of feedback traders will not necessarily be exploited by the 'smart-money' investors. On the contrary, in anticipation of the responses of positive feedback (trend-chasing) investors, rational speculators tend to 'jump on the bandwagon' and demand more shares than they would otherwise do and thus, the combination of feedback traders and speculators is to contribute to the movements of prices away from fundamentals.

[15] In subsequent investigations, this negative relationship between serial correlation and volatility has also been found to be a feature of return series for other stock markets (Koutmos, 1997), foreign exchange markets (Laopodis, 2005), stock index futures markets (Salm and Schuppli, 2010), and the exchange-traded fund markets (Chau et al., 2011).

2.2 Feedback trading over the business cycle

In this paper we assume the existence of a group of investors who in a sense lie in-between the smart-money investors and feedback traders of SW model. These investors do not explicitly take risk into account; however, they are less naïve than feedback traders who simply react to price changes. Rather, they believe that the performance of the stock market is to some extent dependent on macroeconomic conditions and consider a business cycle indicator when deciding whether to invest in the stock market.[16] As in SW (1992), we assume there are two distinct groups of investors: smart-money investors and feedback traders, and let the relative demand by smart-money investors be given by the demand function in equation (1). Consider first extending SW model so that the demand for shares by feedback traders depends in an additive way on the business cycle regime:

$$F_t = \gamma R_{t-1} + \theta I_{t-1} \tag{5}$$

where I_t is a dummy variable that is equal to 1 in a period of expansion and 0 in a period of recession.[17] Substituting (1), (5) into (3) and rearranging gives:

$$R_t = \alpha + \mu(h_t) - \gamma\mu(h_t)R_{t-1} - \theta I_{t-1}\mu(h_t) + \varepsilon_t \tag{6}$$

Thus the return in period t depends additively on the business cycle indicator I_{t-1} and the extent of this dependence varies with volatility. Note that if we assume a linear form for $\mu(h_t)$: $\mu(h_t) = \bar{\gamma}_0 + \bar{\gamma}_1 h_t$, then (6) can be re-parameterised as:

$$R_t = \alpha_0 I_{t-1} + \alpha_1(1 - I_{t-1}) + \beta_0 I_{t-1} h_t + \beta_1 (1 - I_{t-1}) h_t + (\gamma_0 + \gamma_1 h_t) R_{t-1} + \varepsilon_t \tag{7}$$

[16] Note that we do not model these traders as an additional group of investors. A further examination of the interaction of three groups of investors (in a similar fashion to Koutmos, 2012) is worthy of a study, but is beyond the scope of the current paper. We are grateful to the referee for this suggestion.

[17] It is unlikely that feedback traders have perfect foresight of the economy so we used the first-lag of business cycle indicators in our model specifications. We thank the referee for pointing out this.

giving a non-linear model similar to the model estimated by SW (1992), but here both the constant and parameter on the conditional variance h_t are allowed to vary across the different stages of business cycle.

However, in the model associated with equations (5) to (7), the reaction of feedback traders to price changes is not itself dependent on the business cycle regime, although their overall demand for shares is. As an alternative model we consider the possibility that their demand function is affected by the business cycle in a multiplicative way:

$$F_t = \{\gamma I_{t-1} + \theta(1 - I_{t-1})\} R_{t-1} \tag{8}$$

where I_t is defined as before. In this case the reaction of feedback traders to price rises and price falls differs over the business cycle if $\gamma \neq \theta$. Substituting (1), (8) into (3) and rearranging gives:

$$R_t = \alpha + \mu(h_t) - \{\gamma I_{t-1} + \theta(1 - I_{t-1})\}\mu(h_t) R_{t-1} + \varepsilon_t \tag{9}$$

Therefore, as in the original SW feedback trading model, a relationship between serial correlation and volatility exists, but here the strength of that relationship varies over the business cycle if $\gamma \neq \theta$.

2.3 Empirical model specifications

In our empirical analysis we estimate a number of time series models for returns R_t. The first is the original feedback trading model of SW (1992):

$$R_t = \alpha + \beta h_t + (\gamma_0 + \gamma_1 h_t) R_{t-1} + \varepsilon_t \tag{10}$$

In terms of modelling the conditional volatility h_t in equation (10), many studies have utilized GARCH-type models as they have been proved to be useful in capturing the conditional heteroscedasticity inherent in stock market returns. Thus in all models we assume a GJR-GARCH (1,1) specification for the conditional variance of returns:[18]

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + b_1 h_{t-1} + a_2\delta_{t-1}\varepsilon_{t-1}^2 \tag{11}$$

where h_t is the conditional volatility, ε_t is the innovation in period t, a_1 is the news coefficient capturing the impact of the most recent innovation, b_1 is a measure of volatility persistence, and a_2 captures the asymmetric impact of positive and negative news. δ_{t-1} is an indicator which takes the value of unity if $\varepsilon_{t-1} < 0$ and zero otherwise. If a_2 is positive and statistically significant, it would indicate that negative innovations increase volatility more than positive innovations.

Hereafter the model given by equations (10) and (11) is referred to as the 'baseline' Model I. The second model (Model II) modifies this baseline model to allow the demand of shares by feedback traders to depend on the business cycle regime in the manner of equation (5). The actual model we estimate is a re-parameterised version of (6):

$$R_t = \alpha_0 I_{t-1} + \alpha_1(1-I_{t-1}) + \beta_0 I_{t-1}h_t + \beta_1(1-I_{t-1})h_t + (\gamma_0 + \gamma_1 h_t)R_{t-1} + \varepsilon_t \tag{12}$$

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + b_1 h_{t-1} + a_2\delta_{t-1}\varepsilon_{t-1}^2 \tag{13}$$

where $I_{t-1} = 0$ in a recession and $I_{t-1} = 1$ in an expansion. The third model (Model III) assumes the demand of feedback traders depends on business cycle regime as in (8). In this case the actual specification is a re-parameterised version of (9):

$$R_t = \alpha + \beta h_t + I_{t-1}(\gamma_0 + \gamma_1 h_t)R_{t-1} + (1-I_{t-1})(\lambda_0 + \lambda_1 h_t)R_{t-1} + \varepsilon_t \tag{14}$$

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + b_1 h_{t-1} + a_2\delta_{t-1}\varepsilon_{t-1}^2 \tag{15}$$

[18] As a robustness check, we also estimate EGARCH versions of our regime shifting models in Table 6. In addition, since the standardised residuals obtained from GARCH models that assume normality tend to be leptokurtic thereby rendering standard t-tests unreliable, we employ a density function with ticker tails i.e., the Generalised Error Distribution (GED).

The fourth model considered (Model IV) is the original SW model augmented so that all parameters in the conditional mean are allowed to shift over the business cycle:

$$R_t = \alpha_0 I_{t-1} + \alpha_1(1 - I_{t-1}) + \beta_0 I_{t-1} h_t + \beta_1(1 - I_{t-1}) h_t$$

$$+ I_{t-1}(\gamma_0 + \gamma_1 h_t) R_{t-1} + (1 - I_{t-1})(\lambda_0 + \lambda_1 h_t) R_{t-1} + \varepsilon_t \qquad (16)$$

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + b_1 h_{t-1} + a_2 \delta_{t-1} \varepsilon_{t-1}^2 \qquad (17)$$

For each model, all parameters in the conditional mean and variance equations were estimated simultaneously by maximum likelihood. The WinRATS 8.0 software was used and the numerical optimisation is based on the Newton-Raphson and Berndt-Hall-Hall-Hausman (BHHH) algorithm.[19]

3. Empirical Findings

3.1 Data and descriptive statistics

The data used in this paper include the daily observations for the stock price indices of the group of seven nations (G-7): Canada, France, Germany, Italy, Japan, the UK, and the US. In particular, the following indices are used to examine the presence of feedback trading in the G-7 stock markets and the extent to which their actions are affected by the business cycle regime: S&P/TSX Composite index (Canada), CAC industrial price index (France), DAX general price index (Germany), Milan price index (Italy), Nikkei 225 (Japan), FT All Share index (UK), and the S&P500 (USA).[20] Daily closing prices on these stock indices were collected from Datastream for the period of 01/01/1970 to 31/12/2012 and returns were calculated as the logarithmic difference $R_t = 100 \times \ln(P_t / P_{t-1})$. The business cycle indicator used to

[19] Due to the increased complexity caused by allowing the parameters to vary over time, no doubt 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.
[20] We also examine the robustness of our main results using DataStream calculated Total Market index for each of the G-7 countries. The results (reported in Table 6) confirm that our main conclusions hold for these alternative stock market indices.

identify recessions and expansions for G-7 economies were obtained from the Economic Cycle Research Institute (ECRI) database. These indicators are constructed using an approach analogous to that used by the National Bureau of Economic Research (NBER) in determining the official U.S. business cycle dates.[21]

The descriptive statistics of each stock market returns are provided in Table 1. The statistics reported are the mean (μ), standard deviation (σ), measures of skewness (S) and excess Kurtosis (K), Jarque-Bera (JB) statistic, the ARCH test and the Ljung-Box statistic (LB) for 12 lags. Consistent with the extant literature, there is a clear evidence of departures from normality in the stock returns series (as indicated by significant JB and ARCH statistics). In particular, we see that all stock market indices are negatively skewed and highly leptokurtic. The LB statistics provide evidence of significant temporal dependencies in the first two moments of G-7 return distribution. The JOINT test of Engle and Ng (1993) suggests that significant asymmetries exist in volatility dynamics, supporting our use of the asymmetric GJR-GARCH specification. Nevertheless, to examine the extent of interaction between serial correlation and volatility, further investigation is required.

To gauge an initial idea on the degree of feedback trading in the G-7 stock markets we estimate an autoregressive model. The common perception is that the positive (negative) feedback trading would lead to positive (negative) autocorrelation in stock returns. To investigate this possibility, it would be helpful to estimate a simple autoregressive model, AR(5). The results reported in Panel B of Table 1 show that there are significant autocorrelations and the coefficients are mostly positive. Nevertheless, as shown in Section 2, the interaction of rational investors and feedback

[21] More detailed information on how these indicators were constructed and the business cycle dates of more than 20 countries are available at the ECRI's website (http://www.businesscycle.com/). Moreover, in addition to using the ECRI business cycle indicators as proxies for the state of G-7 economies, we also use their growth rate cycle to identify periods of accelerating and decelerating economic growth. The results of using this alternative indicator can be found in Table 6.

traders can give rise to autocorrelation patterns that are more complex than a simple autoregressive model can capture. Thus, it is interesting and informative to investigate the extent to which the actions of feedback traders drive the link between volatility and autocorrelation, and whether that relationship varies over the business cycle.

[TABLE 1 ABOUT HERE]

3.2 Evidence on the feedback trading in G-7 stock markets

Tables 2 to 5 report the maximum likelihood estimates of the feedback trader models described by equations (10) to (17), incorporating the possible impact of business cycle on feedback trading behaviour. Consider first the results for the 'baseline' model (equations (10) and (11)) given in Table 2. It can be seen that the coefficients describing the conditional variance process, a_0, a_1, and b_1 are all highly significant. This implies that current volatility is a function of last period's squared innovation and last period's volatility. Interestingly, parameter a_2 is also significant in all cases, suggesting that the 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 (γ_0 and γ_1). The important point to note is that, as in SW (1992) and Koutmos (1997), we find that the estimates $\gamma_0 > 0$ and $\gamma_1 < 0$ and that both parameters are highly significant in all cases, with the only exception of France. Thus we find empirical support for the notion that positive feedback trading exists in the G-7 stock markets and their influences tend to be greater in periods of high volatility. Other points to note are that, for all seven markets, the estimated parameter ν is well below 2 (the value required for normality), and varies very close to unity suggesting that the empirical distributions of returns are close to Laplace distribution. Also, diagnostics performed show no serious misspecification of the baseline Model I.

[TABLE 2 ABOUT HERE]

3.3 The effect of business cycle on feedback trading

Turning our attention to the focus of this paper and consider the impact of business cycle on the degree of positive feedback trading. In this case, we allow the business cycle regime to additively affect the demand for shares by feedback traders. This leads to the Model II as described by equations (12) and (13) in which the constant and the parameter on the conditional variance in (12) are allowed to shift with business cycle regime. The estimation results for Model II are given in Table 3. We find that as one might expect, in expansions (i.e. the economic upturns) the average return (α_0) is higher than in the recession periods (α_1). The parameter on the conditional variance is generally more positive in recessions than in expansions, with the exception of Germany and USA, which is consistent with the argument that investors become more risk averse after a negative wealth shock (Paravisini et al., 2014). However, using a likelihood ratio test we test the restrictions $H_0 : \alpha_0 = \alpha_1, \beta_0 = \beta_1$, $H_{01} : \alpha_0 = \alpha_1$, $H_{02} : \beta_0 = \beta_1$ and find that these hypotheses cannot be rejected for the majority of cases. Thus while allowing for this type of parameter change over the business cycle yields parameter values that have their expected signs, the statistical support for Model II is relatively weak.

[TABLE 3 ABOUT HERE]

The results for Model III as specified in equations (14) and (15) are given in Table 4. Recall that this model allows the reaction of feedback traders to price changes to vary multiplicatively across business cycle regimes. Across both regimes, we still find a negative relationship between autocorrelation and volatility (see the parameters $\gamma_1; \lambda_1$) consistent with argument that positive feedback traders exert a greater influence in periods of high volatility. Note however that this relationship is much stronger in expansion (γ_1) than in recession (λ_1) for all seven markets. Interpreted within the context of our augmented feedback trading Model III, these parameter values reveal an interesting result that positive feedback trading is more active in the economic upturns than in downturns. This finding is consistent with the evidence of Antoniou et al. (2007) who document that the level and profitability of momentum trading vary systematically with business conditions. Furthermore, McKenzie and Kim (2007) also find a stronger negative relationship between volatility and autocorrelation following market upturns and they interpret this as "*a greater response by feedback traders to volatility increases caused by rising prices compared to falling prices* (p.33)" which is caused by "*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 is consistent with our finding that positive feedback trading is less evident during the recession. However, our results are in stark contrast to evidence of SW and Koutmos (1997) which shows that positive feedback trading is likely to be stronger during market falls, possibly as a consequence of stop-loss orders and portfolio insurance strategies.[22] Similar arguments could not be used to explain our finding that positive feedback trading is more intense in expansions.

Within the context of the models proposed, another possible explanation for this result concerns sentiment-induced risk adversity. If the risk adversity of smart-money investors is higher in high sentiment state (expansionary periods), then the relative

[22] Koutmos (1998) documents the 'asymmetric stock returns' phenomenon and implies a stronger negative relationship between volatility and autocorrelation during market declines. He attributes this to the partial adjustment model and the fact that investors have a higher risk-aversion to downside risk.

demand for shares by smart-money investors will decrease and, given the constraint that all shares must be held, the relative demand by feedback traders will increase. This argument is supported by the recent evidence of Chau et al. (2011) who find that the level of positive feedback trading intensifies when investors are feeling optimistic in the economic upturns. From Model III we also find that there is a higher base level of positive autocorrelation in expansions (γ_0) than in recessions (λ_0). Note that in contrast to Model II, in the case of Germany, Japan, and USA at least, the hypothesis of parameter stability over the business cycle ($H_{02}: \gamma_0 = \lambda_0, \gamma_1 = \lambda_1$) is rejected by the likelihood ratio test. This indicates that if parameter constancy is assumed for these markets, as in our baseline Model I, then such a model is mis-specified.

[TABLE 4 ABOUT HERE]

The results for Model IV are given in Table 5. In this case we find similar results to our previous models; the average return is consistently higher in expansions as one would expect, and we find a stronger negative relationship between autocorrelation and volatility in expansion (γ_1) than in recession (λ_1). Also note that the hypothesis of parameters on the lagged return are stable over business cycle ($H_{02}: \gamma_0 = \lambda_0, \gamma_1 = \lambda_1$) is rejected by a likelihood ratio test at the 5% significance level, in five cases. Overall, among those feedback trading models considered in this paper, Model III appears to be the preferred model for capturing the variability of feedback trading over the business cycle. Furthermore, in all four models, the diagnostics on standardised residuals show no evidence of serious misspecification. 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).

[TABLE 5 ABOUT HERE]

3.4 Is the effect of business cycle on feedback trading robust?

The analysis presented so far has revealed evidence of significant positive feedback trading in the G-7 stock markets, and the extent of feedback trading varies over the business cycle. In this section, we examine the robustness of our results by implementing (i) an alternative indicator for the state of G-7 economies, (ii) different proxies for the major stock market returns, and (iii) EGARCH specification. First we re-estimate the preferred feedback Model III in equations (14) and (15) using the growth rate cycle to identify periods of accelerating and decelerating economic growth. The results presented in panel A of Table 6 show that, in general, the findings for the ECRI's business cycle indicator carry over to the growth rate cycle indicator. To keep the discussion compact, we report only the values of the parameters from (14) which indicate the level of feedback trading and the influence of business cycle. Next, we estimate the same specification by employing the Datastream calculated total market index for each country. Consistent with our earlier findings from the national stock market indices, the evidence reported in panel B of Table 6 confirms a stronger negative relationship between autocorrelation and volatility in expansions. This supports the notion that our previous results are not driven by the choice of market index. Finally, consideration is also given to the possible changes of our results when an E-GARCH specification is used to estimate the conditional volatility. Overall, the robustness tests results presented in Table 6 are qualitatively similar to that reported previously in Table 4 and confirm that our conclusions from the 'augmented' feedback trading Model III hold for these alternative specifications.

[TABLE 6 ABOUT HERE]

4. Conclusion

This paper has considered several extensions of the feedback trading model of Sentana and Wadhwani (1992) that allow for the possibility that, *ceteris paribus*, the demand for shares by feedback traders varies according to the business cycle regime. Given the extant literature on stock return predictability and the business cycle, it would seem overly restrictive to assume that feedback traders do not take general macroeconomic conditions into account when deciding whether to invest in stock market. Using the Economic Cycle Research Institute (ECRI) business cycle indicators and the major stock market returns for the G-7 countries, we find significant evidence suggesting that the negative relationship between autocorrelation and volatility (driven by positive feedback traders) varies over the business cycle. Specifically, our results reveal that positive feedback trading is stronger in expansions than in recessions. This finding is in line with the results of Antoniou et al. (2007) who document that the level and profitability of momentum-style feedback trading vary systematically with business conditions. This in turn suggests that positive feedback trading is influenced, at least in part, by the overall state of economies.

As with any empirical investigation the results reported in this paper must be taken in context. We estimate relatively simple extensions of the basic feedback trading model and applied them to the data from seven industrialised nations (G-7). Also, we split the business cycle into expansion and recession while it may be more practical to allow for three business cycle regimes: recession, recovery, and expansion. Further research which seeks to resolve these issues may provide additional insights into the effect of business cycle on investor trading behaviour. Besides, since the ECRI recession and expansion periods are in some cases very long, it is plausible that additional parameter instability may exist. Indeed over such a long time period a Markov-switching approach may yield interesting results if applied to this issue. Future research in this area may also seek to identify the reasons why feedback trading is linked to the macroeconomic conditions. As Koutmos (2014) points out there are still some important issues remain in the extant literature that requires further investigation. For instance, future extensions of the basic feedback model should account for the existence of negative feedback trading and allow for the feedback trading in individual assets in addition to the aggregate market portfolios. Furthermore, since it is likely that feedback trading depends on longer lags of past return and not just the return in the previous period, further investigations concerned with the behaviour of feedback traders should also account for this long memory characteristic in the feedback mechanism.

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Table 1: Descriptive statistics of G-7 stock market returns

	Canada		France		Germany		Italy		Japan		UK		USA	
Panel A: Summary statistics														
μ	0.0219		0.0136		0.0266		0.0159		0.0133		0.0271		0.0243	
σ	0.9307		1.4062		1.0620		1.2750		1.2534		1.0732		1.0724	
S	-0.8089		-0.1376		-0.3222		-0.5500		-0.4309		-0.2648		-1.0226	
K	14.0750		5.4993		8.6068		7.1538		11.0124		8.7009		26.1567	
JB	93805.9	***	8396.8	***	34813.0	***	24482.3	***	57021.5	***	35510.6	***	321691	***
LB(12)	123.07	***	41.45	***	102.47	***	292.30	***	35.36	***	146.09	***	31.47	***
$LB^2(12)$	7297.09	***	3475.58	***	7586.03	***	3160.29	***	4784.06	***	7015.21	***	1991.76	***
ARCH	1947.36	***	974.52	***	1834.52	***	1100.3	***	1618.89	***	2114.79	***	907.26	***
JOINT	818.94	***	259.44	***	759.95	***	480.41	***	493.96	***	936.43	***	369.74	***
Panel B: Autocorrelation														
b_0	0.020	**	0.015		0.025	**	0.014		0.014		0.025	**	0.026	**
b_1	0.081	***	-0.002		0.073	***	0.156	***	0.002		0.083	***	0.006	
b_2	-0.023		-0.023		-0.012		-0.055	***	-0.037	*	-0.010		-0.028	
b_3	0.019		-0.057	***	-0.015		0.018		-0.002		-0.019		-0.009	
b_4	0.031		0.021		0.041	**	0.033	**	0.015		0.059	***	-0.015	
b_5	-0.031		-0.038		-0.026		-0.009		-0.009		-0.022		-0.007	

Notes:

μ = sample mean; σ = standard deviation; S = skewness; K = Excess Kurtosis; JB = Jarque-Bera test for normality LB(n) & $LB^2(n)$ are the Ljung-Box Q test of serial correlation for the level & squared stock returns, respectively; the test statistics are distributed as χ^2 with n degree of freedom where n is the number of lags. ARCH is the Lagrange Multiplier LM test for ARCH effects and distributed as a χ^2 with 1 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.

b_n are the estimated parameters for 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 G-7 stock markets

	Baseline Model I													
	Canada		France		Germany		Italy		Japan		UK		USA	
Panel A: Mean Equation														
α	0.0321	***	0.0164		0.0233	***	0.0147		0.0322	***	0.0333	***	0.0231	***
	(3.909)		(0.912)		(3.546)		(1.216)		(5.172)		(3.418)		(2.746)	
β	0.0045		0.0067		0.0054		0.0050		-0.0074	**	-0.0005		0.0045	
	(0.394)		(0.599)		(0.608)		(0.656)		(-1.998)		(-0.049)		(0.485)	
γ_0	0.1972	***	0.0104		0.2090	***	0.1743	***	0.0252	***	0.0997	***	0.0493	***
	(19.438)		(0.728)		(18.576)		(13.129)		(5.362)		(8.412)		(4.993)	
γ_1	-0.0310	***	-0.0036		-0.0290	***	-0.0126	***	-0.0069	***	-0.0110	***	-0.0076	***
	(-8.164)		(-1.044)		(-8.883)		(-3.596)		(-3.578)		(-2.878)		(-4.486)	
Panel B: Variance Equation														
a_0	0.0098	***	0.0329	***	0.0048	***	0.0267	***	0.0142	***	0.0168	***	0.0106	***
	(4.414)		(3.901)		(4.121)		(4.409)		(4.806)		(4.777)		(4.818)	
a_1	0.0717	***	0.0127	**	0.0525	***	0.0773	***	0.0495	***	0.0537	***	0.0177	***
	(6.579)		(2.108)		(7.113)		(10.249)		(5.794)		(6.439)		(4.484)	
b_1	0.8971	***	0.9081	***	0.9173	***	0.8829	***	0.8865	***	0.8945	***	0.9294	***
	(65.724)		(73.034)		(96.758)		(70.735)		(79.106)		(75.239)		(127.68)	
a_2	0.0364	***	0.1189	***	0.0553	***	0.0536	***	0.1242	***	0.0711	***	0.0848	***
	(3.427)		(7.838)		(5.286)		(4.367)		(6.423)		(6.609)		(6.927)	
ν	1.2272	***	1.4385	***	1.3889	***	1.2227	***	1.1758	***	1.4366	***	1.3089	***
	(40.249)		(25.121)		(26.214)		(38.555)		(49.757)		(25.331)		(37.056)	
Panel C: Diagnostic Tests														
$E(Z_t)$	-0.022		-0.016		-0.007		-0.010		-0.007		-0.011		-0.006	
$E(Z^2_t)$	1.016		1.031		1.013		1.015		1.007		1.001		1.002	
LB(12)	26.247	***	24.145	***	35.154	***	64.506	***	41.477	***	32.783	***	21.525	***
$LB^2(12)$	38.563	***	9.379		2.206		5.964		4.693		15.801	**	2.612	
ARCH(5)	29.120	***	7.807		0.424		3.002		1.602		14.381	**	0.667	
JOINT	13.992	***	33.025	***	9.972	**	4.433		15.939	***	2.871		17.739	***

Notes:
This table presents maximum likelihood estimates for the Sentana and Wadhwani (1992) feedback trading model I given by equations (10) and (11) from 01/01/1970 to 31/12/2012 for the major stock markets of G-7 countries. In particular, the estimated mean equation is

$$R_t = \alpha + \beta h_t + (\gamma_0 + \gamma_1 h_t) R_{t-1} + \varepsilon_t$$

The variance equation is given by

$$h_t = a_0 + a_1 \varepsilon_{t-1}^2 + b_1 h_{t-1} + a_2 \delta_{t-1} \varepsilon_{t-1}^2$$

Errors are assumed to follow the Generalised Error Distribution (GED) 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.

Table 3: Additive effect of business cycle on feedback trading

	Model II													
	Canada		France		Germany		Italy		Japan		UK		USA	
Panel A: Mean Equation														
α_0	0.0327	***	0.0137		0.0193	***	0.0239	*	0.0376	***	0.0359	***	0.0214	***
	(5.324)		(0.802)		(3.085)		(1.920)		(5.415)		(3.566)		(4.357)	
α_1	-0.0377		0.0018		0.0414	*	-0.0686		-0.0101		-0.0058		0.0016	
	(-0.768)		(0.048)		(1.683)		(-1.483)		(-0.532)		(-0.085)		(0.053)	
β_0	0.0076		0.0013		0.0153	*	0.0056		-0.0059		-0.0041		0.0118	**
	(0.571)		(0.090)		(1.748)		(0.551)		(-1.356)		(-0.337)		(1.999)	
β_1	0.0130		0.0115		-0.0352	***	0.0177		0.0033		0.0158		0.0011	
	(0.533)		(0.984)		(-2.831)		(0.697)		(0.632)		(0.659)		(0.099)	
γ_0	0.1962	***	0.0107		0.2120	***	0.1725	***	0.0236	***	0.0995	***	0.0493	***
	(17.645)		(1.077)		(23.111)		(19.399)		(3.717)		(8.796)		(7.217)	
γ_1	-0.0306	***	-0.0038	*	-0.0312	***	-0.0122	***	-0.0066	***	-0.0108	***	-0.0074	***
	(-8.598)		(-1.923)		(-15.170)		(-6.589)		(-2.731)		(-2.578)		(-4.707)	
Panel B: Variance Equation														
a_0	0.0097	***	0.0327	***	0.0049	***	0.0265	***	0.0142	***	0.0168	***	0.0105	***
	(4.828)		(4.519)		(4.265)		(4.439)		(5.147)		(4.565)		(4.817)	
a_1	0.0726	***	0.0132	**	0.0520	***	0.0782	***	0.0511	***	0.0539	***	0.0188	***
	(6.972)		(2.083)		(6.476)		(8.726)		(7.339)		(6.191)		(4.207)	
b_1	0.8970	***	0.9082	***	0.9171	***	0.8828	***	0.8856	***	0.8944	***	0.9291	***
	(74.468)		(90.311)		(91.956)		(67.081)		(83.317)		(73.645)		(115.73)	
a_2	0.0351	***	0.1178	***	0.0560	***	0.0522	***	0.1229	***	0.0711	***	0.0835	***
	(3.114)		(7.976)		(6.098)		(3.881)		(8.055)		(6.638)		(6.811)	
ν	1.2269	***	1.4376	***	1.3880	***	1.2253	***	1.1756	***	1.4370	***	1.3074	***
	(63.195)		(22.349)		(24.201)		(40.792)		(46.665)		(24.116)		(33.814)	
Panel C: Likelihood Ratio Tests														
LR	1.975		0.078		0.657		3.894	**	5.053	**	0.375		0.387	
LR1	0.036		0.295		11.079	***	0.205		2.660		0.595		0.746	
LR2	2.646		1.272		11.089	***	8.203	**	5.086	*	0.619		4.619	*
Panel D: Diagnostic Tests														
$E(Z_t)$	-0.020		-0.016		-0.009		-0.012		-0.010		-0.011		-0.006	
$E(Z^2_t)$	1.016		1.030		1.013		1.015		1.007		1.008		1.002	
LB(12)	25.594	***	23.980	***	35.915	***	61.731	***	41.295	***	32.314	***	21.434	***
$LB^2(12)$	38.323	***	9.175		2.180		5.986		4.701		15.517	**	2.640	
ARCH(5)	29.003	***	7.581		0.415		2.999		1.598		14.090	**	0.703	
JOINT	13.313	***	31.547	***	9.963	**	3.833		15.157	***	2.673		17.355	***

Notes:
This table presents maximum likelihood estimates for the "augmented" feedback trading model II given by equations (12) and (13) from 01/01/1970 to 31/12/2012 for the major stock markets of G-7 countries. In particular, the estimated mean equation is

$$R_t = \alpha_0 I_{t-1} + \alpha_1(1-I_{t-1}) + \beta_0 I_{t-1} h_t + \beta_1(1-I_{t-1})h_t + (\gamma_0 + \gamma_1 h_t)R_{t-1} + \varepsilon_t$$

The variance equation is given by

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + b_1 h_{t-1} + a_2\delta_{t-1}\varepsilon_{t-1}^2$$

Errors are assumed to follow the Generalised Error Distribution (GED) 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.
I_t is a dummy variable that is equal to 1 in a period of expansion and 0 in a period of recession.
LR is the likelihood ratio statistic for testing the restriction in Model II H_0: $\alpha_0=\alpha_1, \beta_0=\beta_1$ (for LR); H_{01}: $\alpha_0=\alpha_1$ (for LR1); H_{02}: $\beta_0=\beta_1$ (for LR2)

Table 4: Multiplicative effect of business cycle on feedback trading

	Model III						
	Canada	**France**	**Germany**	**Italy**	**Japan**	**UK**	**USA**
Panel A: Mean Equation							
α	0.0321 ***	0.0156	0.0224 ***	0.0142	0.0321 ***	0.0343 ***	0.0231 ***
	(4.099)	(1.273)	(3.384)	(1.473)	(3.935)	(4.221)	(2.651)
β	0.0042	0.0073	0.0072	0.0049	-0.0056	-0.0022	0.0046
	(0.372)	(0.992)	(0.785)	(0.906)	(-1.087)	(-0.270)	(0.513)
γ_0	0.2002 ***	0.0138	0.2943 ***	0.1780 ***	0.0479 ***	0.1056 ***	0.1197 ***
	(18.830)	(0.971)	(9.370)	(12.730)	(4.647)	(8.846)	(5.464)
γ_1	-0.0345 ***	-0.0036	-0.0393 ***	-0.0126 ***	-0.0129 ***	-0.0153 ***	-0.0062 ***
	(-5.868)	(-0.940)	(-9.971)	(-3.497)	(-4.853)	(-4.776)	(-4.661)
λ_0	0.1842 ***	-0.0166	0.2143 ***	0.1506 ***	-0.0315 ***	0.0309	0.0395 ***
	(9.760)	(-0.407)	(17.751)	(8.011)	(-3.363)	(0.602)	(3.512)
λ_1	-0.0267 ***	-0.0017	-0.0184 ***	-0.0111	-0.0003	-0.0048	-0.0016 ***
	(-3.306)	(-0.266)	(-2.793)	(-0.958)	(-0.144)	(-0.478)	(-2.954)
Panel B: Variance Equation							
a_0	0.0096 ***	0.0329 ***	0.0046 ***	0.0267 ***	0.0142 ***	0.0165 ***	0.0106 ***
	(4.435)	(4.017)	(4.735)	(4.466)	(5.373)	(5.713)	(4.710)
a_1	0.0718 ***	0.0124 **	0.0519 ***	0.0771 ***	0.0497 ***	0.0536 ***	0.0174 ***
	(7.780)	(2.058)	(7.182)	(8.172)	(7.531)	(7.728)	(4.562)
b_1	0.8981 ***	0.9083 ***	0.9196 ***	0.8830 ***	0.8860 ***	0.8956 ***	0.9296 ***
	(70.675)	(74.224)	(113.35)	(68.778)	(97.599)	(90.950)	(115.07)
a_2	0.0350 ***	0.1189 ***	0.0520 ***	0.0538 ***	0.1239 ***	0.0697 ***	0.0849 ***
	(3.115)	(7.681)	(4.944)	(4.130)	(9.537)	(7.064)	(6.925)
ν	1.2276 ***	1.4390 ***	1.3837 ***	1.2225 ***	1.1804 ***	1.4362 ***	1.3115 ***
	(59.524)	(22.952)	(26.906)	(40.664)	(35.862)	(26.498)	(36.861)
Panel C: Likelihood Ratio Tests							
LR	0.512	0.499	6..149 **	1.440	25.504 ***	2.039	5.463 **
LR1	0.627	0.064	7.983 ***	0.016	15.802 ***	3.766 *	3.058 *
LR2	0.825	0.561	20.108 ***	3.439	25.847 ***	4.003	5.713 *
Panel D: Diagnostic Tests							
E(Z_t)	-0.022	-0.016	-0.008	-0.010	-0.011	-0.011	-0.006
E(Z^2_t)	1.016	1.031	1.013	1.015	1.008	1.008	1.002
LB(12)	26.240 ***	24.177 ***	35.206 ***	64.451 ***	40.570 ***	32.547 ***	21.485 ***
LB²(12)	39.863 ***	9.258	2.263	5.929	4.422	18.165 **	2.674
ARCH(5)	30.500 ***	7.712	0.483	2.996	1.337	16.784 ***	0.776
JOINT	14.214 ***	31.912 ***	9.865 **	4.301	14.588 ***	2.923	18.016 ***

Notes:
This table presents maximum likelihood estimates for the "augmented" feedback trading model III given by equations (14) and (15) from 01/01/1970 to 31/12/2012 for the major stock markets of G-7 countries. In particular, the estimated mean equation is

$$R_t = \alpha + \beta h_t + I_{t-1}(\gamma_0 + \gamma_1 h_t)R_{t-1} + (1 - I_{t-1})(\lambda_0 + \lambda_1 h_t)R_{t-1} + \varepsilon_t$$

The variance equation is given by

$$h_t = a_0 + a_1\varepsilon^2_{t-1} + b_1 h_{t-1} + a_2\delta_{t-1}\varepsilon^2_{t-1}$$

Errors are assumed to follow the Generalised Error Distribution (GED) 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.
I_t is a dummy variable that is equal to 1 in a period of expansion and 0 in a period of recession.
LR is the likelihood ratio statistic for testing the restriction in Model III H_0: $\gamma_0=\lambda_0$ (for LR); H_{01}: $\gamma_1=\lambda_1$ (for LR1); H_{02}: $\gamma_0=\lambda_0, \gamma_1=\lambda_1$ (for LR2)

Table 5: Full effect of business cycle on feedback trading

	Model IV													
	Canada		France		Germany		Italy		Japan		UK		USA	
Panel A: Mean Equation														
α_0	0.0332	***	0.0131		0.0289	***	0.0234	*	0.0371	***	0.0376	***	0.0213	***
	(5.053)		(0.751)		(3.502)		(1.817)		(3.897)		(4.487)		(2.799)	
α_1	-0.0444		0.0040		0.0208		-0.0686	**	-0.0151		-0.0114		-0.0021	
	(-1.211)		(0.093)		(1.171)		(-2.245)		(-1.399)		(-0.186)		(-0.107)	
β_0	0.0063		0.0117		0.0122		0.0059		-0.0041		-0.0073		0.0121	
	(0.475)		(0.945)		(1.400)		(0.603)		(-0.508)		(-0.725)		(1.641)	
β_1	0.0194		0.0010		-0.0199		0.0175		0.0056		0.0198		0.0023	
	(0.731)		(0.062)		(-0.972)		(0.814)		(1.085)		(0.758)		(0.299)	
γ_0	0.1996	***	0.0132		0.2953	***	0.1765	***	0.0484	***	0.1059	***	0.1192	***
	(16.565)		(0.887)		(7.870)		(13.470)		(6.559)		(8.503)		(3.775)	
γ_1	-0.0344	***	-0.0034		-0.0389	***	-0.0124	***	-0.0128	***	-0.0157	***	-0.0059	***
	(-6.034)		(-0.847)		(-9.979)		(-3.302)		(-4.796)		(-5.081)		(-3.999)	
λ_0	0.1684	***	-0.0123		0.2137	***	0.1445	***	-0.0259	*	0.0316		0.0393	***
	(3.057)		(-0.477)		(17.404)		(5.077)		(-1.714)		(0.997)		(4.118)	
λ_1	-0.0247	**	-0.0026		-0.0191	***	-0.0102		-0.0007		0.0046		-0.0017	***
	(-2.522)		(-0.866)		(-5.558)		(-1.008)		(-0.324)		(0.952)		(-3.307)	
Panel B: Variance Equation														
a_0	0.0096	***	0.0328	***	0.0046	***	0.0264	***	0.0142	***	0.0165	***	0.0105	***
	(4.436)		(4.769)		(4.821)		(4.129)		(4.844)		(5.012)		(4.724)	
a_1	0.0725	***	0.0131	**	0.0520	***	0.0780	***	0.0515	***	0.0537	***	0.0186	***
	(7.051)		(2.233)		(7.403)		(8.313)		(6.754)		(6.817)		(4.754)	
b_1	0.8981	***	0.9081	***	0.9197	***	0.8830	***	0.8851	***	0.8955	***	0.9292	***
	(70.751)		(84.614)		(118.11)		(61.903)		(90.899)		(82.003)		(126.52)	
a_2	0.0338	***	0.1180	***	0.0515	***	0.0522	***	0.1225	***	0.0698	***	0.0835	***
	(2.892)		(7.995)		(4.999)		(4.273)		(7.208)		(6.307)		(7.294)	
ν	1.2271	***	1.4379	***	1.3829	***	1.2252	***	1.1800	***	1.4364	***	1.3098	***
	(62.646)		(35.227)		(24.445)		(43.198)		(50.740)		(25.945)		(45.058)	
Panel C: Likelihood Ratio Tests														
LR	5.035	*	0.898		1.533		9.059	**	11.672	***	1.025		2.042	
LR1	0.961		0.784		32.904	***	1.358		20.554	***	15.165	***	7.530	**
LR2	5.204		1.580		32.928	***	15.692	***	25.415	***	15.703	***	12.971	**
Panel D: Diagnostic Tests														
$E(Z_t)$	-0.021		-0.016		-0.008		-0.012		-0.012		-0.010		-0.005	
$E(Z^2_t)$	1.016		1.031		1.013		1.015		1.008		1.007		1.002	
LB(12)	25.990	***	23.806	***	35.458	***	62.072	***	39.210	***	32.124	***	20.411	***
$LB^2(12)$	39.779	***	9.101		2.244		5.938		4.406		18.136	**	2.716	
ARCH(5)	30.525	***	7.527		0.472		2.980		1.314		16.751	***	0.830	
JOINT	13.581	***	30.488	***	10.120	**	3.760		13.790	***	2.932		17.397	***

Notes:
This table presents maximum likelihood estimates for the "augmented" feedback trading model IV given by equations (16) and (17) from 01/01/1970 to 31/12/2012 for the major stock markets of G-7 countries. In particular, the estimated mean equation is

$$R_t = \alpha_0 I_{t-1} + \alpha_1(1-I_{t-1}) + \beta_0 I_{t-1}h_t + \beta_1(1-I_{t-1})h_t + I_{t-1}(\gamma_0+\gamma_1 h_t)R_{t-1} + (1-I_{t-1})(\lambda_0+\lambda_1 h_t)R_{t-1} + \varepsilon_t$$

The variance equation is given by

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + b_1 h_{t-1} + a_2\delta_{t-1}\varepsilon_{t-1}^2$$

Errors are assumed to follow the Generalised Error Distribution (GED) 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.
I_t is a dummy variable that is equal to 1 in a period of expansion and 0 in a period of recession. LR is the likelihood ratio statistic for testing the restriction in Model IV H_0: $\gamma_0=\lambda_0$ (for LR); H_{01}: $\gamma_1=\lambda_1$ (for LR1); H_{02}: $\gamma_0=\lambda_0, \gamma_1=\lambda_1$ (for LR2)

Table 6: Robustness checks for the effect of business cycle on feedback trading

	Model III						
	Canada	France	Germany	Italy	Japan	UK	USA
Panel A: Growth Rate Cycle							
α	0.0320 ***	0.0162	0.0229 ***	0.0143 **	0.0315 ***	0.0336 ***	0.0228 **
	(5.490)	(1.141)	(4.839)	(2.292)	(3.621)	(3.624)	(2.566)
β	0.0043	0.0070	0.0061	0.0056	-0.0066 *	-0.0008	0.0043
	(0.429)	(0.786)	(1.031)	(1.204)	(-1.832)	(-0.082)	(0.426)
γ_0	0.2034 ***	0.0062	0.2141 ***	0.1682 ***	0.0330 ***	0.0928 ***	0.0864 ***
	(15.781)	(0.414)	(10.000)	(13.627)	(2.646)	(7.851)	(4.287)
γ_1	-0.0307 ***	-0.0079	-0.0385 ***	-0.0191 ***	-0.0121 ***	-0.0127 ***	-0.0198 ***
	(-5.212)	(-1.167)	(-11.170)	(-5.713)	(-3.064)	(-3.871)	(-7.887)
λ_0	0.1859 ***	0.0164	0.2099 ***	0.1919 ***	0.0242 *	0.1171 ***	0.0401 ***
	(13.924)	(0.505)	(14.452)	(9.489)	(1.896)	(6.263)	(4.302)
λ_1	-0.0304 ***	0.0040	-0.0275 ***	-0.0101 ***	-0.0051 ***	-0.0023	-0.0070 ***
	(-10.048)	(0.697)	(-8.848)	(-4.419)	(-4.982)	(-0.337)	(-4.734)
LR	0.838	0.080	0.029	1.081	0.243	1.021	5.133 **
LR1	0.004	0.972	4.960 **	3.649 *	2.793 *	1.369	7.243 ***
LR2	1.026	1.988	8.388 **	3.710	3.065	2.822	8.336 **
Panel B: DS Total Market Indices							
α	0.0294 ***	0.0302 ***	0.0226 ***	0.0249 *	0.0198 ***	0.0362 ***	0.0253 ***
	(3.748)	(2.596)	(2.802)	(1.692)	(9.326)	(3.572)	(2.954)
β	0.0039	-0.0008	0.0116	0.0030	-0.0082 **	-0.0017	0.0068
	(0.335)	(-0.076)	(1.403)	(0.299)	(-2.330)	(-0.167)	(0.689)
γ_0	0.1911 ***	0.1058 ***	0.1747 ***	0.1021 ***	0.1095 ***	0.0873 ***	0.0851 ***
	(16.105)	(8.352)	(5.401)	(10.681)	(9.392)	(7.497)	(4.940)
γ_1	-0.0334 ***	-0.0193 **	-0.0208 ***	-0.0086 **	-0.0179 ***	-0.0150 ***	-0.0129 ***
	(-5.912)	(-2.179)	(-5.505)	(-2.442)	(-9.151)	(-3.605)	(-3.429)
λ_0	0.1732 ***	0.1222 ***	0.0936 ***	0.1419 ***	0.0537 ***	0.0358	0.0483 ***
	(3.023)	(4.389)	(9.629)	(4.134)	(4.141)	(1.021)	(3.317)
λ_1	-0.0304 ***	-0.0094 **	-0.0199 ***	-0.0081	-0.0067 ***	0.0029	-0.0072 **
	(-4.576)	(-2.302)	(-5.046)	(-0.989)	(-6.076)	(0.469)	(-2.010)
LR	0.096	0.315	4.974 **	1.192	11.365 ***	2.024	1.650
LR1	0.139	1.175	0.016	0.003	54.423 ***	6.665 ***	0.738
LR2	0.149	1.180	5.864 *	1.273	54.428 ***	7.469 **	1.689
Panel C: E-GARCH Specification							
α	0.0294 ***	0.0079	0.0185 ***	0.0183	0.0285 ***	0.0340 ***	0.0174 **
	(3.048)	(0.410)	(2.826)	(1.629)	(4.802)	(5.059)	(1.985)
β	0.0101	0.0135	0.0126	0.0034	-0.0046	0.0006	0.0097
	(0.652)	(1.056)	(1.448)	(0.335)	(-1.413)	(0.175)	(0.829)
γ_0	0.2141 ***	0.0202	0.3027 ***	0.1842 ***	0.0400 ***	0.1126 ***	0.1253 ***
	(17.620)	(1.099)	(8.692)	(10.314)	(5.230)	(12.501)	(5.069)
γ_1	-0.0572 ***	-0.0066	-0.0474 ***	-0.0166 **	-0.0113 ***	-0.0225 ***	-0.0228 **
	(-4.869)	(-1.053)	(-13.210)	(-2.345)	(-7.168)	(-91.619)	(-4.043)
λ_0	0.2040 ***	-0.0061	0.2198 ***	0.1481 ***	-0.0280	0.0434	0.0451 ***
	(10.255)	(-0.147)	(24.790)	(5.043)	(-1.256)	(0.445)	(4.218)
λ_1	-0.0384 ***	-0.0048	-0.0249 ***	-0.0102 ***	-0.0034	0.0039	-0.0138 ***
	(-2.754)	(-0.548)	(-3.491)	(-4.464)	(-0.578)	(0.135)	(-2.444)
LR	0.158	0.334	4.899 **	1.322	9.674 ***	0.499	6.764 ***
LR1	1.022	0.026	7.105 ***	0.717	1.589	0.847	1.215
LR2	1.544	0.463	36.747 ***	1.413	14.265 ***	1.226	6.855 **

Notes:

This table presents maximum likelihood estimates for the "augmented" feedback trading model III given by equations (14) and (15) from 01/01/1970 to 31/12/2012 for the major stock markets of G-7 countries. In particular, the estimated mean equation is

$$R_t = \alpha + \beta h_t + I_{t-1}(\gamma_0 + \gamma_1 h_t)R_{t-1} + (1 - I_{t-1})(\lambda_0 + \lambda_1 h_t)R_{t-1} + \varepsilon_t$$

The variance equation is given by either

$$h_t = a_0 + a_1\varepsilon_{t-1}^2 + b_1 h_{t-1} + a_2\delta_{t-1}\varepsilon_{t-1}^2 \qquad \text{[GJR-GARCH]}$$

Or

$$\ln(h_t) = a_0 + a_1[(|z_{t-1}| - E|z_{t-1}|) + a_2 z_{t-1}] + b_1\ln(h_{t-1}) \qquad \text{[E-GARCH]}$$

Errors are assumed to follow the Generalised Error Distribution (GED) 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.

I_t is a dummy variable that is equal to 1 in a period of expansion and 0 in a period of recession.

LR is the likelihood ratio statistic for testing the restriction in Model III H_0: $\gamma_0=\lambda_0$ (for LR); H_{01}: $\gamma_1=\lambda_1$ (for LR1); H_{02}: $\gamma_0=\lambda_0, \gamma_1=\lambda_1$ (for LR2)