THE IMPACT OF SINGLE STOCK FUTURES ON FEEDBACK TRADING AND THE MARKET DYNAMICS OF THE CASH MARKET: THE CASE OF DOMESTIC AND CROSS-BORDER UNIVERSAL STOCK FUTURES

by

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Abstract

The impact of trading domestic and cross-border Universal Stock Futures (USFs) on underlying market dynamics (volatility and the level of feedback trading) is investigated. Examination of USFs provides a number of advantages compared to investigation of index futures. Specifically: (1) any impact of derivatives is more likely to be evident in the behaviour of individual stocks; (2) unlike the case of index futures where the cash position itself is not tradable, with USFs it is possible to directly observe the behaviour of the underlying; (3) USFs have multiple introduction dates within a given market; (4) since USFs are listed on stocks traded in markets with different characteristics and across industries, differential country/industry effects can be identified; (5) designing a control sample based on the determinants of the listing decision addresses endogeneity concerns. Thus reliable and wider ranging insights into the impact of derivatives result. Findings suggest limited feedback trading in USF stocks, but listing has reduced this further. While news has less impact and persistence and asymmetry effects are more evident post-futures, control sample results suggest these changes are not futures induced. Differences are evident across industries. The need for analysis of an appropriate (industry based) control sample if reliable policy conclusions are to be reached is highlighted.

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INTRODUCTION

In recent years empirical analysis of the impact of futures trading on the underlying market has moved beyond consideration of the simple issue of whether or not the level of volatility has changed post-futures, to consideration of the effect of derivatives on wider market dynamics (see, for example, Antoniou, et al (1998), Gulen and Mayhew (2000), and Kavussanos et al (2004)). This change in empirical focus reflects the recognition at a theoretical level that the traditional destabilisation/stabilisation debate is too simplistic. In particular, the view that increased (decreased) volatility following the onset of futures trading is necessarily undesirable (desirable) lacks validity once the relationship between information and volatility is considered (see, for example, Ross (1989) and Antoniou and Holmes (1995)). Concern about the extent to which derivatives influence the underlying market cannot be resolved at the level of theory, since increased volatility can be the result of either destabilising speculation or improved information flows. However, if reliable conclusions, and associated policy implications, are to be drawn from empirical analysis, it is necessary to adopt an approach which can distinguish between these different causes of changes in volatility levels. Furthermore, to clearly understand the impact of futures trading on the underlying market it is necessary not only to consider the second moment of the distribution of asset returns, but also to give consideration to the first moment. By considering both the extent of serial correlation of returns and the nature of volatility pre- and post-futures more reliable conclusions can be drawn about the extent to which further regulation of derivative markets, such as higher margins, narrow price fluctuation limits and restrictions on the issue of contracts, is justified. To this end Antoniou et al (2005) examine the effect of futures trading on a range of indexes utilising

Sentana and Wadhwani's (1992) heterogeneous trader model[1]. This model explicitly recognises the existence of both market participants who are rational expected utility maximisers and also those who are positive feedback (trend chasing) investors. This allows consideration of the consequences of derivatives not only on underlying volatility, but also on the extent to which futures inhibit or promote feedback trading in the cash market. Antoniou et al (2005) find that as far as index futures are concerned derivative trading appears to stabilise the market by reducing the impact of feedback traders.

While Antoniou et al (2005) undoubtedly move the debate forward and provide important insights, their analysis is limited to the effects of trading index futures in six countries, with only one event date in each country. As McKenzie et al (2001) point out, studies of stock indexes are useful in assessing the market-wide impact, but any effect on the underlying stock market can be dissipated across the many constituent stocks in the index, making the true effect difficult to detect. In addition, the index itself is not a tradeable asset, whereas stocks clearly are. Hence, the influence of futures on feedback trading and volatility might be more noticeable at the level of individual stocks. Indeed, concern that single stock futures (SSFs) might have an adverse impact on the underlying has led to tighter restrictions on such instruments than on index futures[2]. An added advantage of analysing SSFs is that they are characterised by multiple introduction dates within a given market.

SSFs were introduced on the London International Financial Futures and Options Exchange (LIFFE[3]) in January 2001 with the introduction of Universal Stock Futures (USFs)[4]. USFs are futures contracts whose underlying securities are individual shares on some of the world's largest companies. Interestingly, USFs are not limited to stocks traded in the London Stock Exchange. Rather the contracts are listed on stocks being traded in a range of different markets and thus LIFFE was the first exchange to launch 'cross-border' SSFs. Thus USFs clearly can be seen as an important additional instrument for investors, since they can allow a better match for investment and risk management purposes than do broad based index futures or domestic SSFs. For example, USFs allow individual components of a portfolio to be hedged without having to change the make-up of the portfolio and they also offer tax benefits (e.g. they are exempt from stamp duty for UK stocks due to them being cash settled). The importance of USFs to market participants can be seen by the rapid growth in the number of stocks on which USFs are written. At the first listing date (29 January 2001) 25 USFs were listed on stocks traded in 8 countries. The number traded had increased to 97 by the end of 2001 (11 countries) and to 433 by June 2005 covering stocks listed in 13 countries[5]. In 2004 trading volume exceeded 12.5 million contracts. However, in spite of their success, concerns about their impact on the underlying market still remain. It is, therefore, interesting and informative to investigate the extent to which USF trading has changed the characteristics of the first and second moment of returns in the stock market.

This paper examines how trading in USFs affected the underlying assets, using the approach previously adopted by Antoniou et al (2005). Thus consideration is given to both feedback trading and volatility, including the asymmetric response of volatility to positive and negative news on a stock by stock basis. Given the significance and unique characteristics of USFs, this market provides a key opportunity to investigate further the impact of futures trading on the underlying in a way which will allow a range of issues not previously addressed to be examined. Because USFs are stock-specific contracts, it is expected that any futures-induced effects on the volatility and/or market dynamics will be easier to identify. Furthermore, studies that have examined the introduction of index futures have by definition only examined one event date, within a given market setting. In the case of USFs, there have been multiple introduction dates and the contracts are listed on stocks being traded in several different markets. Since USFs are traded on stocks listed in a range of countries, each of which has different market characteristics, it will be possible to determine if these characteristics influence the impact on the underlying[6]. In addition, the cross-border nature of USFs allows us to investigate a further issue, namely the impact of foreign-listed futures on their domestic underlying stock markets. Moreover, given the large number of different USFs listed, it is possible to examine whether the impact of futures differs across industries, for example because of differences in analyst coverage. Also, with USFs it is possible to consider how market dynamics have changed over the sample period for a control sample of individual stocks, in a way which is not feasible for index futures. By first modelling the listing decision for USFs and basing the choice of the control sample on this model, it is possible to overcome potential endogeniety issues inherent in previous studies. Hence, any conclusions drawn can be considered to be more robust. Thus, investigation of the introduction of USFs should provide important and reliable insights about the extent to which futures trading affects the market dynamics of the underlying and, hence, the extent to which further regulation is warranted.

The rest of the paper is organised as follows. The next section briefly discusses the literature on the impact of futures trading, sets out the main features of the feedback trading model and identifies hypotheses to be tested. The third section provides brief information on USFs, discusses the data to be used in the empirical analysis and the methodology for selecting a control sample. Results are then presented and the final section concludes the paper.

FUTURES TRADING, THE UNDERLYING MARKET AND FEEDBACK TRADING

Concern over the impact of derivatives predates the introduction of contracts written on financial instruments, but arguably has intensified since stock based futures were introduced in 1982[7]. The main argument levelled against futures is that their existence might attract destabilising speculators, which may in turn lead to higher stock market volatility, a perception of higher risk, thus, potentially raising the cost of capital and impacting on the wider economy[8]. Such concerns have led to restrictions of stock based futures, including the ban on trading SSFs in the US until 2002. At a theoretical level it has been recognised in recent years that such a restricted view of the potential impact of futures on volatility is misguided. Following the work of Ross (1989) it has been acknowledged in the futures literature that increased volatility may be the result of greater information flows to the market rather than necessarily being the result of destabilising speculation (see, for example, Antoniou and Holmes (1995) and Chatrath and Song (1998)). Hence, based on theoretical considerations alone it is not possible to reach unambiguous conclusions about the impact of futures on underlying market volatility and, more importantly, about the causes of any changes in volatility in the cash market. Rather, such conclusions can only be drawn after appropriate empirical analysis.

More recently, research in this area has taken account of the possible existence of noise and other non-rational traders in the market and of how these might impact on the volatility of the underlying following the introduction of futures trading. For example, the asymmetric response of volatility to news has been examined using an asymmetric GARCH framework (see, for example, Antoniou et al (1998), McKenzie et al (2001) and Kavussanos et al (2004)). In an important and interesting development, Antoniou et al (2005) argue that it is not sufficient to examine the impact of futures trading on volatility, rather it is necessary to also investigate how serial correlation of returns changes post-futures. Specifically they argue that "If derivative markets were to attract noise traders in general and *positive feedback traders* in particular, then the potential for destabilization would be real and the claim for further regulation warranted." (Antoniou et al (2005), p221, emphasis added). Thus, rather than simply looking at the volatility of the underlying market, Antoniou et al (2005) investigate the first and second moments of returns behaviour using a model in which there are both rational traders and feedback traders. By using Sentana and Wadhwani's (1992) heterogeneous trader model it is possible for Antoniou et al (2005) to determine not only whether the market dynamics have changed post-futures, but crucially why any change has occurred. Specifically, by examining the extent to which the introduction of futures promotes/inhibits positive feedback trading, it is possible to determine whether any changes in market dynamics are due to improved information flows or whether they are the result of destabilizing speculation.

Sentana and Wadhwani (1992) model the behaviour of two groups of investors: rational 'smart money' investors who responds rationally to expected returns subject to their wealth limitation and; feedback traders (or trend chasers) who do not base their asset decisions on fundamental value, but rather react to previous price changes.

The demand for stocks by feedback traders F_t is modelled as:

$$F_t = \gamma R_{t-1} \qquad (1)$$

where R_{t-1} denotes the return in the previous period. The value of the parameter γ allows discrimination between two types of feedback traders: $\gamma > 0$ refers to the case of positive feedback traders, who buy stocks after a price rise and sell after a price fall; $\gamma < 0$ indicates negative feedback traders, who sell after a price rise and buy after a price fall. Positive feedback trading can result from extrapolating expectations about stock prices or trend chasing. Note that positive feedback traders have the effect of moving prices away from their fundamental value. If futures trading promotes feedback trading in the cash market, then a case may be made for further regulation since the market's ability to allocate resources efficiently will be undermined.

The demand for stocks by rational/smart money traders S_t is determined by a mean-variance model:

$$S_t = (E_{t-1}R_t - \alpha)/\mu_t \qquad (2)$$

where E_{t-1} denotes the expectation operator, α is the return on a risk free asset and μ_t is the risk premium and is modelled as a positive function of the conditional variance (σ^2_t) of the stock price. Thus, $\mu_t = \mu(\sigma_t^2)$, where μ is the coefficient of risk aversion.

Equilibrium in the stock market requires that all stocks are held:

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

If all investors are smart money/rational investors (F_t = 0), then market equilibrium (S_t = 1) yields Merton's (1973) dynamic capital asset pricing model:

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

Allowing the existence of both groups in the stock market, substituting (1) and (2) in (3) and assuming rational expectations yields:

$$R_t = \alpha + \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2)R_{t-1} + \varepsilon_t \tag{5}$$

As can be seen from equation (5) in a market with rational investors as well as feedback traders the resulting return equation contains the additional term R_{t-1}, so that stock returns exhibit autocorrelation. The pattern of autocorrelation in returns depends on the type of feedback traders captured by the parameter, γ. Positive (negative) feedback trading $\gamma > 0$ ($\gamma < 0$) implies negatively (positively) autocorrelated returns. Furthermore, the extent to which returns exhibit autocorrelation varies with volatility, $\mu(\sigma_t^2)$. For example, consider the case when there is an increase in volatility. Due to the rise in volatility, smart money traders reduce their demand for stocks (see equation 2), thus allowing feedback traders to have a greater impact on the stock price. Consequently, a larger discrepancy between the current stock price and its fundamental value results, so that returns exhibit stronger autocorrelation. Modifications of equation (5) are required to account for autocorrelation due to market frictions/inefficiency. Thus, the empirical version of the model is given by:

$$R_{it} = \alpha + \mu\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{it-1} + \varepsilon_t \quad ; \qquad \varepsilon_t \sim GED(0, \sigma_t^2) \qquad (6)$$

where R_{it} is the return of the underlying stock i on day t. σ^2_t is the conditional variance of returns at time t, and ε_t is the residual that is assumed to follow a Generalized Error Distribution (GED) with mean zero and time-varying variance σ^2_t. The coefficient φ_0 is used to capture the autocorrelation induced by potential market frictions or thin-trading.[9] The coefficient $\varphi_1 = -\gamma\mu$ and the presence of positive feedback trading implies that φ_1 is negative and statistically significant.

It is clear from equation (6) that the variance of returns is time varying. Thus to complete the model it is necessary to specify the conditional variance. It is now well established in the literature that stock returns are characterized by conditional heteroskedasticity. The model is, therefore, completed by using a GARCH specification for the conditional volatility. In order to determine which GARCH specification to use in the analysis, extensive tests were conducted to see which form of the conditional volatility equation best seems to model the return data. The symmetric model was compared with the two most popular asymmetric models, namely the asymmetric GARCH model of Glosten, Jagannathan and Runkle (1993), GJR-GARCH, and the exponential GARCH (EGARCH) model of Nelson (1991). On the basis of the log-likelihood, Akaike Information Criterion

(AIC) and Schwarz Bayesian Criterion (SBC), the asymmetric models tend to fit the data better than the symmetric GARCH model, with GJR-GARCH performing better than EGARCH.[10] Therefore, the main analysis is based on the GJR-GARCH (1,1) model and conditional variance of returns are specified by the following process:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \delta S_{t-1} \varepsilon_{t-1}^2 \qquad (7)$$

where σ^2_t is the conditional volatility at time t, ε_{t-1} is the innovation at time t-1 and S_{t-1} is a dummy variable which assumes a value of one in response to bad news ($\varepsilon_{t-1}<0$) and zero in response to good news ($\varepsilon_{t-1}\geq 0$). If the coefficient δ is positive and statistically significant, then it would indicate that a negative shock has a greater impact on future volatility than a positive shock of the same size. α_1 is typically referred to as the news coefficient, since it captures the impact of the most recent innovation and β is a measure of persistence. α_0 represents the unconditional volatility.

While there is a vast literature examining the impact of equity derivatives trading on the underlying stock market, most of the evidence comes from studies of either stock index futures or single stock options[11]. The results of previous studies are mixed; with some suggesting volatility has increased after the introduction of futures (or options) trading while others have suggested volatility has decreased. To date, futures on single stocks (such as USFs) have been subject to very little attention in the academic literature. One notable exception is the study by McKenzie et al (2001) which investigates the effects of the introduction of individual share futures (ISF) on stock market volatility in Australia.

However, at the time of McKenzie et al's (2001) work there were only 10 stocks on which ISFs were traded and all of these were shares listed on the domestic market. Also, the level of trading in ISFs during the period analysed was low compared to USFs[12]. Furthermore, McKenzie et al (2001) examine the impact on the level of systematic risk and volatility of the underlying shares, rather than using an approach which recognizes the existence of non-rational traders.

In the light of the above discussion and the characteristics of USFs outlined in the introduction, this paper seeks to examine a number of issues relating to the impact of trading in USFs on the underlying market using Sentana and Wadhwani's (1992) heterogeneous trader model approach. Following Antoniou et al (2005) we estimate the model as described in equations (6) and (7) for both a pre-futures period and a post-futures period. Comparisons can then be made of the estimated coefficients to draw conclusions about whether differences exist between pre- and post-futures periods in terms of the degree of feedback trading and the level and nature of the volatility of the underlying market. Specifically, with respect to equations (6) and (7) we test the null hypotheses that there is no difference between the pre- and post-futures period in relation to the coefficient relating to feedback trading $\varphi_{1,}$ that relating to the constant component of autocorrelation, φ_0, and the coefficients which describe the conditional volatility of returns, α_0, α_1, β and δ. The alternative hypotheses are that there are differences in the coefficients between the two time periods.

If the view that the introduction of futures will lead to an improved information flow, an associated improvement of informational efficiency and a reduction in the impact of feedback and other noise traders is correct, then we would expect that we would reject the null hypotheses (see, for example, the arguments put forward by Cox (1976) and Ross (1989)). In particular, we would expect there to be a reduction in feedback trading, in the constant component of autocorrelation, in the asymmetric response of volatility to news post futures and in the persistence coefficient and an increase in the news coefficient. On the other hand, if futures trading is destabilizing and promotes feedback trading we might expect the opposite. We will also examine whether there are differences in findings for USFs written on stocks listed in different countries (to examine cross-border and market regulation effects) and in different industries.

It needs, of course to be recognised, that it is possible that factors, other than the introduction of futures contracts, may affect the variables considered in each of our hypothesis tests. For example, market-wide changes that altered the dynamics of the market may have occurred around the time of the USF introduction dates. Tests may erroneously attribute such a change, if it occurred, to the introduction of USFs. Therefore, to ensure the reliability of any conclusions and policy implications drawn from the empirical analysis of the impact of USFs, it is necessary to implement a control procedure to account for these possible sources of bias. Thus, to test the robustness of any results about the effect of futures on the underlying market, equations (6) and (7) are also estimated for a sample of control stocks on which USFs are not written. As McKenzie et al (2001) point out, one problem associated with a control group is that the distinguishing feature between the USF sample stocks and the control sample stocks, namely that the former sample contains stocks with individual futures written on them, may be endogenous. In other words, USF stocks may have futures written on them *because* of their characteristics in the pre-listing period. Thus, even using a control sample may fail to provide a true test of robustness unless this endogeneity problem is addressed. Therefore, in this paper the control sample is chosen by identifying the 'nearest-neighbour' stocks that were eligible, but not selected for futures listing, using the procedure outlined in the next section.

By comparing apparent listing effects between the sample of USF stocks and the control sample, it is possible to distinguish between the changes that may have been caused by futures listing and those caused by other factors, such as the endogenous nature of the USF listing decision and/or changes in market-wide trends. If the USF sample behaves differently to the control stocks, then conclusions drawn with respect to the impact of futures introduction are strengthened.

DATA AND THE CHOICE OF CONTROL STOCKS

LIFFE began trading 25 USFs on January 29, 2001. Each USF contract represents 100 shares of the underlying stocks, except contracts written on UK and Italian based stocks which represent 1000 stocks. The level of volume and open interest has increased rapidly from the early months of trading as illustrated by figure I which shows the monthly total volume and open interest on all USFs traded on LIFFE from its launch date to June 2005. The LIFFE website provides comprehensive information of all the USF stocks and the dates of their listing (see http://www.databyeuronext.com).

INSERT FIGURE I ABOUT HERE

The first step in the sample selection process was to identify all the stocks that have USFs listed between January 2001 and December 2001. The sample is restricted to such stocks for two reasons. First, being the earliest listed USFs it is believed that these might have a more prominent impact on the underlying market than USFs listed later. Second, GARCH estimates are less reliable in small samples and by restricting the sample to USFs listed in 2001 a sufficiently long post-futures period is available. Next, the existing sample was screened using several criteria, to remove any observation that may have introduced a potential bias to the results. In order to focus our analysis on the effect of USF trading, the only stocks included are those with futures first introduced on LIFFE and not listed in any other futures exchange within the sample period. Including stocks which have futures traded in their domestic markets would make it difficult to identify the effect of USF listing. For example, since LIFFE introduced USFs, the Finland Helsinki Stock Exchange has started trading SSFs on one of the USF stocks, Nokia. In order to avoid interpretation problems, this particular stock was excluded from the empirical analysis. Furthermore, any stocks with futures delisted in the sample period were also omitted from the analysis since there may be other fundamental factors affecting their returns or their USFs may be characterised by very thin trading. Finally, to be selected, a stock must also have daily price data for the whole sample period.

INSERT TABLE I ABOUT HERE

In total, there are 80 USF stocks that fulfil these criteria. Table I provides a list of the sample of USF stocks used in this study, with information on their market capitalisation, industry sector and home country. Daily closing stock prices are obtained from Datastream for a period of three years prior, to three years after the listing of each stock, yielding in excess of 750 observations per stock for each of the sub-periods. The daily returns for selected individual stocks are adjusted for any capitalisation changes. Returns are calculated as in equation (8):

$$R_{i,t} = 100 * (\ln P_{i,t} - \ln P_{i,t-1}) \tag{8}$$

where $R_{i,t}$ and $P_{i,t}$ are the return and the closing price of stock i on day t.

The next stage involves selecting stocks to be included in the control sample. To this end, analysis is undertaken of the futures listing choices by LIFFE, to allow determination of control stocks that explicitly account for any endogeneity issues in the futures listing decision. First, the relative importance of various firm-specific characteristics influencing the exchange's listing choice is examined using a logit model similar to that of Mayhew and Mihov (2004)) and Ang and Cheng (2005) who successfully modeled the selection for derivatives listing in the U.S. The following versions of the logistic regression are used:

$$\log(\frac{p}{1-p}) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SIZE + \varepsilon \tag{9}$$

$$\log(\frac{p}{1-p}) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SVOL + \alpha_4 SSTD + \alpha_5 SIZE + \varepsilon \tag{10}$$

$$\log(\frac{p}{1-p}) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SIZE + \alpha_4 MKT + \alpha_5 IND + \varepsilon \quad (11)$$

$$\log(\frac{p}{1-p}) = \alpha_0 + \alpha_1 VOL + \alpha_2 STD + \alpha_3 SVOL + \alpha_4 SSTD + \alpha_5 SIZE + \alpha_6 MKT + \alpha_7 IND + \varepsilon \quad (12)$$

The dependent variable is the log-odds ratio of being selected for USF listing. p is the probability of being selected. If a stock is picked up for futures listing by LIFFE, the listing dummy is 1, otherwise it is 0. VOL is the daily average trading volume over the 250 trading days prior to the listing month. STD is the standard deviation of daily stock return over the same period. SIZE is the market capitalisation of the firm at the month end prior to the listing month. The variables SVOL and SSTD are ratios of 30-day to 250-day average daily trading volume and standard deviation, which are used as proxies for the short-term volume and volatility relative to the volume and volatility within the year prior to the listing months. MKT and IND are market and industry indicators used to test whether trading location and the industry group affect the probability of a stock being selected for futures listing. Equations (9) - (12) are estimated for a pooled dataset containing daily observations for all stocks that were classified as eligible for futures listing, but had not yet had futures listed.

Next, following the estimation of the logistic regressions, the predicted probability of being listed for each eligible stock at each listing month is generated (i.e. the propensity-score). Finally, the control sample is selected by choosing the stocks that trade in the same market and industry as their USF counterpart and which match the USF sample as closely as possible in terms of the propensity-score, as estimated by the logit model (i.e.

the 'nearest-neighbour'). The results suggest that the logistic regression models capture the selection process well, with between 82% and 86% of stocks being correctly classified. Since the base model (equation (9)) performs best, classifying 86% of the eligible stocks correctly, the control sample is selected using the propensity-score estimated with this model.[13,14]

INSERT TABLE II ABOUT HERE

Table II provides summary statistics for portfolios of USF stocks and the control sample stocks, based on country (panel A) and industry (panel B). The table shows the mean (μ), standard deviation (σ), measures of skewness (S) and Kurtosis (K), the Jarque-Bera test of normality (JB), the ARCH test and the Ljung-Box statistic (LB) for 5 lags. There is clear evidence of significant departures from normality (see JB) across all portfolios (USF and control) and clear evidence of ARCH effects. The LB statistics show evidence of temporal dependencies in the first moment of the distribution of returns in more than half of all portfolios, while for squared returns, the LB statistic is significant in all cases. To examine the extent of interrelationships between autocorrelation and volatility, further investigation is required.

EMPIRICAL RESULTS

Consideration is now given to the main research question addressed in this paper, relating to the impact of trading in USFs on the underlying market dynamics. In undertaking the empirical analysis, equations (6) and (7) are estimated for the 80 USF stocks in the sample for pre- and post-futures periods separately[15]. The same 160 estimations are undertaken for the control sample of stocks. In order to analyse the hypotheses identified in the second section the results of these estimations are summarized in a number of tables, rather than presenting the results of all 320 estimations separately.[16]

INSERT TABLE III AND IV ABOUT HERE

Tables III and IV summarise the results of the maximum likelihood estimates of the empirical version of the feedback model, allowing for asymmetric responses of volatility to news (i.e. equations (6) and (7)) for USF stocks. Summary results relating to the six key coefficients (φ_1, φ_0, α_0, α_1, β and δ) are reported. Table III shows the percentage of stocks for which each coefficient was statistically significantly different from zero for the pre-futures and post-futures periods, based on the t-statistic and the 10% level of significance. Panel A shows results for the whole USF sample, panel B provides the figures broken down by country, while panel C provides the same information by industry[17]. Table IV shows the percentage of USF stocks for which the relevant coefficient post-futures was either significantly increased or significantly decreased compared to the pre-futures value or for which there was no significant change in the post-futures period, based on the Wald statistic at the 10% level. Again, panel A shows the results for the whole USF sample, panel B shows the figures broken down by country and panel C broken down by industry. Tables V and VI show the same information, but this time for the control stocks.

INSERT TABLE V AND VI ABOUT HERE

Overall, there is clear evidence of GARCH effects with α_1 (the impact of news on volatility) being significant in more than a third of cases pre-futures and β (the persistence of innovations) being significant in all cases pre- and post-futures for both USF and control stocks. In addition, the GJR-GARCH model appears generally appropriate given that in both time sub-samples and for both USF and control stocks the asymmetry coefficient, δ, is significant in considerably more than half of the estimations. However, a striking feature of the results is the overall low level of feedback trading (φ_1) either pre- or post-futures. In the pre-futures period, as shown in table III, panel A, only 13.75% of USF stocks exhibit feedback trading and this falls to 5% for the post-futures period. This is in contrast to the evidence presented in Antoniou et al (2005) where five out of six markets exhibit statistically significant feedback trading pre-futures. However, Antoniou et al (2005) also find that in the post-futures period only one market has statistically significant feedback trading. Since all of the markets considered in this study have index futures traded on them prior to the onset of trading in USFs, the finding of low feedback trading in the current study is, perhaps, not surprising. The fall in the number of stocks for which φ_1 is statistically significant post-futures suggests that, to the extent that futures trading has any impact, USFs have a positive effect by reducing the level of feedback trading. This is confirmed by the results presented in table IV, panel A, which show that for only 2.5% of USF stocks is there a significant increase in φ_1, while there is a significant reduction in the feedback coefficient for 11.25% of stocks. While a similar pattern is evident for the control sample (table VI, panel A), the changes post-futures are less clear, with 7.5% of stocks exhibiting a significant increase in φ_1 and 12.5% a decrease. Thus the changes for the USF stocks appear more marked, suggesting the change post-futures, while limited, is at least in part due to the onset of trading. Nonetheless, the overall level of, and impact of USFs on, feedback trading is limited.

The results in relation to φ_1 in panel B of table III show that there are differences in the level of feedback trading between countries. Of the nine countries examined, three markets (Italy, Switzerland and the US) exhibit feedback trading in 20% or more of the stocks pre-futures[18], while in four markets there are no stocks for which φ_1 is significant. In the post-futures period there is no market in which more than 20% of the stocks exhibit feedback trading and it is only for Switzerland for which the figure is 20% (representing one stock). The pattern for the control stocks (table V, panel B) are broadly similar, although again the reduction in feedback trading is less marked. Finally panel C in tables III-VI suggests that there are some differences across industries, but that these are not related to the onset of trading USFs.

In relation to the constant component of the autocorrelation, φ_0, the findings for USF stocks (table III, panel A) are broadly similar to those for φ_1. Specifically, while the coefficient is significant for less than 30% of stocks pre-futures, this falls by more than ten percentage points post-futures. Antoniou et al (2005) state that “improvements in efficiency will most likely show up as reductions in φ_0 rather than changes in φ_1." (p231). Examination of the results for the control sample in table V reveals that the percentage of stocks which exhibit a significant φ_0 pre-futures is the same as for the USF stocks. However, post-futures the percentage rises for the control sample by over 6 percentage points. Thus, this provides some evidence to suggest that trading in USFs has had a positive effect on the efficiency of the underlying market. Again, the results for USF stocks by country (table III, panel B) show differences, with big improvements in efficiency for Italy and the Netherlands, while for the control stocks the movements are much less marked. Panel C of all four tables again demonstrates industry effects, but with the exception of the consumer goods and financial industries, the findings for the USF and control stocks are broadly similar.

The impact of USF trading on stock market volatility can be assessed first through a comparison of the α_0 coefficient in the pre-and post-USF periods. An increase in α_0 would be an indication of increased unconditional volatility in the post-USF period. From table III panel A it is evident that the number of stocks with a significant α_0 has increased marginally post futures (from 53 to 57). In contrast, for the control sample, there has been a decrease (from 62 to 51, table V panel A). However, examination of panel A of tables IV and VI reveals that the two samples (USF and control) have very similar patterns in terms of statistically significant differences. α_0 has shown a significant increase for 23.75% of USF stocks and 18.75% of control stocks, while the percentages exhibiting a decrease are 57.5% and 60% respectively. From panel B of the four tables there is no clear pattern of country differences, while panel C of tables III-VI suggests that again there are differences across industries, but that these are not related to the onset of futures trading.

Consideration of changes in α_1 and β from pre- to post-futures provide some initially surprising results. The number of stocks for which α_1 is statistically significant falls post-futures (table III, panel A), while the percentage of stocks exhibiting a statistically significant increase in α_1 post-futures (16.25%) in less than that exhibiting a decrease (18.75%) (see, table IV). Similarly, the percentage of USF stocks for which there is a statistically significant increase in β (56.25%, see table IV, panel A) is much greater than that for which there is a decrease (15%). This suggests that news is having less impact and old innovations more persistence post-futures. However, when the control sample is examined (table VI), a very similar pattern of results emerges (α_1 increases for 20% and falls for 31.25% of stocks, while β is significantly higher for 55% and lower for 21.25% post-futures). Thus, to the extent that there is a change from the pre-futures to the post-futures period, this does not appear to be futures induced. These results clearly highlight the need for a control sample to be analysed to ensure that inappropriate inferences and policy recommendations are not reached concerning the impact of futures. If consideration had only been given to USF stocks a conclusion may have been incorrectly drawn that futures trading had impacted negatively on market dynamics and, hence, further regulation was warranted. Analysis of panels B and C of the four tables provide no clear evidence of country or industry effects, although again there are some differences by industry.[19] However, there is no evidence that these differences are futures induced. Again, this provides important insights about the control sample. Not only is there a need to undertake analysis for a control sample, but it is important that the make up of the control sample is determined by a number of factors including industry.

The asymmetry coefficient, δ, shows marked changes from the pre- to the post-futures period for USF stocks. The percentage of stocks with a value of δ significantly different from zero increases from 57.5% pre-futures to 88.75% post-futures (table III, panel A), while table IV panel A demonstrates that there is a significant increase in δ in 50% of all USF stocks. One explanation which has been put forward in relation to δ is that asymmetries are related to noise trading (see Antoniou et al (1998)). Thus, the increase in δ could be indicative of more movements away from fundamental value post-futures, although the evidence in relation to φ_1 discussed above suggests that it is not feedback trading which has increased. However, it is again informative to examine the results for the control stocks. The pattern for these stocks as shown in panel A of tables V and VI is very similar to that for the USF stocks (40% exhibit a statistically significant increase in the value of δ post-futures), again suggesting that any changes are unrelated to the introduction of USFs. Country differences are evident from panel B of the tables, with the US showing a reduction in the percentage of USF stocks for which δ is significant (similar to Antoniou et al (2005) which finds that δ decreases post-futures for the US), while other markets are subject to an increase. For the control sample even the US exhibits an increase in the number of stocks for which δ is significant. Once again, there are differences across industries, but no clear pattern of differences between the USF and control samples.

To check the robustness of the results further estimations were undertaken. Specifically, two types of equally weighted portfolios of stocks were created, namely portfolios based on the country in which the underlying is traded (9 portfolios each for USF stocks and control stocks) and portfolios based on the industry of the stock (6 portfolios for USF and 6 for control). Equations (6) and (7) were then estimated for these 30 portfolios[20]. Overall, the findings are qualitatively similar to the results presented in tables III toVI. This finding, together with the results presented earlier, is interesting given that the markets on which the stocks underlying USFs are traded vary significantly. For example, there are major differences in the characteristics of market participants and the regulation and the size of the markets between the UK, the US, larger continental markets, such as France and Germany, and the smaller continental markets, like Sweden and Switzerland. Concerns about the impact of derivative trading on the underlying market are arguably stronger for smaller, less liquid markets[21]. This is particularly true in relation to cross-border futures on underlyings traded in small markets, where the futures contracts are traded in a major derivatives market such as LIFFE. However, the results presented here suggest that such concerns are unfounded, since they indicate that there is no systematic difference between the way small and large markets are affected by the introduction of USFs. For example, the country portfolio results suggest there were no countries in which the post-futures value of φ_1 was significantly different from the pre-futures value and only two countries in which φ_0 was significantly different post-futures. Given that the two countries are Switzerland and the US, changes do not appear to be related to the size of the markets.

The results in relation to the industry-based portfolios, again suggest that there are differences across industries in terms of feedback trading and autocorrelation. For example, for the USF stock portfolios φ_0 and φ_1 are both significant pre-futures for the resources and consumer goods industries, but not significant post-futures, while for other industries there is no evidence of feedback trading or autocorrelation, with the exception of the services industry for which φ_0 is statistically significant. However, while industry differences in feedback trading are interesting and possibly worthy of further investigation, the overall pattern of results from tables III-VI suggests that these industry-based differences are unrelated to futures trading[22].

Consideration is also given to the possibility of there being asymmetries in the feedback mechanism to investigate whether feedback trading is more intense during market declines. Hence, following Antoniou et al (2005) an additional term, $\varphi_2 | R_{t-1} |$, is added to equation (6) to capture any such possible effects (see Antoniou et al (2005) equation (9)). In all cases the additional term is insignificantly different from zero and the general results in relation to other coefficients are very similar. Finally, the feedback model was also estimated for windows of two years either side of the introduction of futures for country and industry portfolios[23]. Generally, the qualitative findings in relation to feedback trading for the two-year and three-year windows are consistent, although there are some differences in relation to the findings for α_0. Specifically, the post-futures α_0 is generally insignificantly different from its pre-futures value when a two-year window is used. However, the findings are similar for both USF and control portfolios suggesting that the conclusion that changes in α_0 are not futures induced remains valid. Thus, the general conclusions discussed earlier appear to be robust, given the range of additional tests undertaken.

CONCLUSION

In this paper, consideration is given to the impact of futures trading on the underlying market dynamics using a model which takes account not only of the volatility of the underlying, but also the extent to which derivatives promote or inhibit feedback trading. By examining the behaviour of the underlying markets for stocks on which USFs are traded, it is possible to gain insights not previously possible. Specifically, since USFs are listed on a range of stocks traded on a number of different markets with different characteristics and across a range of industries, it is possible to identify the extent to which there are country/market or industry specific effects. This is particularly important given the cross-border nature of USFs and that concerns about futures listing might be greater for stocks listed in less liquid, smaller markets. Furthermore, to the extent that derivatives do have an impact on the cash market, such effects are more likely to be evident in the behaviour of individual stocks which are tradable, rather than in the market dynamics of a non-tradable index. In addition, given the nature of USFs it is possible to address endogeniety issues inherent in previous studies, by designing a control sample based on the factors affecting the listing decision, and to examine more than one event date within a given market. Taking these factors into account means that results from this analysis will provide more reliable and wider ranging insights into the impact of derivative trading on the underlying market.

There is clear evidence that the level of feedback trading is low in both the pre-futures and post-futures period for the USF and control stock samples, with the pre-futures period exhibiting marginally more feedback trading. To the extent that there is a change post-futures, there is a greater reduction in feedback trading in the USF sample than in the control sample. Thus, any effect of futures on feedback trading appears to be small, but beneficial. For USF stocks changes in relation to the impact of news on volatility (α_1) and the persistence of innovations (β) and the extent to which volatility is affected asymmetrically by good and bad news (δ) look initially surprising. $\alpha 1$ tends to fall post futures, and β and δ rise. On the face of it, this appears to suggest that futures are having a destabilising impact. However, when these coefficients are examined for the control sample, the same picture is evident, suggesting that any changes in these parameters from the pre- to the post-futures period are not futures related. Equally, unconditional volatility (α_0) behaves in a similar manner for both the USF and control stocks. These findings demonstrate the importance of undertaking estimations not only for stocks on which USFs are written, but also for a control sample. In the absence of the results for the control sample, inappropriate policy conclusions may have been reached. Specifically, the evidence in relation to α_1, β and δ suggests that post-futures there has been a negative effect on market dynamics and, hence, further regulation of USFs may have been called for. However, by also examining a control sample selected on the basis of modeling the listing decision, it is clear that such calls are unwarranted.

Examination of any possible differential impact by country suggests that systematic differences between the way small and large markets are affected by the introduction of

USFs do not exist. Thus, concerns that USFs might impact (more) negatively on smaller, less liquid markets appear unfounded. The results also suggest that there are clear differences in the pattern of market dynamics between industries, but that such differences are not futures induced. Examination of why such differences exist is worthy of further study, but is beyond the scope of this paper. However, the results in relation to industry differences clearly demonstrate the need to construct control samples in a way which directly takes account of the industry in which the stock is based.

Overall, the findings provide interesting and useful insights and suggest that the listing of USFs has not impacted negatively on the underlying markets. It should, of course, be remembered that in all of the markets considered here index futures already existed prior to the introduction of USFs. Furthermore, all of the stocks in the USF sample are highly liquid stocks. Thus, it might be expected that these stocks would be less affected by the introduction of single stock futures. Nonetheless, to the extent that USFs have impacted on feedback trading and wider market dynamics, the influence appears to have been positive, leading to a small reduction in feedback trading and improved efficiency, as indicated by the reduction in φ_0.

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Figure I : USF Monthly Volume and Open Interest (January 2001 - June 2005)

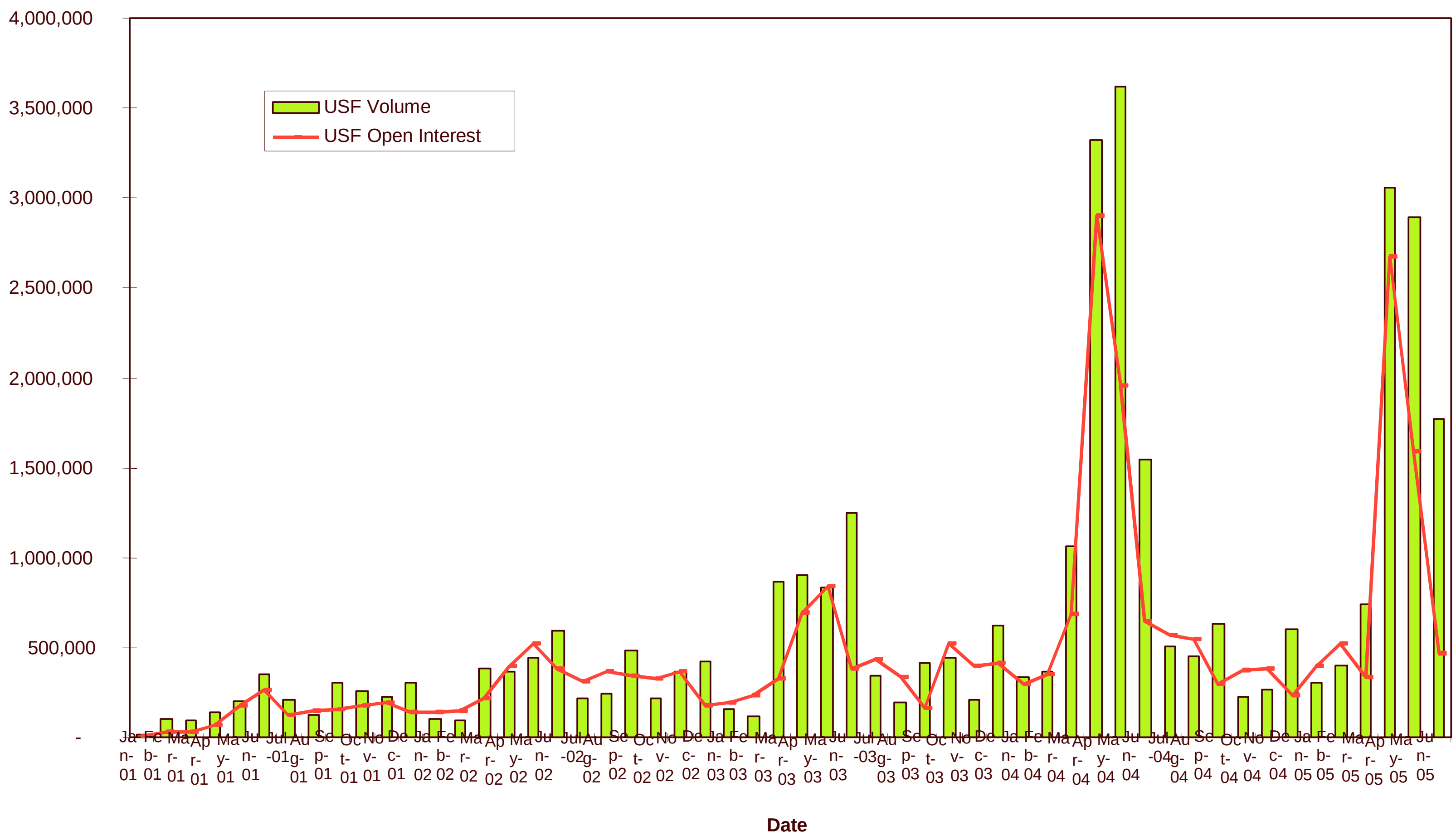

Table I: The sample of stocks used on which Universal Stock Futures are listed

I.D Code	Stock Name	Country	Sector	Market Cap (€m) 25 Oct 2001	Introduction Date	I.D Code	Stock Name	Country	Sector	Market Cap (€m) 25 Oct 2001	Introduction Date
FR1	Total Fina Elf SA	France	Resources	114,402	01/29/01	UK4	GlaxoSmithKline plc	UK	Consumer Goods	185,898	01/29/01
FR2	France Telecom SA	France	Services	48,138	01/29/01	UK5	AstraZeneca plc	UK	Consumer Goods	88,156	01/29/01
FR3	Alcatel SA	France	Technology	20,209	01/29/01	UK6	BT Group plc	UK	Services	48,100	04/02/01
FR4	Axa SA	France	Financial	42,590	04/02/01	UK7	Lloyds TSB Group plc	UK	Financial	62,597	04/02/01
FR5	Vivendi Universal SA	France	Services	55,095	05/14/01	UK8	Shell Transport & Trading Company plc	UK	Resources	80,652	05/14/01
FR6	BNP Paribas SA	France	Financial	41,021	05/14/01	UK9	Barclays plc	UK	Financial	55,576	05/14/01
FR7	Carrefour SA	France	Services	40,749	05/14/01	UK10	Royal Bank of Scotland Group plc	UK	Financial	75,901	05/14/01
FR8	Sanofi-Synthelabo SA	France	Consumer Goods	55,660	31/10/01	UK11	Tesco Plc	UK	Services	26,585	31/10/01
FR9	Suez SA	France	Resources	34,681	31/10/01	UK12	Diageo Plc	UK	Consumer Goods	36,958	31/10/01
GER1	Deutsche Telekom AG	Germany	Services	78,414	01/29/01	UK13	Legal & General Group Plc	UK	Financial	12,334	31/10/01
GER2	Deutsche Bank AG	Germany	Financial	38,532	01/29/01	UK14	Unilever Plc	UK	Consumer Goods	22,723	31/10/01
GER3	Siemens AG	Germany	General	48,399	01/29/01	UK15	HBOS Plc	UK	Financial	44,783	31/10/01
GER4	Allianz AG	Germany	Financial	72,356	04/02/01	UK16	Sainsbury (J) Plc	UK	Services	11,425	31/10/01
GER5	Münchener Rücksversicherungs Gesellschaft AG	Germany	Financial	55,720	04/02/01	UK17	Abbey National Plc	UK	Financial	24,039	31/10/01
GER6	DaimlerChrysler AG	Germany	Consumer Goods	40,582	05/14/01	US1	Microsoft Corporation	USA	Technology	369,701	01/29/01
GER7	E.ON AG	Germany	Resources	44,577	05/14/01	US2	Cisco Systems Inc	USA	Technology	141,138	01/29/01
GER8	Bayerische Hypo-und Vereinsbank AG	Germany	Financial	18,574	05/14/01	US3	Intel Corporation	USA	Technology	191,186	01/29/01
GER9	Volkswagen AG	Germany	Consumer Goods	11,592	05/14/01	US4	Exxon Mobil Corporation	USA	Resources	305,899	01/29/01
GER10	BASF AG	Germany	General	23,630	31/10/01	US5	Citigroup Inc	USA	Financial	273,381	01/29/01
GER11	Bayer AG	Germany	General	24,518	31/10/01	US6	Merck & Co. Inc	USA	Consumer Goods	170,835	01/29/01
GER12	SAP AG	Germany	Technology	36,302	31/10/01	US7	Oracle Corporation	USA	Technology	91,066	04/02/01
IT1	Eni SpA	Italy	Resources	55,968	01/29/01	US8	Sun Microsystems Inc	USA	Technology	33,250	04/02/01
IT2	Assicurazioni Generali SpA	Italy	Services	38,467	03/19/01	US9	General Electric Company	USA	General	411,450	04/02/01
IT3	Enel SpA	Italy	Resources	40,144	03/19/01	US10	Qualcomm Inc	USA	Technology	45,218	05/14/01
IT4	Telecom Italia SpA	Italy	Services	49,137	01/29/01	US11	JDS Uniphase Corporation	USA	Technology	13,415	05/14/01
IT5	UniCredito Italiano SpA	Italy	Financial	20,209	03/19/01	US12	Amgen Inc	USA	Consumer Goods	66,756	05/14/01
IT6	San Paolo-IMI SpA	Italy	Financial	16,230	31/10/01	US13	Juniper Networks Inc	USA	Technology	9,659	05/14/01
IT7	Mediaset SpA	Italy	Services	8,412	31/10/01	US14	Pfizer Inc	USA	Consumer Goods	302,898	05/14/01
NET1	Royal Dutch Petroleum Company	Netherlands	Resources	118,521	01/29/01	US15	Wal-Mart Stores Inc	USA	Services	261,832	05/14/01
NET2	ING Groep NV	Netherlands	Financial	55,253	01/29/01	US16	International Business Machines Corporation	USA	Technology	210,002	05/14/01
NET3	Koninklijke Philips Electronics NV	Netherlands	General	31,809	04/02/01	SWD1	Telefonaktiebolaget LM Ericsson AB	Sweden	Technology	34,833	31/10/01
NET4	ABN AMRO Holdings NV	Netherlands	Financial	26,036	05/14/01	SWD2	Nordea AB	Sweden	Financial	16,068	31/10/01
NET5	Aegon NV	Netherlands	Financial	40,463	05/14/01	SWD3	Telia AB	Sweden	Services	15,029	31/10/01
NET6	Koninklijke Ahold NV	Netherlands	Services	27,844	05/14/01	SWD4	Hennes & Mauritz AB	Sweden	Services	15,007	31/10/01
SP1	Telefonica SA	Spain	Services	63,538	01/29/01	SWD5	Svenska Handelsbanken AB	Sweden	Financial	9,373	31/10/01
SP2	Santander Central Hispano SA	Spain	Financial	42,153	01/29/01	SWT1	Novartis AG	Switzerland	Consumer Goods	111,729	31/10/01
SP3	Banco Bilbao Vizcaya Argentaria SA	Spain	Financial	41,930	05/14/01	SWT2	Nestle SA	Switzerland	Consumer Goods	89,023	31/10/01
UK1	Vodafone Group plc	UK	Services	174,397	01/29/01	SWT3	UBS AG	Switzerland	Financial	66,815	31/10/01
UK2	BP plc	UK	Resources	198,232	01/29/01	SWT4	Roche Holding AG	Switzerland	Consumer Goods	54,455	31/10/01
UK3	HSBC Holdings plc	UK	Financial	116,313	01/29/01	SWT5	Credit Suisse Group	Switzerland	Financial	47,309	31/10/01

Table II: Descriptive statistics of portfolios returns

	USF STOCKS								CONTROL SAMPLE							
	μ	σ	S	K	JB	LB(5)	LB²(5)	ARCH	μ	σ	S	K	JB	LB(5)	LB²(5)	ARCH
Panel A : Country																
France (9)	-0.013	1.238	-0.117 *	2.005 ***	265.580 ***	26.473 ***	138.316 ***	16.625 ***	0.016	1.004	0.005	1.172 ***	89.628 ***	5.982	104.372 ***	15.151 ***
Germany (12)	-0.022	1.113	-0.065	0.700 ***	33.068 ***	11.113 **	141.092 ***	15.955 ***	-0.033	1.021	-0.029	1.029 ***	69.243 ***	9.134	44.196 ***	5.853 **
Italy (7)	0.015	1.129	0.143 **	1.318 ***	118.540 ***	4.246	107.963 ***	9.265 ***	0.042 *	0.982	0.083	1.257 ***	104.870 ***	15.223 ***	99.741 ***	13.282 ***
Netherlands (6)	-0.031	1.500	-1.206 ***	17.518 ***	20392.000 ***	27.612 ***	54.352 ***	7.016 ***	-0.052	1.591	-0.033	1.705 ***	189.830 ***	10.752 *	53.547 ***	31.758 ***
Spain (3)	0.006	1.684	-0.096	1.704 ***	191.760 ***	11.914 **	132.800 ***	57.561 ***	0.007	1.099	0.079	4.095 ***	1095.000 ***	5.031	100.007 ***	33.982 ***
UK (17)	-0.007	0.854	-0.014	1.080 ***	76.129 ***	31.150 ***	112.697 ***	25.588 ***	-0.015	0.797	-0.118 *	1.233 ***	102.770 ***	19.539 ***	28.615 ***	5.535 **
US (16)	0.032	1.357	0.124 **	0.882 ***	54.788 ***	0.786	113.163 ***	37.962 ***	0.031	1.358	-0.030	0.930 ***	56.658 ***	6.016	42.958 ***	13.152 ***
Switzerland (5)	-0.001	1.411	-0.023	3.550 ***	822.080 ***	13.202 **	486.960 ***	115.690 ***	-0.006	1.764	0.067	4.221 ***	1163.100 ***	21.551 ***	562.649 ***	97.538 ***
Sweden (5)	0.004	1.892	-0.009	2.671 ***	465.110 ***	14.098 **	287.588 ***	119.840 ***	-0.007	2.082	0.165 ***	2.049 ***	280.780 ***	10.224 *	211.372 ***	27.061 ***
Panel B : Industry																
Resource (9)	-0.001	0.979	-0.142 **	1.010 ***	71.836 ***	24.267 ***	107.582 ***	16.354 ***	0.020	1.067	0.036	1.230 ***	98.930 ***	8.940	42.087 ***	2.668
Services (16)	-0.005	1.016	-0.143 **	2.638 ***	459.180 ***	21.938 ***	66.573 ***	2.842 *	0.002	0.772	-0.033	1.155 ***	87.305 ***	14.231 **	42.695 ***	13.893 ***
Consumer Goods (13)	-0.001	0.845	-0.127 **	0.690 ***	35.197 ***	20.272 ***	112.953 ***	29.568 ***	0.024	0.756	-0.027	0.653 ***	28.032 ***	14.568 **	135.889 ***	13.756 ***
Technology (12)	0.023	1.663	0.136 **	1.098 ***	83.397 ***	2.346	129.339 ***	54.250 ***	0.016	1.730	-0.038	0.446 ***	13.322 ***	4.541	44.833 ***	15.379 ***
Financial (25)	-0.011	0.927	-0.014	1.593 ***	165.500 ***	38.192 ***	230.591 ***	39.055 ***	-0.029	0.865	-0.056	1.798 ***	211.560 ***	33.187 ***	171.087 ***	29.162 ***
General (5)	0.009	1.332	0.233 ***	1.703 ***	203.360 ***	12.364 **	78.300 ***	21.212 ***	-0.012	1.516	0.245 ***	2.564 ***	444.450 ***	1.367	43.403 ***	38.008 ***

Notes: *,**,*** denotes significant at 10%, 5% and 1% level, respectively.

( ) Number of stocks in each portfolios.

μ = mean; σ = standard deviation; S = skewness; K = excess Kurtosis; JB = Jarque-Bera test for normality and distributed as chi-squared with 2 degree of freedom.

ARCH Test is the Lagrange Multiplier (LM(1)] test for ARCH effects and distributed as chi-squared with 1 degree of freedom.

LB(N) and LB²(N) are the Ljung-Box statistics for R_t and R^2_t respectively distributed as chi-squared with N degree of freedom where N is the number of lags.

The Ljung-Box statistics for N lags is calculated as $LB(N) = T(T+2)\sum_{j=1}^{N}(\rho_j^2/T-j)$ where ρ_i is the sample autocorrelation for j lags and T is the sample size.

Table III: Percentage of statistically significant coefficients from equations (6) and (7) in the pre- and post-futures periods, USF stocks.

	φ_0		φ_1		α_0		α_1		β		δ	
	Pre-Futures	**Post-Futures**	**Pre-Futures**	**Post-Futures**	**Pre-Futures**	**Post-Futures**	**Pre-Futures**	**Post-Futures**	**Pre-Futures**	**Post-Futures**	**Pre-Futures**	**Post-Futures**
Panel A : Total												
Total (80)	28.75	17.50	13.75	5.00	66.25	71.25	33.75	23.75	100.00	100.00	57.50	88.75
Panel B : Country												
France (9)	22.22	33.33	11.11	0.00	66.67	77.78	33.33	11.11	100.00	100.00	55.56	88.89
Germany (12)	8.33	16.67	0.00	0.00	50.00	66.67	41.67	25.00	100.00	100.00	41.67	91.67
Italy (7)	42.86	14.29	28.57	0.00	100.00	57.14	42.86	14.29	100.00	100.00	42.86	71.43
Netherlands (6)	66.67	16.67	0.00	0.00	66.67	83.33	16.67	16.67	100.00	100.00	66.67	100.00
Spain (3)	0.00	0.00	0.00	0.00	66.67	100.00	33.33	33.33	100.00	100.00	100.00	100.00
UK (17)	29.41	11.76	17.65	11.76	64.71	82.35	41.18	23.53	100.00	100.00	41.18	94.12
US (16)	31.25	25.00	25.00	6.25	75.00	56.25	31.25	31.25	100.00	100.00	81.25	75.00
Switzerland (5)	40.00	20.00	20.00	20.00	80.00	100.00	20.00	20.00	100.00	100.00	100.00	100.00
Sweden (5)	20.00	0.00	0.00	0.00	20.00	40.00	20.00	40.00	100.00	100.00	20.00	100.00
Panel C : Industry												
Resources (9)	0.00	55.56	0.00	0.00	66.67	100.00	0.00	11.11	100.00	100.00	66.67	88.89
Services (16)	50.00	12.50	18.75	6.25	50.00	50.00	62.50	6.25	100.00	100.00	31.25	93.75
Consumer Goods (13)	23.08	23.08	23.08	15.38	61.54	84.62	23.08	30.77	100.00	100.00	38.46	69.23
Technology (12)	16.67	8.33	8.33	0.00	83.33	16.67	41.67	41.67	100.00	100.00	75.00	83.33
Financial (25)	28.00	8.00	12.00	4.00	68.00	96.00	36.00	28.00	100.00	100.00	72.00	96.00
General (5)	60.00	20.00	20.00	0.00	80.00	60.00	0.00	20.00	100.00	100.00	80.00	100.00

This table summarises the estimates of the feedback trading model (Eq. 6 and 7) for each USF stock in both the pre- and post-futures periods:

$$R_{it} = \alpha + \mu\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{it-1} + \varepsilon_t \qquad \varepsilon_t \sim GED(0,\sigma_t^2)$$

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

The percentage of stocks for which the coefficient is statistically significant at 10% level is reported. Panel A shows results for the whole USF sample, panel B provides the figures broken down by the country in which the underlying stocks are traded, while panel C provides the same information by industry. The number of stocks in each subsample are shown in parentheses.

Table IV: Test of significance of differences in the coefficients from the pre-futures to the post-futures period by direction of change, USF stocks

	φ_0			φ_1			α_0			α_1			β			δ		
	Sign. Increase	Sign. Decrease	No Sign. Change	Sign. Increase	Sign. Decrease	No Sign. Change	Sign. Increase	Sign. Decrease	No Sign. Change	Sign. Increase	Sign. Decrease	No Sign. Change	Sign. Increase	Sign. Decrease	No Sign. Change	Sign. Increase	Sign. Decrease	No Sign. Change
Panel A : Total																		
Total (80)	2.50	30.00	67.50	2.50	11.25	86.25	23.75	57.50	18.75	16.25	18.75	65.00	56.25	15.00	28.75	50.00	21.25	28.75
Panel B : Country																		
France (9)	11.11	44.44	44.44	0.00	11.11	88.89	22.22	66.67	11.11	11.11	33.33	55.56	55.56	33.33	11.11	55.56	0.00	44.44
Germany (12)	0.00	16.67	83.33	0.00	0.00	100.00	33.33	41.67	25.00	16.67	25.00	58.33	50.00	16.67	33.33	66.67	8.33	25.00
Italy (7)	0.00	57.14	42.86	0.00	14.29	85.71	0.00	100.00	0.00	14.29	28.57	57.14	57.14	0.00	42.86	28.57	28.57	42.86
Netherlands (6)	0.00	33.33	66.67	0.00	0.00	100.00	16.67	33.33	50.00	0.00	0.00	100.00	16.67	16.67	66.67	66.67	0.00	33.33
Spain (3)	0.00	0.00	100.00	0.00	0.00	100.00	33.33	66.67	0.00	33.33	0.00	66.67	66.67	0.00	33.33	33.33	0.00	66.67
UK (17)	5.88	35.29	58.82	5.88	17.65	76.47	23.53	47.06	29.41	11.76	23.53	64.71	47.06	29.41	23.53	70.59	0.00	29.41
US (16)	0.00	18.75	81.25	6.25	12.50	81.25	25.00	68.75	6.25	18.75	18.75	62.50	75.00	0.00	25.00	18.75	68.75	12.50
Switzerland (5)	0.00	60.00	40.00	0.00	40.00	60.00	20.00	80.00	0.00	20.00	0.00	80.00	80.00	20.00	0.00	20.00	40.00	40.00
Sweden (5)	0.00	0.00	100.00	0.00	0.00	100.00	40.00	20.00	40.00	40.00	0.00	60.00	60.00	0.00	40.00	80.00	20.00	0.00
Panel C : Industry																		
Resources (9)	0.00	55.56	44.44	0.00	0.00	100.00	33.33	44.44	22.22	11.11	0.00	88.89	22.22	22.22	55.56	55.56	0.00	44.44
Services (16)	6.25	37.50	56.25	12.50	12.50	75.00	25.00	50.00	25.00	0.00	50.00	50.00	62.50	12.50	25.00	62.50	18.75	18.75
Consumer Goods (13)	0.00	30.77	69.23	0.00	23.08	76.92	23.08	46.15	30.77	23.08	15.38	61.54	69.23	15.38	15.38	46.15	30.77	23.08
Technology (12)	0.00	8.33	91.67	0.00	0.00	100.00	8.33	83.33	8.33	33.33	33.33	33.33	91.67	0.00	8.33	25.00	66.67	8.33
Financial (25)	4.00	24.00	72.00	0.00	12.00	88.00	32.00	56.00	12.00	16.00	4.00	80.00	32.00	24.00	44.00	60.00	4.00	36.00
General (5)	0.00	40.00	60.00	0.00	20.00	80.00	0.00	80.00	20.00	20.00	0.00	80.00	100.00	0.00	0.00	20.00	20.00	60.00

This table summarises the Wald statistics testing the equality of the feedback trading model coefficients (Eq. 6 and 7) for pre- and post-futures periods for USF stocks:

$$R_{it} = \alpha + \mu\sigma_t^2 + (\varphi_0 + \varphi_1\sigma_t^2)R_{it-1} + \varepsilon_t \qquad \varepsilon_t \sim GED(0, \sigma_t^2)$$

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

The percentages of stocks for which the coefficient is significantly changed (increase, decrease or no change) at 10% level are reported. Panel A shows results for the whole USF sample, panel B provides the figures broken down by the country in which the underlying stocks are traded, while panel C provides the same information by industry. The number of stocks in each subsample are shown in parentheses.

Table V: Percentage of statistically significant coefficients from equations (6) and (7) in the pre- and post-futures periods, Control stocks.

	φ_0		φ_1		α_0		α_1		β		δ	
	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures	Pre-Futures	Post-Futures
Panel A : Total												
Total (80)	28.75	35.00	25.00	15.00	77.50	63.75	51.25	41.25	100.00	100.00	55.00	77.50
Panel B : Country												
France (9)	33.33	33.33	33.33	0.00	66.67	55.56	22.22	0.00	100.00	100.00	55.56	88.89
Germany (12)	25.00	41.67	0.00	0.00	75.00	50.00	66.67	58.33	100.00	100.00	83.33	91.67
Italy (7)	28.57	28.57	14.29	14.29	57.14	85.71	71.43	57.14	100.00	100.00	14.29	71.43
Netherlands (6)	66.67	50.00	50.00	50.00	83.33	100.00	50.00	50.00	100.00	100.00	33.33	50.00
Spain (3)	0.00	100.00	0.00	33.33	100.00	33.33	100.00	100.00	100.00	100.00	0.00	33.33
UK (17)	29.41	35.29	29.41	29.41	82.35	70.59	52.94	47.06	100.00	100.00	52.94	70.59
US (16)	25.00	12.50	31.25	12.50	75.00	56.25	31.25	25.00	100.00	100.00	68.75	93.75
Switzerland (5)	40.00	80.00	60.00	0.00	100.00	80.00	80.00	60.00	100.00	100.00	60.00	80.00
Sweden (5)	0.00	0.00	0.00	0.00	80.00	40.00	40.00	20.00	100.00	100.00	60.00	60.00
Panel C : Industry												
Resources (9)	33.33	44.44	22.22	22.22	77.78	88.89	22.22	44.44	100.00	0.00	44.44	66.67
Services (16)	37.50	25.00	37.50	12.50	75.00	43.75	62.50	50.00	100.00	100.00	43.75	62.50
Consumer Goods (13)	38.46	61.54	15.38	15.38	69.23	69.23	69.23	38.46	100.00	100.00	30.77	92.31
Technology (12)	8.33	7.69	25.00	7.69	75.00	30.77	16.67	30.77	100.00	0.00	91.67	84.62
Financial (25)	24.00	40.00	24.00	20.00	88.00	84.00	76.00	40.00	100.00	100.00	60.00	80.00
General (5)	40.00	20.00	20.00	0.00	60.00	40.00	20.00	40.00	100.00	100.00	60.00	80.00

See table III for details.

Table VI: Test of significance of differences in the coefficients from the pre-futures to the post-futures period by direction of change, Control stocks

	φ_0			φ_1			α_0			α_1			β			δ		
	Sign. Increase	Sign. Decrease	No Sign. Change	Sign. Increase	Sign. Decrease	No Sign. Change	Sign. Increase	Sign. Decrease	No Sign. Change	Sign. Increase	Sign. Decrease	No Sign. Change	Sign. Increase	Sign. Decrease	No Sign. Change	Sign. Increase	Sign. Decrease	No Sign. Change
Panel A : Total																		
Total (80)	13.75	30.00	56.25	7.50	12.50	80.00	18.75	60.00	21.25	20.00	31.25	48.75	55.00	21.25	23.75	40.00	15.00	45.00
Panel B : Country																		
France (9)	22.22	22.22	55.56	0.00	33.33	66.67	11.11	66.67	22.22	0.00	22.22	77.78	77.78	11.11	11.11	55.56	0.00	44.44
Germany (12)	8.33	16.67	75.00	0.00	0.00	100.00	16.67	50.00	33.33	33.33	16.67	50.00	33.33	41.67	25.00	25.00	8.33	66.67
Italy (7)	14.29	14.29	71.43	14.29	0.00	85.71	57.14	42.86	0.00	28.57	42.86	28.57	28.57	42.86	28.57	71.43	0.00	28.57
Netherlands (6)	33.33	66.67	0.00	16.67	16.67	66.67	16.67	50.00	33.33	50.00	33.33	16.67	66.67	16.67	16.67	50.00	33.33	16.67
Spain (3)	0.00	100.00	0.00	0.00	33.33	66.67	0.00	100.00	0.00	0.00	33.33	66.67	66.67	0.00	33.33	33.33	0.00	66.67
UK (17)	11.76	35.29	52.94	11.76	11.76	76.47	17.65	58.82	23.53	23.53	29.41	47.06	41.18	23.53	35.29	41.18	5.88	52.94
US (16)	6.25	18.75	75.00	12.50	6.25	81.25	18.75	75.00	6.25	12.50	31.25	56.25	68.75	6.25	25.00	31.25	37.50	31.25
Switzerland (5)	40.00	60.00	0.00	0.00	40.00	60.00	0.00	40.00	60.00	0.00	60.00	40.00	80.00	20.00	0.00	40.00	20.00	40.00
Sweden (5)	0.00	0.00	100.00	0.00	0.00	100.00	20.00	60.00	20.00	20.00	40.00	40.00	60.00	20.00	20.00	20.00	20.00	60.00
Panel C : Industry																		
Resources (9)	22.22	44.44	33.33	11.11	22.22	66.67	33.33	66.67	0.00	44.44	11.11	44.44	33.33	11.11	55.56	44.44	11.11	44.44
Services (16)	12.50	31.25	56.25	18.75	12.50	68.75	12.50	56.25	31.25	25.00	37.50	37.50	56.25	18.75	25.00	37.50	18.75	43.75
Consumer Goods (13)	7.69	69.23	23.08	7.69	15.38	76.92	23.08	61.54	15.38	7.69	46.15	46.15	53.85	23.08	23.08	69.23	7.69	23.08
Technology (12)	8.33	0.00	91.67	8.33	0.00	91.67	8.33	75.00	16.67	25.00	16.67	58.33	83.33	0.00	16.67	8.33	50.00	41.67
Financial (25)	20.00	16.00	64.00	0.00	12.00	88.00	16.00	52.00	32.00	12.00	40.00	48.00	52.00	36.00	12.00	44.00	4.00	52.00
General (5)	0.00	40.00	60.00	0.00	20.00	80.00	40.00	60.00	0.00	20.00	0.00	80.00	40.00	20.00	40.00	20.00	0.00	80.00

See table IV for details.

ENDNOTES

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[1] Sentana and Wadhwani (1992) originally investigated stock returns for the US using this model. It has also been used to examine the behaviour of stock returns in a range of other markets. See, for example, Koutmos (1997), Koutmos and Saidi (2001) and Bohl and Reitz (2005).

[2] For example, in the United States futures on individual stocks were banned for 20 years under the Shad-Johnson Accord and such trading only began in the US in November 2002.

[3] Following the purchase of LIFFE by Euronext in January 2002, LIFFE became part of Euronext.liffe, comprising of the Amsterdam, Brussels, LIFFE, Lisbon and Paris derivatives markets. For convenience we use the term LIFFE throughout the paper to refer to either LIFFE or Euronext.liffe.

[4] It should be noted that SSFs were traded on some smaller exchanges such as the Sydney Futures Exchange prior to 2001, but that the level of trading in these contracts was relatively low.

[5] For the original 25 USFs traded the countries in which the underlying stocks were listed are: Finland (1 stock), France (3), Germany (3), Italy (2), Netherlands (2), Spain (2), UK (5) and USA (7). By the end of 2001 the numbers were: Finland (2 stocks), France (10), Germany (12), Greece (2), Italy (9), Netherlands (6), Spain (4), Sweden (5), Switzerland (5), UK (21) and USA (21). The additional countries with stocks on which USFs were listed as of June 2005 are Belgium, Denmark and Norway, while the USFs on stocks traded in Greece had been delisted.

[6] According to Harris (1989), stock option/futures listing does not have a uniform impact on the volatility of the underlying stocks He argues that the effect of option listing will depend on: i) the sophistication of the market participants; ii) the existence of constraining regulations such as a prohibition of short selling; and iii) the liquidity of the markets. It is possible that for these reasons, authors, such as Damodaran and Lim (1991) and Bollen (1998) have suspected that options may have a differential impact in different trading locations. Indeed, their empirical evidence supports this.

[7] Examples of huge losses incurred using derivatives include the cases of Metallgesellschaft AG and Proctor and Gamble, while for evidence about the concern relating to financial futures see, for example, the Report of the Presidential Task Force (1988).

[8] Futures are seen to be attractive to speculators because of the relatively low transactions costs, trading on margin (which offers leveraged positions), ease of closing out the position and cash settlement, rather than physical delivery, in the case of stock based futures.

[9] Although the stocks on which USF are traded tend to be the most frequently traded and largest stocks in their domestic markets, they may not be completely free of thin-trading bias because they might not trade every day.

[10] The results of these specification tests are not reported here, but are available from the authors on request.

[11] See, for example, Edwards (1988a, 1988b), Choi & Subrahmanyam (1994), Antoniou & Holmes (1995), Antoniou et al. (1998), Bollen (1998), Gulen & Mayhew (2000), Rahman (2001) and Antoniou et al (2005).

[12] During the period analysed the annual volume of ISFs contracts traded ranged from 8,646 (1998) to 111,696 (1995). From 1995 to 1998 the volume of trade fell. For USFs the number of contracts traded annually increased from 2.326 million in 2001 to 6.349 million in 2003 and in excess of 12.5 million in 2004.

[13] Details of the logistic regression are available from the authors on request.

[14] Compared to the conventional 'characteristics matching' method, it is believed that choosing the control stocks by this 'propensity-score matching' approach is more likely to correct for the possible bias due to both the endogeneity of futures listing and changes in market-wide trends when examining the effect of futures listing on the underlying market. See, for example, Mayhew and Mihov (2004). In addition, Cheng (2003) also presents a detailed comparison of these two types of matching approaches.

[15] The method of estimation used in this paper is based on the Berndt et al (1974) algorithm.

[16] Results of the individual estimations are available from the authors on request.

[17] The stocks are assigned to one of six industry groups, namely resources, services, consumer goods, technology, financial and general based on the Datastream Industry Classification level 3 sector definitions.

[18] It should be noted that the number of stocks is small in the samples for Italy (7 stocks) and Switzerland (5 stocks).

[19] For example, for technology stocks β increases significantly post-futures for 11 of the 12 USF stocks and 10 control stocks. In contrast, for resource stocks only 2 out of 9 exhibit a significant increase for USF stocks and 3 out of 9 for the control sample.

[20] In the interests of brevity, detailed results of these and other tests of robustness, set out below, are not presented here, but are available from the authors on request.

[21] Gulen and Mayhew (2000) empirically investigated the impact of stock index futures trading on 25 markets**.** They found very different results for highly developed and less developed countries.

[22] These industry based differences may be due to other factors unrelated to futures, the identification of which is beyond the scope of this paper.

[23] The method of trading changed for USFs written on UK based stocks at the end of November 2003, with the introduction of the MATCH facility. See the LIFFE web site for details. By estimating the model for 2 years either side of the introduction of USFs the sample period excludes the change to the MATCH system and allows determination of the extent to which the change impacted on the findings.