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Competitive Aspects of Cross Listed Futures Contracts on Synchronous Markets

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IS THERE LIF(F)E AFTER DTB?[1]

Abstract

This paper analyzes the interaction between exchanges trading in identical assets. Issues like price leadership, market spreads and activity/volume are related to different trading systems. Bid-ask spread estimation is conducted for each market individually taking account of conditional expectations. A VECM-ARCH model incorporates the modeling implications of these findings when extending the analysis to a multivariate setting. Both univariate and multivariate tools are applied to the competition in BUND futures trading between LIFFE (London International Financial Futures Exchange) and DTB (Deutsche Terminbörse). At the same time, a computerized dealer system (DTB) is compared to an open outcry system (LIFFE). In a broader context, this paper has implications for the survival potential of duplicative contracts traded at simultaneous markets.

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I. Introduction

Globalization and computerization of financial markets has led to intensive competition among exchanges, not only in a complementary sense (options and index contracts) but also in a substitutionary sense (cross listing of identical assets). The former may add to the completeness of the market and, as such, may absorb latent liquidity and raise new volume. The latter to the contrary usually plunges the competing exchanges in a battle for contract survival. A tentative approach to identify causes for a contract's failure or success is given in Black (1986). The main determinant for a contract's potential to survive is its ability to attract volume. Combined with the necessary generation of liquidity, these are the competitive issues that we focus upon. Measures for competitive strength are discussed for a 'direct' competition case. Even though potential (and indirect, e.g. options versus futures) competition might be equally important in measuring these issues, we confine this analysis to a perfectly homogeneous contract which is cross listed at two exchanges with simultaneous trading times.

Several strands of research are available to assess the competitive forces in financial markets. Studies on market microstructure aspects focus on institutional differences, while those that analyze price behavior consider the regulatory aspects as given parameters. The availability of high frequency transaction data, however, allows researchers to blend both approaches. Even more, they force the time series type of research to consider the market environment. Apparent leads, lags and other patterns like overreactions (see e.g., Kaul and Nimalendran, 1990) suddenly become mere reflections of bid-ask spreads, commission fees, margin requirements and the like.

This paper, therefore, integrates both directions. First, we propose estimators for the individual markets' characteristics which are subsequently fit into the multivariate model for market interaction. The univariate characteristics are usually discovered in analyzing the bid-ask spread of one particular market. Lack of bid-ask quotes, however, requires estimation of the market spread. Even if quoted spreads become available they are still difficult to assess in terms of realized or effective spreads. Roll (1984) introduces a simple spread estimator based on the autocovariance in observed transaction returns, reflecting the bouncing phenomenon (price reversals within the spread). The necessary assumptions and measurement interval are discussed in Stoll (1989), where it is shown that violation of these assumptions causes severe underestimation of the true effective spread. High frequency (tick-to-tick) estimation relaxes the inventory holding part of the problem but the bias caused by adverse selection may become relatively more important. George et al. (1991) discuss a technique where the expected-return component can be extracted from the transactions returns. Unfortunately, this technique requires bid (or ask) quotes. Their alternative expected returns generating process, avoiding the required bid-ask availability, also seems improper for high frequency series. We propose a simple alternative to remove this disturbance in continuously recorded transactions.

Next, we consider interaction between exchanges. In a fully efficient and integrated market context, news flows should be incorporated in both exchanges' transaction prices giving instantaneous and bi-directional causality. If these conditions are however not satisfied, there might be a case for distinguishing leader and follower. An elegant approach to detect such evidence is given by a bivariate error correction modeling procedure. This captures both long-run equilibrium (Engle-Granger type cointegration relationship) in levels as well as the dynamic-adjustment path (Vector AutoRegressive model) in returns. The errors, which are probably time-varying, are assumed to follow a bivariate GARCH(1,1) process. Interactive flows are thus distinguished according to three sources: levels, returns and innovations.

A typical example of such a competitive case is given by the BUND futures contract as it is traded on LIFFE (London International Financial Futures Exchange) and on DTB (Deutsche Terminbörse). The distinguishing feature between these exchanges is the trading system, respectively a mixture of open outcry and automated pit trading versus a fully computerized system. The estimation results for liquidity and information flows indicate that news flows predominantly from LIFFE towards DTB with the exception of (German) news releases and a typical monday effect. The overall findings conform to the bid-ask spread and volatility patterns. We also compare estimates across the different trading systems.

In the next section we will give an outline of our modeling strategy by evaluating some standard tools to tackle both univariate issues as well as multivariate ones. Section 3 applies these tools to the BUND futures contract case and extends the analysis to a short discussion of influential news items. Section 4 concludes this paper with a couple of remarks and limitations.

II. Competitive Modelling

Zero arbitrage implies that simultaneous prices for two futures contracts on the same underlying asset are cointegrated. Thus, their prices may diverge temporarily, but eventually converge to their long-run relationship. However, suppose one contract trades in a thin market, the other trades in a deeper market. The question is whether prices in the deeper market Granger cause prices in the thinner market. If one has information that current prices on both markets are out of line with fundamentals, then the incentive would be to trade in the deeper market. Orders placed in this liquid market are executed more quickly and with a smaller price impact for a given order size, see Kyle (1985). Thus a link is established between microstructural measures like bid-ask spreads, and time series dynamics in prices. The following two sections discuss techniques for both issues.

II.1 Estimating bid-ask spreads

Dealers' processing of bid/ask orders entails costs. The required compensation (the bid-ask wedge) implies that transaction returns will be negatively autocorrelated. This feature can be usefully employed in providing estimates of the spread. Roll's (1984) well known estimator has one major advantage over alternative spread estimators. It uses only transaction prices without knowledge of the market quotes nor whether the transaction takes place at the bid or ask. It is based upon the serial covariance in the returns:

$$S_{ROLL} = 2 * \sqrt{-COV(\Delta X_t, \Delta X_{t+1})} \tag{1}$$

Problems with this estimator are well documented. In Stoll (1989) the three determinants of bid-ask spreads are categorized as order processing, adverse information and inventory costs. The Roll estimator includes only order processing revenues. Several alternative estimators (mostly adaptations of Roll) have been proposed. Of these, we will discuss one which is known to account for most of the bias in Roll's estimator.

In Choi, Salandro and Shastri (1988) the Roll estimator (corrected for asymmetry in the transaction type) is applied to continuously recorded transaction prices. Problems with positive serial correlations, which regularly occur in Roll's paper, disappear in that case. George et al. (1991), however argue that even though the Roll estimator proves to be rather efficient for high frequency transaction data, there can still be a considerable bias if expected returns are time-varying[2]. Time variance implies conditional behavior of returns instead of the usual connotation of a time-varying generating process. Conditionality in the mean implies positive autocorrelation which induces a negative bias to the estimator for the bid-ask spread estimate. Stoll (1989) mentions that this reduction from quoted spreads is the wedge between quoted and effective spread which can be regarded as compensation for inventory holding costs.

George et al. argue that the bias is separated from the adverse selection argument discussed in Glosten and Milgrom (1985). However, if there is information asymmetry, the bid-ask spread will necessarily be larger to provide protection against informed traders. A particular order may come from an informed trader. If the news underlying the trade subsequently becomes public, the dealer may be exposed to non-covered risk. Such risk will be larger if these informed traders can not be identified in the trading process. This anonymity aspect is sometimes argued to favor computerized trading over open outcry. According to Benveniste et al. (1992), identification and sanctioning is more easily achieved in the open outcry market. Especially in the computerized trading context, information asymmetry may induce positive autocorrelation which can not be distinguished from the inventory holding part in the time-varying expectations compensation.

In any case, incorporating the time-variance of expected returns corrects for a source of severe underestimation in Roll's estimator. In George et al. (1991) two alternative estimators are introduced to deal with, or put differently, estimate this compensation:

$$\begin{aligned} S_{GKN,1} &= 2 \; * \; \sqrt{-COV(\Delta \; X_{BT,t}, \Delta \; X_{BT,t+1})} \\ S_{GKN,2} &= 2 \; * \; \sqrt{-COV(\Delta \; X_{ET,t}, \Delta \; X_{ET,t+1})} \end{aligned} \tag{2}$$

Both formulas are based on the extraction of the expectations process from transaction returns. True expectations are, of course, not observed but can be approximated by either method. $S_{GKN,1}$ presumes that market makers adjust their subsequent bids (and asks) according to revisions in expected returns. Adjusted returns can then be calculated as

2 There may even be a causal link since Roll's estimator precludes an efficiency gain from switching to transactions frequency (Roll uses daily data). According to Stoll (1989), this gain can only occur because of time-varying expected price changes. This phenomenon is detected in George et al. (1991).

follows:

$$\Delta X_{BT,t} = (X_t - X_{t-1}) - (X_{B,t} - X_{B,t-1}) \tag{3}$$

where the bid quote $X_{B,t}$ is measured subsequent to transaction price X_t. If, however, bid and ask quotes are not available, a second estimator ($S_{GKN,2}$) employs a model for the conditional expectation of ΔX_t. This model is characterized by an AR(1)-process that induces positive autocorrelation in the observed transaction returns[3]:

$$\Delta X_{ET,t} = (X_t - X_{t-1}) - \rho (X_{t-1} - X_{t-2}) \tag{4}$$

where ρ is the first-order autocorrelation coefficient. Both estimators exceed the Roll estimate and therefore reduce this particular bias while simultaneously indicating the impact of the conditionality in the quoted spread. This latter estimate is in turn informative on the heterogeneity of traders' information processing capabilities. As such it is not distinguishable from adverse-selection motivations for spread revision. The next section elaborates on these micro-structural aspects by showing how they affect the variance process.

II.2 Vector error correction with GARCH distributed errors

To assess the interactive forces between markets' prices or returns, one is required to purge these prices of institutional disturbances. Toward this end, Stephan and Whaley (1990) mention that bid-ask effects imply that the transaction returns have to be modeled as a moving average process. Combined with the autocorrelation pattern due to conditionality in expected returns, this would indicate an ARMA modeling type. In addition to these aspects, one typically finds a high persistence and clustering in high frequency financial time series. These characteristics are either caused by the time-varying arrival of news or the time-varying processing of these news items (even a combination of the two is possible). To model these phenomena one usually applies the (G)ARCH methodology. Engle et al.(1990), and Hamao et al.(1990) apply this technique to uncover correlations in returns across markets situated in different time zones. Due to this very time gap their

3 Conrad and Kaul (1988) employ a Kalman-Filter technique to extract the expectations generating proces. This implies that realized returns can be described by an ARMA process. Different methods, e.g. risk related expectations models, lead to similar results.

approach is of the "open-to-close" type and not informative on the high frequency relations in synchronous price movements[4]. Even though Hamao et al. (1990) take the bid-ask induced moving average component into account, they do not relate the levels nor returns of the considered market prices. The approach we propose here, stresses this synchronicity as multivariate conditionality in the means equations. It therefore combines cointegration in levels, a vector autoregression in first differences and time-varying conditional variance. Purging the error process from time-varying components gives us standardized residuals. This is equivalent to the distinction between fundamental and observed variance, Amihud and Mendelson (1987). A simple variance ratio test indicates whether standardized or fundamental variance is equal across markets. Such equality is to be expected in a duplicated asset setting, where disturbances should be attributed to technical differences between market places. This 'technical' adjustment links the previously discussed micro-structural aspects to standard time series analysis.

The mean equation is specified as a vector error correction model. Since financial time series are known to be non-stationary processes, a first-differenced VAR-system usually applies. If a long-term equilibrium relation exists between some of the series, this differencing implies a loss of information. Our model therefore consists of a simple vector autoregressive (VAR) structure of order *p* to account for the short term dynamics supplemented by an error correction component to incorporate the long term relationship in the series.

$$\Delta X_t = \Theta + \sum_{i=1}^{p} \Gamma_i \, \Delta X_{t-i} + \Pi \, X_{t-p} + E_t \tag{5}$$

where X_t is a matrix of logarithmic transaction prices, θ is a vector of intercepts. The Γ_i matrix contains estimates for the traditional VAR-system of returns. 'Long-run' or error correction (equilibrium restoring) estimates are provided in Π. We do not model equation (5) as in Hamao et al. (1990) where a MA-component is included in the mean equation. Instead, the bid-ask plus expected returns bias is in our specification better captured by an AR-part in the equation. Since we focus on two markets trading in an identical asset, the long-run Π-matrix is constrained to contain identical elements for each row in the matrix:

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4 In fact they explicitly exclude the synchronous observations to focus on time-spaced spillovers.

$$\Pi = \begin{bmatrix} \pi_j & -\pi_j \\ -\pi_k & \pi_k \end{bmatrix} \tag{6}$$

The zero mean process for the residuals in (5), E_t, conditional on information set Ψ, which includes past information at (t-1) both intra- as inter-market, can be described by a multivariate GARCH(1,1) model, as in Engle et al. (1990):

$$\begin{aligned} E_t | \Psi_t &\sim N(0, H_t) \\ H_t &= \Omega + A E_{t-1}^2 + B H_{t-1} \end{aligned} \tag{7}$$

where H_t is the conditional variance vector for the considered markets, Ω is a vector of intercepts, $(E_{t-1})^2$ is a row vector of per-minute squared innovations/news. This particular specification allows us to discriminate between sources of volatility, whether they originate in the considered market or spillover from other markets. Equation (7) allows lagged, but not contemporaneous spillovers. Consistent with the Engle et al. approach we will not complicate matters and restrict the multivariate correlations to be constant through time. Combined with the other restrictions in Engle et al., relaxation of these assumptions is relatively simple. The resulting structure would, however, make economic interpretation rather cumbersome. Consistent with Pagan (1986), this allows us to generate consistent and efficient estimates for $\Gamma, \Pi, \Theta, A, B$ and, Ω, by single equation estimation of this 'multi-variate' GARCH model[5]. Numerical solutions are, as usual, obtained by applying Berndt, Hall, Hall, and Hausman's (1974) algorithm. The set of estimated equations allow us to make inferences on causality by means of a Granger-type F-test on exogeneity of each markets' returns system. Furthermore, dynamic return responses to unit shocks in either market's return are given to illustrate the causality (or more correctly: predictability) pattern in cross market returns. Both impact measures are, however, dependent on the chosen order for the VECM process. Franses and Kofman (1991) indicate that standard Akaike and Schwartz criteria may not be appropriate in this setting. A multivariate portmanteau (MPM) test is preferably used to determine *p*.

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[5] Correlations are found to be time-dependent unlike the common restrictions on the diagonality of the information matrix. In our case, testing of a simple complete (fully specified matrix) multivariate ARCH(1) model indicates that the estimation bias is small.

Standard model specification tests (restrictions on parameters, lag structure), and standardized residuals tests are required to assess the model's robustness.

III. Empirical Results for the BUND Market

Bund trading was initiated at LIFFE in 1988. Following recession of the German prohibition of futures trading in November 1990, DTB listed its Bund contract with the explicit purpose of repatriating trading volume from LIFFE. Exhibit 1 outlines the main (publicly announced) competitive actions undertaken by both exchanges since the contract's inception date.

insert Exhibit 1

The mentioned DTB measures were rather successful. The advantages which are normally attributed to contract innovation were not, in this case, retained by LIFFE. Whereas DTB initially attracted limited trading volume (about 10% early 1991), its market share surged to 40% in our sample period (see Table 1). Since then a stabilization of market position seems to have taken place with DTB at a 35% level. Interestingly, this shift did not shrink LIFFE's volume (about 0.2 million contracts a month) in absolute terms. Presumably demand was rationed until then.

To get a prior on the market structure, let us first describe the contract and the mode of operation at both exchanges. The BUND futures contract, traded both on LIFFE and DTB, is an agreement between buyer and seller to exchange a notional 6% German Government Bond (DM 250,000 face value and 10 years to maturity), for cash with delivery four times per year. Our sample consists of data obtained from DTB and LIFFE's Time and Sales (TAS) tapes and covers a six-week period (March 2 until April 10) for the nearby June contract. The LIFFE market opens at 7^{30} and open outcry (OOC) trading lasts until 16^{15} hours. After a five minute break (16^{20}) the Automated Pit Trading system (APT) takes over until 17^{55} hours. DTB opens at 7^{00} hours and trades without breaks until 17^{00} hours operating a computerized trading system. Hours are related according to London time (GMT). Table 1 below gives an idea of the distribution among the two exchanges, different trading systems and across trading days:

insert Table 1

LIFFE accounts for about 1.6 times as many observations as DTB, measured in terms of transactions as well as in number of contracts. If these figures are related to trading time, LIFFE has about 2.5 transactions each minute (with 22.5 contracts per trade) while DTB has 1.6 transactions each minute (with 23.3 contracts per trade). If APT-hours are excluded from the LIFFE sample LIFFE's number of contracts per trade still exceeds DTB's. Across both exchanges the daily number of transactions seems to be moving in the same proportion. Trading of this nearby contract has a very quick start once the roll-over from the previous nearby contract has taken place. Average daily volume is reached on thursday of the first week. According to Stephan and Whaley (1991) some care is needed when aggregating the transactions data to avoid an unduly number of non-trading intervals. These zero-price changes could bias our estimation results by putting too much weight on contemporaneous interaction.

Transaction prices for our considered period are given in Figures 1 and 2 below. Figure 1 shows prices for the full six-week period. For the first three weeks the market slumped due to predominantly 'negative' news on rising German inflation, a DMark devaluation (versus the USdollar) and the Bundesbank's resistance to cut interest rates. During weeks 4 and 5 news is mixed, which is reflected in prices. Week 6 is indicative of market recovery due to expectations of a Bundesbank interest 'realignment'. Figure 2 shows a snapshot of a typical period (March 2 morning session). Only on this scale does the step pattern reflecting bid-ask spread and distinguished DTB/LIFFE pattern become visible. Our test, further on, try to establish this pattern for the full period.

insert Figures 1 and 2

Our daily samples of transaction returns exclude overnight returns and non-synchronous time periods since our paper focuses on the simultaneity aspect in trading an identical asset. Besides, including overnight returns would not be very informative on a separate mean/variance processes for this subset due to a lack of a sufficient number of observations.

III.1 *Liquidity*

Liquidity of the BUND market is assessed by two indicators, bid-ask spreads and volatility aspects. Active trading on liquid markets induces small price changes whereas markets characterized by extensive non-trading intervals are typically confronted with sudden and large price changes. In the latter case, inventory holding costs will be considerably higher than for the low volatility case. A further implication of this trading intensity issue exists if it implies time-varying volatility instead of constant. This can also be caused by adverse selection problems leading to revisions in the quotes. To complete the circle, these quote revisions impede liquidity.

Bid-ask spread

Table 2 below gives the estimates for the sample of 30 trading days. Like Stoll (1989) we assume that the spread is constant, in our case over the daily period (while still allowing random variations). We estimate autocovariances of logarithmic returns instead of absolute price changes. The estimated spreads are therefore interpretable as percentages. One-hundredth percentage is equal to one tick (25 DMark) in market terms. Although there is some evidence of time variation, the results are overall stable. Whereas the Roll columns indicate average spreads of 0.65 (DTB), 0.41 (APT)[6] and 0.82 (OOC) ticks, the adjusted GKN spreads are more consistent with quoted spreads, Napoli (1992), of about one and a half ticks (respectively 1.4, 1.86 and 1.26 ticks). Note also that standard deviations are much smaller for OOC than for DTB (which is, in turn, smaller than for APT).

insert Table 2

To adjust for the known bias in Roll's estimator, we estimate both versions of the GKN estimator. The problem is, of course, how to disentangle the positive (expected returns induced) autocorrelation from the negative (bid-ask induced) autocorrelation. $S_{GKN,1}$ in equation (2), being preferable, can only be estimated for LIFFE's data since this set also contains bid and ask quotes. From these estimates we infer that the implicit autocorrelation coefficient is, on average, 0.4. To get some idea of the comparative autocorrelation between LIFFE and DTB, we next conduct a series of Box-Jenkins tests on residual autocorrelation. For the continuous series autocorrelation is significantly negative, indicating the dominant impact of the bid-ask spread. However, when measuring the data at lower frequencies the positive autocorrelation tends to take over (see also footnote 2). Time aggregation shows that the switch from negative to positive autocorrelation occurs at about a 5-minute measurement interval. It shows that the DTB coef-

6 There is one occasion where the estimated serial correlation was positive. This rarely occurs for such high frequency data, Choi et al. (1988). The problem might be that the APT observations are relatively more clustered with occasional non-trading gaps. This clustering may induce the positive phenomenon.

ficient is about one and a half times as large as the LIFFE coefficient. This autoregressive process generates an expected returns series for DTB which is consequently extracted from the observed continuous series (giving ΔX_{ET}).

As in George et al. (1991), our results indicate a non-trivial impact of the conditional nature of expected returns. Spreads increase by about 45% for OOC estimates, 350% for APT estimates and, 133% for DTB estimates. Whereas Roll estimates indicate that the computerized systems (DTB and APT) offer tighter spreads, after correction for expected return revisions this advantage is reversed. Suppose, e.g., that bid-ask quotes are updated less often on APT/DTB than on OOC, then the former will take longer to reflect changes in expected returns. This persistence implies relatively more positive autocorrelation in expected return changes and, hence a larger downward bias in the Roll measure. In economic terms this means that adverse selection costs are weighing heavily in computerized systems.

Price volatility

One of the determining cost components in market making is self insurance against adverse price movements due to inventory holding. If liquidity is low, it usually takes longer to offset positions, and leads to higher risk exposure. However, in our two-market setting traders can access either market and will obtain liquidity in whatever market is cheapest. The more liquid a market, the less price impact from market orders of regular size (this is also called resiliency). Absorption of large orders without inducing too much price fluctuation is of similar importance. If market switching is not easily achieved, high observed volatility is then an indicator of higher 'cost' to market making. According to Amihud and Mendelson (1987), we explicitly have to refer to observed volatility since fundamental volatility is restricted to equality across both markets. To establish the relative variability of each market, a synopsis of the series' statistics is given in Table 3. Note that, anticipating on Section 3.2, the sample is now based on minute-by-minute observations (the rationale is explained below).

insert Table 3

Variance at LIFFE is always exceeding variance at DTB, which is a nice illustration of the experimental floor/computer finding in Bollerslev and Domowitz (1991). Kurtosis seems to be a serious problem. Once again (in line with Bollerslev and Domowitz) this is particularly the case for the computerized exchange. This is an indication of the already mentioned characteristic of relatively often occurring sudden, large price changes. Generally, two explanations are given. Either the time-varying nature of variance or a non-normal underlying distribution (e.g., a Student-t) accounts for this characteristic.

Significant ARCH effects are recorded in both DTB and LIFFE returns. For both exchanges these processes account for most of the detected kurtosis. Skewness is of limited importance, though sometimes significant. Evidence for autocorrelation is mixed according to the Box-Ljung statistics. It seems that at the one-minute measurement interval there is not much evidence of either positive or negative autocorrelation.

III.2 *Market leadership*

To trace return innovations, we first have to 'aggregate' the data to get matching time spaced price pairs. Furthermore, to keep as many observations as possible while avoiding too many non-trading observations, we have chosen an optimal partition interval of one minute. The last recorded price during each minute is used. If no price is observed, then the previous interval's price is repeated, implying a zero return. Samples are of size 570 (9.5 trading hours) with the exception of March 9 missing one hour and, March 24 and 26 missing one quarter of an hour.

Testing for cointegration in the mean between the two futures prices as in Engle and Granger (1987) fails to reject the null hypothesis of no cointegration, suggesting simple bivariate simultaneous modelling (the ADF column in Table 4). Estimates of this cointegrating relation strongly indicate the restriction on the Π-matrix is appropriate. Both series show time variation in the respective conditional variances. Since the underlying asset is strictly identical, fundamental news applies to both series which argues for the case of a common time variation. A bivariate GARCH(1,1) model is therefore added to the Vector Error Correction Model. This is similar to the Chan et al. (1991) approach except for the VECM specification in the means equations.

insert Table 4

The F-test values in Table 4 are consistent with the inference that LIFFE's price influences DTB's price and vice versa for the full sample. If the day-by-day results are considered, however, it becomes obvious that LIFFE predominantly leads. There are a few interesting exceptions nevertheless. Of the six included mondays, on five occasions the leadership relation points in the other direction. Schmidt and Iversen (1992) mention that this phenomenon is due to overnight interruption of trading which, in general, affects spreads unfavorably. The monday 'price search' may have a larger impact on the leading market where, necessarily, quotes will be (relatively) larger to counter informed traders.

The error correction term π_{ij} is very often significant. DTB estimates indicate, e.g. a strong correction behavior in the first week, and weeks 4 and 6. LIFFE reacts strongly to 'long-run' misalignments also in the first week, and weeks 3 and 5. The 'short-run' adjustments (γ_{ij}) indicate that DTB is significantly influenced by LIFFE but less so vice versa. The insignificance of γ_{ij}-estimates reflects the already mentioned shift in positively and negatively induced autocorrelation.

Conditional variance is heavily dependent on past conditional variance (β_{11} and β_{22}) and past squared innovations (α_{11} and α_{22}), but also on past squared cross-innovations (α_{12} and α_{21}). The latter cross-parameters are predominantly significant for news flowing from LIFFE to DTB, see panel A (note the exceptional week 5 when this pattern is reversed). To simplify the cross equation influences, impulse response functions are graphed in Figure 3.

insert Figure 3

One time (t=1) innovations in either LIFFE or DTB returns are evaluated in their minute-by-minute impact on both markets. Persistence of shocks is limited according to the rapid decay at LIFFE and DTB. Three minutes after occurring, responses have become negligible. In line with parameter findings, there is however a distinction between LIFFE's and DTB's responses. DTB shocks do not instantaneously affect LIFFE, but only one period later. Shocks at LIFFE do cause an instantaneous (and relatively large) adjustment in DTB's return.

Though not reported, we also tested for the inclusion of traded volume as an explanatory variable for the conditional variance. Equivalent to the results in Lamoureux and Lastrapes (1990), this leads to highly significant estimates for this exogenous variable while considerably reducing the estimates for the A(α_{ij})- and B(β_{ij})-matrices. More often than not, these latter estimates remained, however, significant. This indicates that the encountered GARCH-effects are not only due to the time-dependent arrival of news but also of the heterogeneity of traders' processing of news. This seems to confirm the rather large impact of the adverse selection component in the bid-ask spread estimates.

III.3 *Identifying components*

Sources of 'news' can be split into 'noise' news originating on the market and 'identifiable' news related to public announcements. A list of events of the latter type has been gathered from the Financial Times for the considered period:

insert Exhibit 2

Bundesbank meetings, tax and inflation rumours (directly related to the underlying value of the BUND), are allegedly known first at DTB (being Frankfurt based). Schmidt and Iversen (1992) provide a strong argument for this allegation: the larger DTB members (German banks that paid to set DTB up) tend to have ready access to Bundesbank information. It is, however, difficult to pinpoint each item (e.g., the rumours) to a particular time or even date. In this section we will therefore only give circumstantial evidence on the importance of certain news items.

Interest tax rumours probably originate in Frankfurt. Take for example March 4 when rumours on interest cuts circulated. Parameter γ_{12} for March 4 is insignificant in Frankfurt, while its counterpart γ_{21} is significant in London. Interestingly, volatility is flowing in the other direction (α_{12} significant, α_{21} not significant). Another, already mentioned, link can be found for week 5. News on German inflation levels was suddenly reversed compared to the March 26 announcement on stabilization. Apparently this caused substantial uncertainty, hence news flowing strongly from DTB towards LIFFE.

Usually, news flows in both directions. This bi-directional effect is typical. It probably indicates that news is at the most bi-directional, but hardly ever only from DTB to LIFFE. The latter effect may however appear if we split the day into morning and afternoon. The Bundesbank meeting on March 19, combined with the potential Chicago-listing made LIFFE vulnerable to DTB news. On March 26, news flows were bi-directional. DTB's impact may have come from German inflation announcements. On April 3, DTB was relatively 'abandoned'. This is reflected in the uni-directional LIFFE towards DTB flow. Elections in Britain come together with strong dependency in DTB returns. In such a case news obviously originates in London.

IV. Conclusion

The results of this paper indicate that LIFFE still is the dominant market maker despite a non-trivial loss in market share. Even with higher commission fees, LIFFE is still capable of attracting most volume. Both computerized systems (DTB and APT) seem to be hurt by a large compensation in bid-ask spreads for the conditionality in expected returns. The multivariate tests confirm this observation both in conditional means as in conditional variances. Benveniste et al. (1992) mention that the intensive computerization of assets like government bonds and index derivatives is caused by their hedging nature, which means that trading ought to be less information driven. Our results indicate that this is clearly not the case for the BUND contract which potentially attracts a proportionally large amount of non-hedging volume. News traders are probably very influential considering the close links between both markets. If time-intervals are chosen in extension of one minute, dependency distinctions can no longer be made. This reflects the rapid arbitrage relation between markets. Though not reported, multivariate portmanteau tests on the optimal lag structure confirm this observation.

Co-persistence in variance, Bollerslev and Engle (1993), is an issue which is potentially influencing our spillover estimates. In addition, this co-persistency feature might lead to a bias in the estimated vector error correction model, as discussed in Franses et al. (1993). Innovations in either market influence volatility in the other market but there would be the possibility of a common unit root in variance biasing variance inferences like Chan et al. (1991). This is an alternative way of assessing whether fundamental variance is equal across the exchanges. Future research will tackle these issues.

Finally, we address the question raised in the abstract whether mere duplication can lead to the simultaneous existence of two identical contracts traded at different market places. Examples listed in Black (1986) seem to reject such a situation. Black's success indicator model points towards failure of the German Bund version. However, three particular DTB characteristics may explain its success. First, since the underlying asset is Germany based, fundamental news seems to leak first at DTB. Second, the distinction in trading systems probably offers DTB an access advantage in the long run. Finally, making this contract the touchstone (quite unlike Black's failure examples) of the exchange puts additional pressure on market makers in guaranteeing its success.

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Exhibit 1

Sep.	1988	BUND contract launched on LIFFE.
Apr.	1989	Option on BUND launched on LIFFE.
Nov.	1990	BUND contract launched on DTB.
Apr.	1991	DTB dealers asked by Exchange to offer maximum three-tick spread and take at least 20 contracts on each side.
Jun.	1991	Margin requirements on BUND lowered on DTB.
Aug.	1991	Option on BUND launched on DTB. BUND futures exchange fees eliminated and BUND option fees are cut on DTB.
Nov.	1991	Market-makers commit to trade (own accounts in) BUNDS on DTB.
Mar.	1992	DTB announces listing of BUND in Chicago.

Exhibit 2 - Spring 1992

March 4	DTB - rumours on interest cut are disturbed due to tight Bundesbank repo
March 5	LIFFE - expiration of March contract (roll-over)
March 6	DTB - expiration of March contract (roll-over) announcement of high German inflation
March 12	DTB - rumours on interest tax (foreign investors)
March 19	Meeting Bundesbank committee - no interest cut
March 20	DMark devalues versus US dollar - market loss
March 19-20	Futures Industry Association Meeting announces DTB-Bund listing at CBOT
March 23	Interest cut rumours from Bundesbank sources
March 24	LIFFE opens strong, collapses, stabilizes
March 26	Deutsche Bank announces: inflation peak reached
March 31	Inflation in Bayern up to 5%
April 1	Bundesbank complains on wage-price spiral
April 3	DTB 'abandoned' due to weekend regional elections
April 9	Elections in Britain; annual report Bundesbank
April 10	Conservatives win elections in Britain

Table 1. Number of Trades and Volume

DAY	DTB trades (volume)	LIFFE[1] trades (volume)	LIFFE - APT trades (volume)
mar2	199 (6,963)	447 (4,980)	133 (1,628)
mar3	299 (7,926)	703 (6,630)	83 (839)
mar4	587 (16,300)	1088 (34,320)	270 (2,813)
mar5	845 (21,800)	1326 (12,517)	177 (1,433)
mar6	984 (21,019)	1650 (22,192)	242 (2,897)
mar9	427 (11,093)	976 (10,595)	79 (724)
mar10	634 (18,035)	1073 (24,366)	158 (2,194)
mar11	737 (18,775)	1254 (31,066)	183 (2,355)
mar12	1183 (29,158)	1650 (53,879)	205 (2,032)
mar13	834 (19,892)	1530 (45,148)	348 (3,008)
mar16	675 (16,067)	961 (23,228)	81 (1,249)
mar17	733 (19,353)	1137 (25,905)	160 (1,787)
mar18	936 (24,801)	1758 (41,518)	366 (5,481)
mar19	963 (21,967)	1530 (39,118)	188 (2,259)
mar20	1095 (28,606)	1581 (41,551)	200 (2,338)
mar23	1139 (24,870)	1745 (44,434)	102 (1,184)
mar24	1403 (29,754)	2139 (56,628)	199 (2,378)
mar25	1154 (26,460)	1772 (43,729)	180 (2,259)
mar26	939 (19,957)	1466 (35,352)	62 (1,500)
mar27	1000 (24,053)	1643 (35,666)	192 (1,571)
mar30	1162 (24,625)	1652 (35,320)	132 (1,390)
mar31	1192 (26,415)	1567 (32,235)	199 (2,459)
apr1	928 (18,775)	1708 (34,286)	233 (2,962)
apr2	1110 (22,390)	1766 (36,609)	203 (1,969)
apr3	786 (16,671)	1414 (33,246)	162 (1,864)
apr6	1439 (32,301)	1951 (43,237)	215 (2,231)
apr7	1046 (23,018)	1730 (35,414)	254 (3,134)
apr8	1082 (23,351)	1787 (39,354)	145 (1,563)
apr9	1112 (25,489)	2169 (41,677)	518 (6,999)
apr10	1211 (28,739)	1764 (44,997)	168 (1,510)
Total	27,834 (648,623)	44,937 (1,009,197)	5,837 (68,010)
Trades/Minute Contracts/Trade	1.6 23.3	2.4 22.5	2.0 11.7

[1] LIFFE column includes APT hours. OOC trades/minute=2.5, and contracts/trade=24.1.

Table 2. Bid Ask Spreads for bunds at LIFFE and DTB[1]

DAY	LIFFE Roll	LIFFE APT Roll	LIFFE OOC Roll	DTB Roll	LIFFE GKN	LIFFE APT GKN	LIFFE OOC GKN	DTB [2] "GKN"
mar2	0.00564	0.00222	0.00646	0.00654	0.01759	0.02503	0.01266	0.01448
mar3	0.00795	0.00444	0.00837	0.00546	0.01394	0.01867	0.01323	0.01478
mar4	0.00862	0.00481	0.00956	0.00790	0.01274	0.01613	0.01145	0.01476
mar5	0.00831	- [3]	0.00891	0.00599	0.01252	0.00872	0.01301	0.01284
mar6	0.00846	0.00298	0.00908	0.00808	0.01383	0.02220	0.01182	0.01577
mar9	0.00957	0.00265	0.00995	0.00412	0.01459	0.02504	0.01314	0.01160
mar10	0.00890	0.00525	0.00940	0.00714	0.01362	0.01705	0.01297	0.01359
mar11	0.00861	0.00293	0.00922	0.00593	0.01209	0.01413	0.01169	0.01187
mar12	0.00883	0.00483	0.00921	0.00680	0.01194	0.01346	0.01171	0.01322
mar13	0.00794	0.00245	0.00894	0.00700	0.01160	0.01120	0.01169	0.01357
mar16	0.00965	0.00365	0.01003	0.00540	0.01397	0.02290	0.01286	0.01197
mar17	0.00842	0.00315	0.00900	0.00447	0.01272	0.01356	0.01260	0.01140
mar18	0.00809	0.00246	0.00901	0.00739	0.01273	0.01427	0.01232	0.01437
mar19	0.00893	0.00176	0.00952	0.00720	0.01315	0.01757	0.01243	0.01493
mar20	0.00883	0.00783	0.00893	0.00638	0.01351	0.02287	0.01159	0.01292
mar23	0.00895	0.00402	0.00921	0.00713	0.01401	0.03272	0.01198	0.01519
mar24	0.00893	0.00408	0.00927	0.00824	0.01317	0.01604	0.01285	0.01693
mar25	0.00814	0.00487	0.00843	0.00566	0.01249	0.01216	0.01253	0.01481
mar26	0.00892	0.01005	0.00883	0.00627	0.01378	0.01367	0.01379	0.01472
mar27	0.00846	0.00300	0.00892	0.00702	0.01377[4]	0.02511[4]	0.01437[4]	0.01435
mar30	0.00792	0.00496	0.00811	0.00531	0.01492	0.02437	0.01383	0.01364
mar31	0.00800	0.00404	0.00848	0.00567	0.01308	0.01266	0.01309	0.01344
apr1	0.00869	0.00453	0.00919	0.00667	0.01421	0.02301	0.01230	0.01439
apr2	0.00867	0.00366	0.00913	0.00661	0.01473	0.02342	0.01321	0.01387
apr3	0.00896	0.00198	0.00947	0.00581	0.01316	0.01824	0.01217	0.01280
apr6	0.00908	0.00414	0.00952	0.00692	0.01295	0.01501	0.01269	0.01468
apr7	0.00940	0.00380	0.01008	0.00587	0.01359	0.01618	0.01310	0.01349
apr8	0.00901	0.00574	0.00923	0.00536	0.01418	0.02534	0.01266	0.01332
apr9	0.00803	0.00592	0.00860	0.00704	0.01447	0.01812	0.01314	0.01592
apr10	0.00756	0.00249	0.00787	0.00832	0.01316	0.01800	0.01241	0.01655
Mean	0.00815	0.00409	0.00900	0.00646	0.01354	0.01856	0.01264	0.01401
St.Dev	0.00073	0.00174	0.00069	0.00103	0.00111	0.00540	0.00070	0.00135

[1] Spread estimator multiplied by 100 to reflect percentages (0.01 is equal to 1 tick).
[2] "GKN" column based upon asserted implicit positive autocorrelation of 0.6.
[3] Covariance estimator is positive (only occasion).
[4] Bid quotes missing - estimates based upon asserted implicit positive autocorrelation of 0.4.

Table 3. Statistics

DAY	Mean	Variance	Skewness	Kurtosis	Q(20)	ARCH
mar2 liffe	$-2.573*10^{6}$	$2.828*10^{-9}$	-0.980	6.910	29.271	0.105
dtb	$-1.979*10^{6}$	$2.183*10^{-9}$	-1.606	22.755	31.712^{*}	38.932^{**}
mar3 liffe	$1.980*10^{6}$	$5.627*10^{-9}$	-0.091	2.315	20.599	5.379^{*}
dtb	$1.782*10^{6}$	$3.415*10^{-9}$	0.097	9.286	21.829	1.008
mar4 liffe	$-5.151*10^{6}$	$6.097*10^{-9}$	-0.322	1.768	21.064	19.890^{**}
dtb	$-5.348*10^{6}$	$4.282*10^{-9}$	-0.811	6.644	25.016	16.363^{**}
mar5 liffe	$-3.174*10^{6}$	$8.388*10^{-9}$	-0.961	3.851	29.400	16.215^{**}
dtb	$-3.175*10^{6}$	$6.140*10^{-9}$	-1.104	11.239	28.230	36.413^{**}
mar6 liffe	$5.956*10^{7}$	$1.015*10^{-8}$	-0.296	1.628	17.881	16.834^{**}
dtb	$5.948*10^{7}$	$6.507*10^{-9}$	-0.711	7.939	26.422	0.006
mar9 liffe	$1.554*10^{6}$	$6.014*10^{-9}$	0.312	3.753	14.002	0.003
dtb	$1.110*10^{6}$	$3.750*10^{-9}$	4.114	55.445	25.272	0.200
mar10 liffe	$-2.383*10^{6}$	$6.100*10^{-9}$	-0.132	1.974	33.390^{*}	0.350
dtb	$-1.191*10^{5}$	$3.542*10^{-9}$	-0.446	4.451	25.163	13.026^{**}
mar11 liffe	$-3.177*10^{6}$	$6.243*10^{-9}$	-0.490	1.387	16.941	1.298
dtb	$-3.177*10^{6}$	$3.681*10^{-9}$	-0.231	2.767	24.462	18.191^{**}
mar12 liffe	$-9.956*10^{7}$	$1.035*10^{-4}$	-0.248	0.938	16.068	4.853^{*}
dtb	$-1.195*10^{6}$	$6.250*10^{-9}$	-0.079	1.685	23.940	1.903
mar13 liffe	$-2.593*10^{6}$	$7.847*10^{-9}$	-0.251	2.801	48.732^{**}	23.945^{**}
dtb	$-2.793*10^{6}$	$5.558*10^{-9}$	-0.538	7.352	44.532^{**}	0.509
mar16 liffe	$-5.992*10^{7}$	$5.885*10^{-9}$	-0.097	1.559	23.728	2.145
dtb	$-7.995*10^{7}$	$3.725*10^{-9}$	-0.212	3.295	14.263	9.532^{**}
mar17 liffe	$4.188*10^{6}$	$7.261*10^{-9}$	-0.262	4.203	28.943	14.602^{**}
dtb	$2.992*10^{6}$	$4.144*10^{-9}$	-0.810	13.104	28.325	2.848
mar18 liffe	$-6.982*10^{6}$	$8.866*10^{-9}$	-0.386	1.339	21.025	26.228^{**}
dtb	$-6.182*10^{6}$	$7.106*10^{-9}$	-0.044	8.541	29.226	7.933^{**}
mar19 liffe	$-1.199*10^{6}$	$8.747*10^{-9}$	-0.018	1.284	28.418	0.497
dtb	$-1.560*10^{6}$	$6.471*10^{-9}$	0.020	2.086	19.626	4.666^{*}
mar20 liffe	$-8.819*10^{6}$	$9.856*10^{-9}$	-0.670	2.761	12.413	0.084
dtb	$-8.218*10^{6}$	$7.053*10^{-9}$	-0.629	3.351	22.415	3.051
mar23 liffe	$-5.837*10^{6}$	$1.146*10^{-8}$	-0.223	1.358	12.954	0.188
dtb	$-6.442*10^{6}$	$1.000*10^{-8}$	-1.245	8.232	26.912	0.177
mar24 liffe	$1.861*10^{6}$	$1.574*10^{-8}$	-0.359	1.275	18.017	26.443^{**}
dtb	$1.655*10^{6}$	$1.424*10^{-8}$	-0.119	4.400	33.645^{*}	9.721^{**}
mar25 liffe	$1.609*10^{6}$	$1.654*10^{-8}$	-0.192	6.291	22.337	8.669^{**}
dtb	$1.408*10^{6}$	$1.236*10^{-8}$	0.242	5.244	16.910	3.141
mar26 liffe	$-2.481*10^{6}$	$1.266*10^{-8}$	-0.152	0.582	21.928	1.182
dtb	$-2.481*10^{6}$	$7.963*10^{-9}$	0.429	2.683	13.369	5.744^{*}
mar27 liffe	$-2.218*10^{6}$	$1.051*10^{-8}$	-0.246	1.154	19.567	1.209
dtb	$-1.815*10^{6}$	$7.544*10^{-9}$	0.150	2.223	28.431	9.122^{**}
mar30 liffe	$4.232*10^{6}$	$1.586*10^{-8}$	0.247	2.260	23.804	7.599^{**}
dtb	$4.432*10^{6}$	$1.041*10^{-8}$	-0.092	1.923	22.586	28.241^{**}
mar31 liffe	$1.207*10^{6}$	$1.366*10^{-8}$	0.377	3.558	32.281^{*}	36.412^{**}
dtb	$6.034*10^{7}$	$9.392*10^{-9}$	0.234	3.043	19.832	10.441^{**}
apr1 liffe	$-4.629*10^{6}$	$1.157*10^{-8}$	-0.150	1.680	27.436	7.156^{**}
dtb	$-4.830*10^{6}$	$7.329*10^{-9}$	-0.465	1.759	17.137	9.160^{**}
apr2 liffe	$-3.226*10^{5}$	$1.356*10^{-8}$	0.036	1.989	11.416	10.473^{**}
dtb	$2.011*10^{7}$	$8.947*10^{-9}$	0.057	4.065	17.632	4.087^{*}
apr3 liffe	$3.624*10^{6}$	$9.193*10^{-9}$	-0.096	1.312	22.725	16.149^{**}
dtb	$3.826*10^{6}$	$5.372*10^{-9}$	-0.151	2.660	23.546	1.193
apr6 liffe	$8.628*10^{6}$	$1.632*10^{-8}$	0.961	7.144	18.085	12.653^{**}
dtb	$9.029*10^{6}$	$1.100*10^{-8}$	1.073	7.360	23.303	34.834^{**}

apr7 liffe dtb	$4.201*10^{6}$ $3.402*10^{6}$	$1.349*10^{-8}$ $8.055*10^{-9}$	0.045 -0.249	1.536 5.342	25.790 7.760	1.381 2.480
apr8 liffe dtb	$-8.003*10^{7}$ $-3.997*10^{7}$	$1.289*10^{-8}$ $8.249*10^{-9}$	0.003 0.089	1.071 1.935	16.523 19.061	7.788^{**} 26.990^{**}
apr9 liffe dtb	$3.598*10^{6}$ $2.200*10^{6}$	$1.672*10^{-8}$ $1.201*10^{-8}$	0.415 0.936	2.125 6.800	28.728 28.664	59.078^{**} 37.283^{**}
apr10 liffe dtb	$-7.970*10^{7}$ $-9.956*10^{7}$	$1.358*10^{-8}$ $9.937*10^{-9}$	-0.405 -1.121	4.106 13.141	23.046 30.009	13.442^{**} 10.359^{**}
total liffe dtb	$-5.723*10^{7}$ $-6.597*10^{7}$	$1.047*10^{-8}$ $7.226*10^{-9}$	-0.040 -0.048	3.432 7.255	22.158 54.412^{**}	510.584^{**} 349.438^{**}

Table 4. Estimates and Tests of Causalities in Mean and Variance
Panel A. DTB

DAY	π_{11}	γ_{11}	γ_{12}	α_{11}	α_{12}	β_{11}	F	ADF
mar2	-0.160**	-0.052	-0.004	0.710**			1.353	-7.15**
mar3	-0.153**	-0.009	0.094		0.071**	0.322*	7.034**	-8.25**
mar4	-0.192**	-0.059	0.071	0.022	0.107**	0.728**	4.174*	-8.92**
mar5	-0.233**	-0.001	0.126**	0.104**	0.065**	0.590**	8.989**	-9.40**
mar6	-0.202**	-0.068	0.104**	0.049**	0.034**	0.859**	8.742**	-9.61**
mar9	-0.207**	-0.037	0.054	0.348**	0.091**		1.067	-7.64**
mar10	-0.038	-0.190**	0.105**	0.075**	0.009**	0.913**	11.595**	-6.58**
mar11	-0.038	-0.095	0.109**	0.073**	0.009**	0.913**	21.454**	-7.78**
mar12	-0.247**	0.016	0.133**	0.021	0.077**	0.568**	10.106**	-10.04**
mar13	-0.147**	-0.205**	0.147**	0.019	0.108**	0.831**	5.448*	-8.55**
mar16	-0.243**	0.009	-0.027		0.014**	0.953**	0.273	-10.25**
mar17	-0.108**	-0.005	0.150**		0.070**	0.798**	19.434**	-6.20**
mar18	-0.063*	-0.138*	0.227**	0.143**	0.063**	0.712**	72.718**	-5.89**
mar19	-0.287**	-0.039	0.137**	0.126**	0.089**	0.615**	8.177**	-11.21**
mar20	-0.175**	-0.030	0.154**	0.043**	0.032**	0.893**	23.204**	-8.66**
mar23	-0.312**	0.053	0.090	0.076	0.014	0.510**	4.321*	-10.51**
mar24	-0.217**	-0.053	0.281**	0.025	0.085**	0.846**	21.374**	-11.21**
mar25	-0.362**	0.006	0.098	0.219**	0.038	0.546**	0.524	-11.72**
mar26	-0.133**	-0.022	0.220**	0.078**		0.818**	31.419**	-7.71**
mar27	-0.114**	-0.107*	0.179**	0.084**	0.042**	0.807**	19.926**	-8.29**
mar30	-0.186**	0.058	0.158**	0.031	0.069**	0.828**	19.019**	-10.48**
mar31	-0.075	-0.130*	0.243**	0.050*	0.047**	0.861**	15.050**	-7.90**
apr1	-0.269**	-0.088	0.140**	0.081*	0.066**	0.687**	11.668**	-11.36**
apr2	-0.274**	-0.060	0.127**	0.128**	0.058**	0.697**	8.487**	-10.68**
apr3	-0.169**	-0.106*	0.105**	0.108**	0.027	0.753**	8.721**	-9.99**
apr6	-0.267**	0.054	0.124**	0.159**	0.110**	0.650**	3.739	-9.36**
apr7	-0.154**	-0.070	0.068	0.128**	0.035**	0.826**	7.534**	-8.67**
apr8	-0.217**	-0.012	0.149**	0.113**	0.129**	0.354**	11.075**	-10.54**
apr9	-0.065**	-0.137**	0.330**	0.206**	0.038*	0.611**	69.780**	-5.93**
apr10	-0.203**	-0.102	0.185**	0.150**	0.092**	0.624**	10.640**	-11.12**
TOTAL	-0.188**	-0.054**	0.157**	0.032**	0.038**	0.738**	2638.27**	-44.44**

*,** indicates significance levels of respectively 5% and 1%.
[1] parameters from equations (5), (6), and (7).
[2] Augmented Dickey Fuller test for cointegration in levels.

Table 4. continued
Panel B. LIFFE

DAY	π_{22}	γ_{22}	γ_{21}	α_{22}	α_{21}	β_{22}	F
mar2	-0.047	-0.031	-0.049	0.032**	0.028**	0.954**	3.940*
mar3	-0.077**	-0.034	0.014	0.032**	0.068*	0.884**	0.0165
mar4	-0.113**	-0.113*	0.154*	0.084**	0.100	0.642**	10.133**
mar5	-0.121*	-0.041	0.138**	0.100**	0.064*	0.808**	3.874*
mar6	-0.132**	-0.122*	0.195**	0.174**	0.018	0.709**	12.088**
mar9	-0.081**	-0.141**	0.119		0.166*		5.340*
mar10	-0.133**	-0.018	-0.057		0.025**	0.983**	0.448
mar11	-0.127**	-0.113*	0.115*	0.020	0.037*	0.931**	2.813
mar12	-0.126*	-0.095	0.161*	0.068**		0.858**	8.599**
mar13	-0.092	-0.087	0.082	0.014	0.077**	0.927**	6.450*
mar16	-0.122**	-0.199**	0.022	0.031**	0.018	0.932**	1.390
mar17	-0.125**	-0.066	0.231**	0.096**		0.834**	5.404*
mar18	-0.101**	-0.031	0.024	0.062**		0.917**	0.431
mar19	-0.127*	-0.064	0.155**	0.013	0.095**	0.854**	6.005*
mar20	-0.121**	-0.074	0.094	0.008	0.041*	0.929**	3.108
mar23	-0.121*	-0.054	0.178**	0.001	0.072*	0.819**	10.942**
mar24	-0.151*	0.187**	0.103	0.133**	0.053	0.760**	1.095
mar25	-0.096	-0.011	0.053	0.103*	0.363**	0.346**	1.454
mar26	-0.131**	-0.102	0.221**	0.030	0.151	0.569**	14.601**
mar27	-0.107*	-0.083	0.137*	0.051	0.085*	0.803**	2.319
mar30	-0.186**	0.004	0.259**	0.075*	0.220**	0.669**	13.221**
mar31	-0.117*	-0.002	0.103	0.057	0.299**	0.256	3.615
apr1	-0.254**	0.038	0.117	0.094*	0.245**	0.637**	2.340
apr2	-0.136*	-0.048	0.034	0.053	0.230**	0.496**	0.409
apr3	-0.166**	-0.090	0.338	0.062*	0.068**	0.854**	1.610
apr6	-0.081	-0.120	0.252**	0.135*	0.379**	0.624**	8.920**
apr7	-0.102*	-0.188**	0.229**	0.040	0.086**	0.864**	13.117**
apr8	-0.135*	-0.040	0.085	0.063	0.041	0.215	1.371
apr9	-0.030	-0.027	0.038	0.099**	0.184*	0.710**	1.549
apr10	-0.161**	0.015	0.098		0.316**	0.784**	0.277
TOTAL	-0.093**	-0.089**	0.142**	0.059**	0.032**	0.740**	277.731**

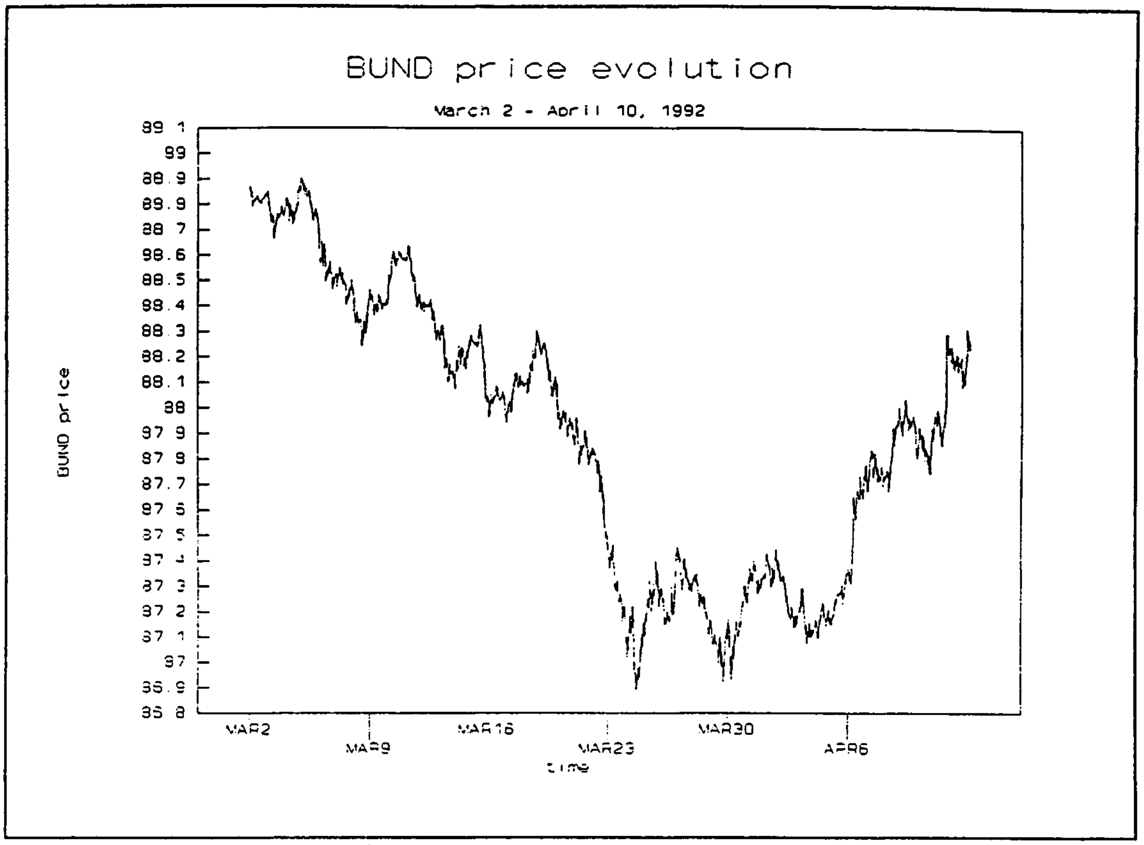
$$\Delta X_t = \Theta + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-i} + \Pi X_{t-p} + E_t$$

$$\text{with } \Theta = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix}, \quad \Gamma_i = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}, \quad \Pi = \begin{bmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{bmatrix},$$

$$\text{and } H_t = \Omega + A E^2_{t-1} + B H_{t-1}$$

$$\text{with } \Omega = \begin{bmatrix} \omega_1 \\ \omega_2 \end{bmatrix}, \quad A = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix}, \quad B = \begin{bmatrix} \beta_{11} & 0 \\ 0 & \beta_{22} \end{bmatrix}.$$

Figure 1. BUND Transaction Prices[1]



[1] Transaction prices used are quoted at LIFFE. On the full six-week scale matching DTB prices can not be distinguished. Overnight prices are connected.

Figure 2. BUND Transaction Prices

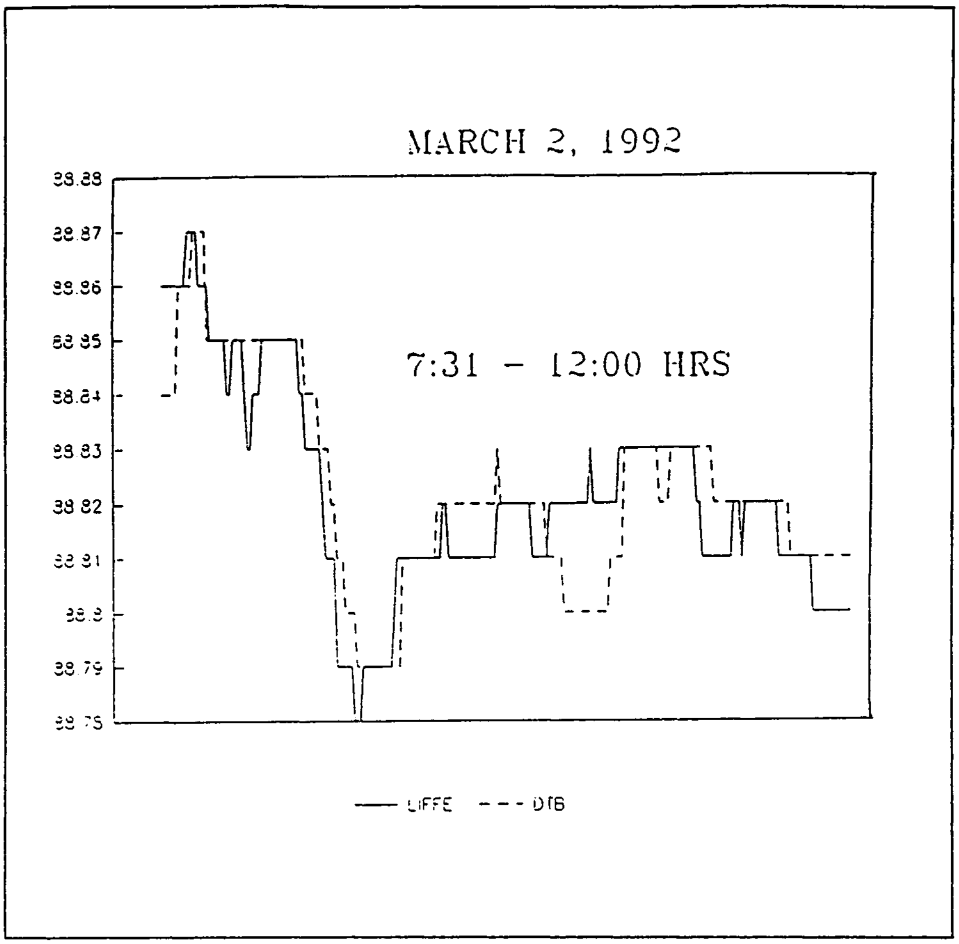


Figure 3. Impulse Response Functions