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Spreads, Information Flows and Transparency Across Trading Systems

Paul Kofman and James T. Moser

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Spreads, Information Flows and Transparency Across Trading Systems

by

Paul Kofman
Department of Econometrics, Monash University
Clayton, VIC 3168, Australia
Phone: 61 (3) 905-5847

and

James T. Moser
Research Department, Federal Reserve Bank of Chicago
230 S. LaSalle Ave., Chicago, IL 60604-1413, U.S.A.
Phone: 1 (312) 322-5769

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Abstract

This paper analyzes the dynamics of price formation for a strictly identical derivatives contract which is traded simultaneously at two competing exchanges. The domestic exchange is situated in the country that issues the underlying instrument. The foreign exchange offers a large international capital centre with many diversification possibilities. In addition, the exchanges are characterized by different trading systems. The domestic exchange operates by automated trading, the foreign exchange uses open outcry with an automated late afternoon session. We will investigate whether these differences support a trading system segmentation hypothesis. Our working hypothesis is two-fold. First, we investigate whether quote setting is related to the transparency of each trading system. Second, we analyze whether the relative transparency of each market influences the lead/lag relationship between the two markets. Both hypotheses will be empirically tested for the Bund futures contract as it is traded in London (LIFFE) and Frankfurt (DTB).

Keywords:
Trading system segmentation, Market transparency, Bid-Ask spreads, Vector Error Correction, GARCH errors.

The conclusions of this paper are strictly those of the authors and not necessarily those of the Federal Reserve Bank of Chicago or the Federal Reserve Board of Governors.

Spreads, Information Flows and Transparency
Across Trading Systems
Is There LIF(F)E After DTB?

Abstract

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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, index contracts and derivatives in general) 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 trading volume. The latter to the contrary usually plunges the competing exchanges in a battle for contract survival.

Consider an asset which is simultaneously traded at two exchanges. In a fully efficient market context, news flows should be incorporated in both exchanges' transaction prices giving instantaneous and bi-directional causality. Usually, however, there will be frictions that result in a lead-lag relation. Differences in trading costs may stimulate traders to choose one exchange in favour of the other. In such a situation, according to Madhavan (1994) the most liquid market will inevitably attract all volume leading to eventual consolidation of the market. The main determinant for a contract's potential to survive is its ability to attract order flow. Ultimately, the lower cost exchange tends to dominate the market and 'crowd out' its competitor. There is, however, an exception to this rule which may lead to sustained market segmentation despite the existence of these frictions. One of the sources of segmentation is a difference in transparency among the market segments. These differences are probably most apparent when comparing floor trading with automated systems. Computerized systems offer anonymity and this confronts market makers with uncertainty about whom they are trading with. Grünbichler et al. (1994) list the pros and cons of screen trading and claim that the anonymity aspect induces informed traders to use the automated system to 'skim off' the market. Hence, the pricing lead of the automated exchange increases. This, of course, is often supposed to be the most cost efficient exchange, and will therefore be chosen anyhow. There is, however, a counteracting force. Market makers on the automated system increase their bid-ask spread for protection against informed traders, thereby increasing the cost of trading. This will automatically induce noise traders to leave this market segment since their single motivation is lowest cost. Thus, it reduces the liquidity of the system and makes it more difficult for informed traders to have their 'informed' trades absorbed smoothly. The informational lead of the automated exchange will then be reduced or even disappear.

This paper tries to find evidence for a situation where both forces offset each other lending support for a sustained segmentation of the market. In that case the marginal trader will be indifferent to a preferred trading system which is consistent with this marginal trader being a noise trader. To test our market segmentation hypothesis, we specify two related hypotheses. First, we investigate whether the difference in transparency across the different trading systems is accounted for in quote setting by market makers. Second, we test whether there is evidence of a lead/lag relationship despite equal trading costs.

Our first hypothesis will be tested by bid-ask spread estimation. Standard technique is the application of Roll (1984). To overcome the known shortcomings of this estimator we also use the George et al. (1991) alternative which enables us to gauge the importance of information asymmetry. An elegant approach to detect evidence for the second hypothesis will be given by bivariate error correction modeling (VECM). 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 information flows are thus distinguished into three sources: levels, changes in levels (returns) and volatility shocks. In addition to the leadership question that we address in this framework, it also enables us to give an interpretation to Amihud and Mendelson's (1987) analysis of fundamental variance. We define fundamental variance as asset-related variance. Our VECM-GARCH approach extracts market-related characteristics from observed variance which should necessarily lead to a variance measure which is unique for both markets since we deal with a single asset. Our specification of market-specific variance captures time-varying returns, volatility and bid-ask spreads that may differ across markets.

A typical empirical example of sustained market segmentation is given by the BUND futures contract as it is currently traded on the LIFFE (London International Financial Futures Exchange) and on the DTB (Deutsche Terminbörse). Whereas the first operates a mixture of mainly open outcry and after hours automated pit trading, the latter operates by fully computerized trading. The estimation results indicate that bid-ask spreads are virtually identical for both exchanges. Their contents differ however, in that DTB's effective bid-ask spread contains a large reservation for information asymmetry. Price leadership tests indicate that market information flows predominantly in both directions with the exception of fundamental (German) news releases. Interestingly our findings lead to the conclusion that there is no obvious relation between price volatility and bid-ask spreads.

In the next section we will give an outline of our testing strategy by evaluating some standard tools to tackle both hypotheses. Section 3 applies these tools to the BUND futures contract and extends the analysis to a short event study of influential news items. Section 4 concludes this paper with a couple of remarks and limitations.

II. Asymmetric Information Costs in Bid-Ask Spreads

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 causes 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). In Section A we will investigate which market offers the tightest spread, and hence, is cheapest to execute these orders. Section B will investigate the causality relationships.

A. Information asymmetry in bid-ask spreads

Dealers' processing of bid and ask orders entails costs. The required compensation theoretically implies that transaction returns will be negatively autocorrelated. This feature has been exploited in obtaining estimates of the bid-ask spread. Roll's (1984) simple approach is based on this serial covariance in the returns. It has one major advantage over alternative spread estimators. It requires only transaction prices without knowledge of the market quotes nor whether the transaction took place at the bid or ask. Roll's estimator is given as:

which measures the autocovariance in the transaction returns. Problems with this estimator are

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

well documented. In Stoll (1989) the three determinants of bid-ask spreads are categorized as order processing, adverse information and inventory costs. Correctness of Roll's estimator depends crucially on the assumption that order processing is the only cost component driving the autocorrelation of returns. This may be valid for highly liquid and frequently traded markets, but for many thin markets this is obviously not true. Several alternative estimators, mostly adaptations of equation (1), have therefore been proposed. Of these, we will focus on one which tends to account for most of the bias in Roll's estimator.

Even if markets are highly liquid, it is still possible that Roll's spread measure is not appropriate. 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. There may even be a causal link between this alleged efficiency gain and the conditionality finding. Roll (1984) argues that his estimator is invariant to changes in the frequency of data measurement. According to Stoll (1989), the efficiency gain can only occur because of time-varying expected returns. This phenomenon is captured in George et al. (1991). Conditionality in the returns implies positive autocorrelation, hence leading to a negative bias in Roll's estimator. An intuitive explanation is as follows. Market makers revise their expectations conditional on the type of order that arrives. Unfortunately (for the market maker) these revisions can be anticipated by traders. To avoid a concerted attack, the market maker will then need to revise his bid and ask prices simultaneously. In George et al. (1991) two alternative estimators are introduced to account for this revision:

$$S_{GKN,1} = 2 * \sqrt{-COV(\Delta X_{BT,t}, \Delta X_{BT,t+1})}$$
$$S_{GKN,2} = 2 * \sqrt{-COV(\Delta X_{ET,t}, \Delta X_{ET,t+1})} \qquad (2)$$

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 follows:

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

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:

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

where ρ is the first-order autocorrelation coefficient. Both estimators exceed the Roll estimate and therefore reduce this particular bias.

How does this bias relate to the components of the spread? George et al. argue that 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 open outcry over computerized trading. Identification and (informal) sanctioning of informed traders is more easily achieved in the open outcry market. If expected returns turn out to be time-varying this risk will even be larger. Hence, the extent of the bias measures the relative importance of information asymmetry. On a higher level, the bias measures the threshold cost of automated trading for a marginal trader to be indifferent to preferred trading system.

Laux and Senchack (1994) mention an additional bias in Roll's estimator if volatility is time-varying. Even if that is true, that is not a serious problem in our approach. Jones et al. (1994) find that the frequency of transactions drives the heteroskedasticity in returns over fixed time intervals. Since we use frequently recorded data for our bid-ask spread estimation, this reduces the problem.

B. Price Leadership

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 time gap their approach is of the "open-to-close" type and not informative on the high frequency relations in synchronous price movements[1]. 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 the synchronicity of trading implying 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. There is an obvious analogy to Amihud and Mendelson's (1987)[2] distinction between fundamental and observed variance. In our setting, observed variance is measured by

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

2 Amihud and Mendelson use 'value' variance instead of fundamental variance.

unconditional variance, whereas fundamental variance is measured by standardized variance. The latter is estimated by creating a series of standardized residuals after removing the conditional components in the observed residuals, and calculating the variance of this 'clean' series. Clean, in the sense that it is only related to asset-related conditions and free from market specific conditions. A simple variance ratio test indicates whether this fundamental variance is equal across markets. This ratio of standardized variances for the DTB and LIFFE is F-distributed. Such equality is particularly important in a duplicated asset setting, where noise should be attributed to technical differences between market places only. 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, however, a long-run equilibrium relation exists between some of the series, this differencing implies a loss of information. Our model therefore consists of a simple autoregressive structure of order *p* incorporating both short term dynamics and an error correction component reflecting the long-run relationship in the series.

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

where X_t is a vector of logarithmic transaction prices, θ is a vector of intercepts. The Γ_i matrix contains estimates for the vector autoregressive (VAR) model of returns. 'Long-run' or error correction estimates are provided in Π. We do not model equation (6) as in Hamao et al. (1990) where a moving average component is included in the mean equation. Instead, our specification better captures bid-ask plus expected returns bias by imposing a simple autoregressive structure. The fact that we deal with two markets trading in an identical asset implies that the coefficient reflecting information arrival should be identical in the long run. Therefore, the Π-matrix is constrained to contain identical elements for each row[3]:

The zero mean process for the residuals E_t in equation (6), conditional on information set Ψ

[3] Bivariate Engle-Granger type testing yields estimates which are not significantly different from 1 for our empirical BUND application.

$$\Pi = \begin{bmatrix} \pi_j & -\pi_j \\ -\pi_k & \pi_k \end{bmatrix} \qquad (6)$$

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):

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

where H_t is the conditional variance matrix for the considered markets, Ω is a matrix of intercepts, $(E_{t-1})^2$ is a vector of per-minute squared innovations/news (and measures unconditional variance). Standardized residuals are given by $E_t/\sqrt{H_t}$, and the variance of this series measures fundamental variance. This particular specification allows us to discriminate between sources of volatility, whether they originate in the considered market or spillover from other markets. Equation (8) allows lagged, but not contemporaneous spillovers. Consistent with the Engle et al. approach we do restrict the multivariate conditional covariance to be constant through time. Combined with the other restrictions, relaxation of these assumptions is relatively simple. The resulting structure would, however, make economic interpretation rather cumbersome. Consistent with Pagan (1986), the present setting allows us to generate consistent and efficient estimates for $\Gamma, \Pi, \Theta, A, \mathbf{B}$ and, Ω, by single equation estimation of this 'multi-variate' GARCH model[4]. 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. Standard Akaike and Schwartz criteria may not

[4] 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 might be small.

be appropriate in this setting. A multivariate portmanteau (MPM) test is preferably used to determine p. Standard model specification tests (restrictions on parameters, lag structure), and standardized residuals tests are required to assess the model's robustness.

III. Empirical Application to BUND Futures

Bund trading was initiated at LIFFE in 1988. Following rescission 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) particularly due to an agressive cost-reducing policy. Since then, a stabilization of market ordering (in the sense of fixed market shares) seems to have taken place with LIFFE and DTB at, respectively a 65% and 35% level. Three years after our sample period this situation is still unaltered. It looks as if we have a case for sustained market segmentation.

To get a prior on the market structure, let us first describe the contract and 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 of trades and volume among the two exchanges, different trading systems and across trading days:

insert Table 1

In our sample LIFFE accounts for about 1.6 times as many observations as DTB, measured in terms of transactions as well as in number of contracts. This is also consistent with the 65%-35% market share distribution mentioned above. 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 exceeds DTB's. Across both exchanges the daily number of transactions seems to be moving in the same direction and proportion. Trading of this nearby contract has a very quick start once the roll-over from the previous nearby contract has taken place. The average daily volume (for the full period) 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 can bias our estimation results by putting too much weight on contemporaneous interaction. Further on, we will trade off this bias against the potential loss of information when aggregating over longer time periods. A one minute interval seems to be appropriate in striking the balance between a limited number of trading gaps and detection of potential lead-lag relations.

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 tests, 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 overnight subset due to a lack of a sufficient number of observations.

A. Liquidity

Liquidity of the BUND market is assessed by two indicators, bid-ask spreads and volatility aspects. Active trading on liquid markets usually implies small price changes. On the other hand, illiquid markets that are often characterized by extensive non-trading intervals are typically fraught with sudden and large price changes. In the latter case, inventory holding costs for market makers will be considerably higher than for the low volatility case. In addition, informed traders may have difficulty to get their informed trades 'through the system' if the market does not offer sufficient liquidity.

In either case, a further problem arises if volatility is time-varying. News will then not immediately be incorporated in prices but instead slowly disperse according to the extent of information asymmetry in the market. This exposes market makers to additional risk which, if realised, will lead them to revise their quotes. These revisions may consist of a shift in the spread but usually, assuming the direction of the price move is unknown, it will mean a widening of the spread. A larger spread increases trading costs and, hence harms liquidity.

In our duplicated market setting, traders can access either market to obtain liquidity wherever and whenever it is cheapest. Competition implies that, in theory, compensation for liquidity will be bid to the lower of the two costs (i.e. bid-ask spreads will be adjusted downwards). Our tests will indicate whether a wedge between both markets' liquidity cost exists and if so, whether it is sustainable (potentially due to other entry costs).

A1. 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). Evidence backing this assumption is given in Franses et al. (1994a). We estimate autocovariances of logarithmic returns instead of absolute price changes. The estimated spreads are therefore interpretable as percentages. One basis point 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)[5] and 0.82 (OOC) ticks, the adjusted GKN spreads are more consistent with quoted spreads. These are, according to Napoli (1992), about one and a half ticks (they are either one or two ticks). The GKN estimates give, respectively 1.4, 1.86 and 1.26 ticks. Note also that the standard deviation of the estimates 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 coefficient 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}).

Equivalence test results based on equation (5) are also given in Table 2. The M-statistic has been calculated for open outcry at LIFFE versus computerized trading at DTB. Whereas equivalence is very often rejected for the Roll estimates (with bid-asks considerably

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[5] 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 autocorrelations.

larger at LIFFE), it can not be rejected for the GKN estimates.

As in George et al. (1991), our results indicate a non-trivial impact of the time variation in expected returns. Implied bid-ask 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 time variation in expected returns, this advantage is reversed. This indicates that information asymmetry weighs heavily in the automated systems. This information asymmetry is particularly harmful for market makers if quotes are not updated quickly enough to reflect expected returns changes. Suppose, e.g., that bid-ask quotes are updated less often on APT/DTB than on OOC, then the former systems 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.

Summing up the evidence contained in our bid-ask spread estimates, several conclusions can now be drawn. Bid-ask spreads turn out to be virtually equal for both exchanges (except for the APT system which is apparently not competitive). However, the components of the spreads differ substantially. Order processing costs are lower in computerized systems, whereas information asymmetry weighs more heavily in these systems. Both findings confirm theoretical and anecdotal evidence. Realized spreads are almost equal which implies that the marginal trader will be indifferent to trading system. We will now proceed by investigating whether the equality of the spreads is also reflected in similar volatility for the exchanges.

A2. Price volatility

One of the cost components in market making is insurance against adverse price movements during 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 no longer based on transaction-spaced but on minute-by-minute observations (the rationale will be explained below).

insert Table 3

Evidence for autocorrelation in the returns 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. 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). Furthermore, equivalence is significantly rejected by means of an F-distributed variance ratio test. Unfortunately, both exchanges' returns exhibit excess kurtosis which may bias the F-test. However, unlike variance, in this case kurtosis is greater for the computerized exchanges. That would bias the F-test in a positive sense, making the rejection even stronger. The excess kurtosis measure 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. Evidence for the first explanation is found in the form of significant ARCH effects in both DTB and LIFFE returns. For both exchanges these processes account for most of the detected kurtosis. However, this 'elimination' of kurtosis does not imply that both markets are equally liquid after fitting an ARCH process. It merely indicates the source of differences in liquidity. In this case, the time-varying nature of variance indicates that absorption of new information may take longer in either one of the exchanges depending on the strength of the ARCH effects. Further evidence will be given in the next section.

B. Lead-lag relationships

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 intervals, 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 last recorded price is repeated, implying a zero return for that interval. 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 according to the ADF column in Table 4. This suggests bivariate simultaneous modeling. Estimates of the cointegrating relation strongly indicate the restriction on the Π-matrix, equation (6) to be 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 in (5). Most papers so far focused on either the cointegration aspect or the ARCH errors, see e.g. Chan et al. (1991). The optimal lag length (p) for the vector autoregressive part of equation (5) is according to a multivariate portmanteau test equal to one. A priori we would not have expected any lead-lag relationship exceeding one minute given the (almost) prompt arbitrage opportunities.

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. Obviously there is not a one-way leader in this market. Let us now elaborate on how this lead/lag can be decomposed.

The error correction term π_{ij} is very often significant. Both DTB and LIFFE estimates indicate a strong error correction behavior. However, LIFFE seems to react a little less to 'long-run' misalignments, particularly in weeks 4 and 6. The 'short-run' adjustments (γ_{ij}, where $i \neq j$) indicate that DTB is significantly influenced by LIFFE and vice versa. The γ_{ij}-estimates (where $i=j$) reflect the bid-ask spread induced autocorrelation, and are mostly significantly negative. Interestingly, these two autoregressive components are of about the same magnitude. Combined, the results for the DTB indicate a slightly stronger conditionality on the competing exchange than for the LIFFE. This would indicate leadership of LIFFE, but not in a very convincing way.

Conditionality in the variance of the returns, equation (7), 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 significant for news flowing in either direction. There is however an interesting switch in weeks 5 and 6 when LIFFE seems to become much more vulnerable to shocks originating at DTB. The results can be used to measure the respective resiliency of the exchanges as given by the half-life of shocks. Once again (as in Section A2) it is found that the computerized system absorbs shocks quicker (half-life = 4.4 trading minutes at DTB) than open outcry (half-life = 8.7 trading minutes). These findings are supported by smaller standard errors for these point estimates.

How can we interpret the volatility transmission estimates? LIFFE lists only best bid-offers whereas DTB generates quotes by auction. Then, news arriving at DTB will generate a shock causing DTB quotes to be updated. The reverse is less likely since the bid-offers at LIFFE are relatively firm. A shock arriving at LIFFE must trade at its bid or offer. By the time the LIFFE bid-offers are updated, the news has arrived at DTB. Hence, news which arrives at LIFFE first would appear to simultaneously arrive at DTB. But news arriving at DTB would generate a shock to LIFFE prices which would appear to precede the arrival of a LIFFE shock. Essentially, the difference is the necessary time to revise the LIFFE's bid and offer quotes. Shortening the interval between trades should cause more lags of DTB volatility to be related to LIFFE shocks. Lengthening the lag interval would decrease the number of related lags.

Though not reported, we conducted the usual tests on stability and robustness of our results. Likelihood Ratio tests ($\alpha_{ij}=\beta_{ij}=0$) are all highly significant indicating the appropriateness of taking account of the conditional dependence in the second moments. None of the LM-tests for inclusion of additional lags in the conditional variance equation are significant[6]. There is still some excess kurtosis remaining in the standardized residuals which is sometimes suggested as indicative of Student-t distributed errors. Ljung-Box tests for the standardized

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6 There are some exceptions, where an ARCH(1) model is preferred to a GARCH(1,1) model, e.g. March 2 and 26 in panel A. Persistence of shocks is usually much lower when the β-term equals zero.

residuals and standardized squared residuals indicate that only incidentally any further first or second order serial dependence remains. Variance estimates of the standardized residuals indicate that "fundamental" variances' equality can not be rejected at the 99% confidence level, which is in line with Amihud and Mendelson's (1987) results.

In addition, we also tested for the inclusion of traded volume and frequency of transactions as an explanatory variable for the conditional variance and the conditional mean. Equivalent to the results in Jones et al. (1994), this leads to highly significant estimates for either variable in the variance equation while considerably reducing the estimates for the $A(\alpha_{ij})$- and $B(\beta_{ij})$-matrices. More often than not however, these latter estimates remained 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 support the rather large impact of the information asymmetry component in the bid-ask spread estimates. Including the activity variable in the conditional mean equation (5) did not turn out to be significant. This is probably an indication of a high degree of absorption of both markets where the size of the transaction has little or no market impact.

C. Events

Sources of 'news' can be split into 'market' news originating on the market and 'fundamental' news related to the underlying instrument. 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. Whereas parameter γ_{21} for March 2 and 3 is insignificant in London, it suddenly appears on March 4. 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 of inflation. Apparently this caused substantial uncertainty, hence news flowing strongly from DTB towards LIFFE. This link is disconnected on April 3 when DTB is 'abandoned'.

With few exceptions, news flows in both directions. This bi-directional effect is typical for a sustained competition case. It indicates that neither exchange is consistently leading the market which would lead to the eventual demise of the follower.

IV. Concluding Remarks

The results of this paper indicate that after an initial loss in market share, LIFFE and DTB have reached some state of sustained competition. Despite higher commission fees, LIFFE is still capable of attracting sufficient order flow. An important factor contributing to that outcome seems to be the compensation for information asymmetry in bid-ask spreads. Both computerized systems (DTB and APT) seem to be hurt by a large reservation in bid-ask spreads due to the loss in transparency. The flow tests in Section III.2 confirm this general finding both in conditional means as in conditional variances. If time intervals are chosen in excess 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 for the tests in Section III.2 confirm this observation. Fundamental (asset-related) variance is shown to be equal for both markets. Obvious differences in observed variance are therefore due to market-specific conditions. These consist of differences in time-variation of expected returns and volatility.

Co-persistence in variance, Bollerslev and Engle (1993), is an issue which is potentially influencing our spillover estimates. In Franses et al. (1994b) this issue is addressed, and it seems unlikely that it affects our error correction estimates. Future research will further investigate this aspect.

Finally, we address the question whether mere duplication can lead to trading system segmentation of the market for a single contract. Chowdhry and Nanda (1991) point towards the eventual dominance of the primary market for this contract. However, our empirical exercise indicates that there is a case for sustained competition. Our tests indicate that the marginal trader on DTB and LIFFE is indifferent to the trading system. Information asymmetry costs add up on order processing costs bringing trading costs to a 'critical' level. At that level the marginal trader no longer has a preference for either system since he is not compensated by anonymity. That is consistent with the marginal trader being a noise trader. Hence it supports our trading system segmentation hypothesis. Almost three years later (after our data period) the relative market share of both exchanges is virtually the same. The relative cost of transparency between the two exchanges leads to an interesting balance of market share. Paradoxical as it may seem, it is possibly best for LIFFE to stick to its floor trading system instead of slowly replacing (some may say modernizing) it by its APT-system.

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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)
march 2	199 (6,963)	447 (4,980)	133 (1,628)
march 3	299 (7,926)	703 (6,630)	83 (839)
march 4	587 (16,300)	1088 (34,320)	270 (2,813)
march 5	845 (21,800)	1326 (12,517)	177 (1,433)
march 6	984 (21,019)	1650 (22,192)	242 (2,897)
march 9	427 (11,093)	976 (10,595)	79 (724)
march 10	634 (18,035)	1073 (24,366)	158 (2,194)
march 11	737 (18,775)	1254 (31,066)	183 (2,355)
march 12	1183 (29,158)	1650 (53,879)	205 (2,032)
march 13	834 (19,892)	1530 (45,148)	348 (3,008)
march 16	675 (16,067)	961 (23,228)	81 (1,249)
march 17	733 (19,353)	1137 (25,905)	160 (1,787)
march 18	936 (24,801)	1758 (41,518)	366 (5,481)
march 19	963 (21,967)	1530 (39,118)	188 (2,259)
march 20	1095 (28,606)	1581 (41,551)	200 (2,338)
march 23	1139 (24,870)	1745 (44,434)	102 (1,184)
march 24	1403 (29,754)	2139 (56,628)	199 (2,378)
march 25	1154 (26,460)	1772 (43,729)	180 (2,259)
march 26	939 (19,957)	1466 (35,352)	62 (1,500)
march 27	1000 (24,053)	1643 (35,666)	192 (1,571)
march 30	1162 (24,625)	1652 (35,320)	132 (1,390)
march 31	1192 (26,415)	1567 (32,235)	199 (2,459)
april 1	928 (18,775)	1708 (34,286)	233 (2,962)
april 2	1110 (22,390)	1766 (36,609)	203 (1,969)
april 3	786 (16,671)	1414 (33,246)	162 (1,864)
april 6	1439 (32,301)	1951 (43,237)	215 (2,231)
april 7	1046 (23,018)	1730 (35,414)	254 (3,134)
april 8	1082 (23,351)	1787 (39,354)	145 (1,563)
april 9	1112 (25,489)	2169 (41,677)	518 (6,999)
april 10	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 **GKN**	APT-liffe Roll **GKN**	OOC-liffe Roll **GKN**	DTB Roll **GKN[2]**	M[5] Roll **GKN**
march 2	0.0056 **0.0176**	0.0022 **0.0250**	0.0065 **0.0127**	0.0065 **0.0145**	0.0 **0.0122**
march 3	0.0080 **0.0139**	0.0044 **0.0187**	0.0084 **0.0132**	0.0055 **0.0148**	0.1210 **0.0091**
march 4	0.0086 **0.0127**	0.0048 **0.0161**	0.0096 **0.0115**	0.0079 **0.0148**	0.0262 **0.0437**
march 5	0.0083 **0.0125**	-[3] **0.0087**	0.0089 **0.0130**	0.0060 **0.0128**	0.1053 **0.0002**
march 6	0.0085 **0.0138**	0.0030 **0.0222**	0.0091 **0.0118**	0.0081 **0.0158**	0.0094 **0.0584**
march 9	0.0096 **0.0146**	0.0027 **0.0250**	0.0100 **0.0131**	0.0041 **0.0116**	0.4914 **0.0102**
march 10	0.0089 **0.0136**	0.0053 **0.0171**	0.0094 **0.0130**	0.0071 **0.0136**	0.0540 **0.0014**
march 11	0.0086 **0.0121**	0.0029 **0.0141**	0.0092 **0.0117**	0.0059 **0.0119**	0.1328 **0.0002**
march 12	0.0088 **0.0119**	0.0048 **0.0135**	0.0092 **0.0117**	0.0068 **0.0132**	0.0625 **0.0101**
march 13	0.0079 **0.0116**	0.0025 **0.0112**	0.0089 **0.0117**	0.0070 **0.0136**	0.0397 **0.0157**
march 16	0.0097 **0.0140**	0.0037 **0.0229**	0.0100 **0.0129**	0.0054 **0.0120**	0.2485 **0.0036**
march 17	0.0084 **0.0127**	0.0032 **0.0136**	0.0090 **0.0126**	0.0045 **0.0114**	0.3099 **0.0069**
march 18	0.0081 **0.0127**	0.0025 **0.0143**	0.0090 **0.0123**	0.0074 **0.0144**	0.0264 **0.0172**
march 19	0.0089 **0.0132**	0.0018 **0.0176**	0.0095 **0.0124**	0.0072 **0.0149**	0.0527 **0.0233**
march 20	0.0088 **0.0135**	0.0078 **0.0229**	0.0089 **0.0116**	0.0064 **0.0129**	0.0742 **0.0078**
march 23	0.0090 **0.0140**	0.0040 **0.0327**	0.0092 **0.0120**	0.0071 **0.0152**	0.0461 **0.0384**
march 24	0.0089 **0.0132**	0.0041 **0.0160**	0.0093 **0.0129**	0.0082 **0.0169**	0.0110 **0.0501**
march 25	0.0081 **0.0125**	0.0049 **0.0122**	0.0084 **0.0125**	0.0057 **0.0148**	0.1019 **0.0197**
march 26	0.0089 **0.0138**	0.0101 **0.0137**	0.0088 **0.0138**	0.0063 **0.0147**	0.0762 **0.0028**
march 27	0.0085 **0.0138[4]**	0.0030 **0.0251[4]**	0.0089 **0.0144[4]**	0.0070 **0.0144**	0.0397 **0.0**
march 30	0.0079 **0.0149**	0.0050 **0.0244**	0.0081 **0.0138**	0.0053 **0.0136**	0.1214 **0.0001**
march 31	0.0080 **0.0131**	0.0040 **0.0127**	0.0085 **0.0131**	0.0057 **0.0134**	0.1081 **0.0004**

april 1	0.0087 **0.0142**	0.0045 **0.0230**	0.0092 **0.0123**	0.0067 **0.0144**	0.0687 **0.0172**
april 2	0.0087 **0.0147**	0.0037 **0.0234**	0.0091 **0.0132**	0.0066 **0.0139**	0.0704 **0.0019**
april 3	0.0090 **0.0132**	0.0020 **0.0182**	0.0095 **0.0122**	0.0058 **0.0128**	0.1626 **0.0016**
april 6	0.0091 **0.0130**	0.0041 **0.0150**	0.0095 **0.0127**	0.0069 **0.0147**	0.0698 **0.0148**
april 7	0.0094 **0.0136**	0.0038 **0.0162**	0.0101 **0.0131**	0.0059 **0.0135**	0.1917 **0.0006**
april 8	0.0090 **0.0142**	0.0057 **0.0253**	0.0092 **0.0127**	0.0054 **0.0133**	0.1885 **0.0015**
april 9	0.0080 **0.0145**	0.0059 **0.0181**	0.0086 **0.0131**	0.0070 **0.0159**	0.0292 **0.0259**
april 10	0.0076 **0.0132**	0.0025 **0.0180**	0.0079 **0.0124**	0.0083 **0.0166**	0.0017 **0.0583**

[1] Spread estimator multiplied by 100 to reflect percentages (0.001 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.
[5] M-test on equivalence of bid-ask estimates for OOC-liffe versus DTB (test for the equivalence of the serial covariances), see Box (1949):

$$M_{jk} = \frac{5}{18}\left[\frac{1}{T_j} + \frac{1}{T_k} + \frac{1}{T_j + T_k}\right] * \left[(T_j + T_k)\ln|\overline{scov}| - T_j \ln|scov_j| - T_k \ln|scov_k|\right] \quad \text{where} \quad \overline{scov} = \frac{T_j scov_j + T_k scov_k}{T_j + T_k} \tag{8}$$

where T_i is the sample size for exchanges j and k, and $scov_i$ is the serial covariance estimate. For independent samples T_j and T_k, the test statistic M_{jk} is χ^2 distributed with three degrees of freedom under the null hypothesis H_0: $scov_j = scov_k$.

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	$-1.191*10^{-6}$	$3.542*10^{-9}$	-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	$-9.956*10^{-7}$	$1.035*10^{-8}$	-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	$4.201*10^{-6}$	$1.349*10^{-8}$	0.045	1.536	25.790	1.381
dtb	$3.402*10^{-6}$	$8.055*10^{-9}$	-0.249	5.342	7.760	2.480
apr8 liffe	$-8.003*10^{-7}$	$1.289*10^{-8}$	0.003	1.071	16.523	7.788**
dtb	$-3.997*10^{-7}$	$8.249*10^{-9}$	0.089	1.935	19.061	26.990**
apr9 liffe	$3.598*10^{-6}$	$1.672*10^{-8}$	0.415	2.125	28.728	59.078**
dtb	$2.200*10^{-6}$	$1.201*10^{-8}$	0.936	6.800	28.664	37.283**
apr10 liffe	$-7.970*10^{-7}$	$1.358*10^{-8}$	-0.405	4.106	23.046	13.442**
dtb	$-9.956*10^{-7}$	$9.937*10^{-9}$	-1.121	13.141	30.009	10.359**

Table 4. Estimates[1] 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[2]
mar2	-0.160**	-0.261**	0.122**	0.710**			23.530**	-7.15**
mar3	-0.153**	-0.162**	0.247**		0.071**	0.322*	64.814**	-8.25**
mar4	-0.192**	-0.263**	0.288**	0.022	0.107**	0.728**	91.735**	-8.92**
mar5	-0.233**	-0.234**	0.359**	0.104**	0.065**	0.590**	115.537**	-9.40**
mar6	-0.202**	-0.270**	0.306**	0.049**	0.034**	0.859**	110.008**	-9.61**
mar9	-0.207**	-0.294**	0.258**	0.348**	0.091**		42.606**	-7.64**
mar10	-0.038	-0.228**	0.143**	0.075**	0.009**	0.913**	41.158**	-6.58**
mar11	-0.038	-0.132**	0.147**	0.073**	0.009**	0.913**	75.140**	-7.78**
mar12	-0.247**	-0.231**	0.380**	0.021	0.077**	0.568**	118.373**	-10.04**
mar13	-0.147**	-0.352**	0.293**	0.019	0.108**	0.831**	88.788**	-8.55**
mar16	-0.243**	-0.234**	0.217**		0.014**	0.953**	50.687**	-10.25**
mar17	-0.108**	-0.113	0.258**		0.070**	0.798**	47.225**	-6.20**
mar18	-0.063*	-0.201**	0.290**	0.143**	0.063**	0.712**	132.821**	-5.89**
mar19	-0.287**	-0.325**	0.425**	0.126**	0.089**	0.615**	131.982**	-11.21**
mar20	-0.175**	-0.205**	0.329**	0.043**	0.032**	0.893**	103.517**	-8.66**
mar23	-0.312**	-0.259**	0.402**	0.076	0.014	0.510**	112.017**	-10.51**
mar24	-0.217**	-0.271**	0.498**	0.025	0.085**	0.846**	168.931**	-11.21**
mar25	-0.362**	-0.356**	0.460**	0.219**	0.038	0.546**	88.026**	-11.72**
mar26	-0.133**	-0.155**	0.353**	0.078**		0.818**	87.062**	-7.71**
mar27	-0.114**	-0.221**	0.293**	0.084**	0.042**	0.807**	94.540**	-8.29**
mar30	-0.186**	-0.128*	0.344**	0.031	0.069**	0.828**	112.451**	-10.48**
mar31	-0.075	-0.207**	0.320**	0.050*	0.047**	0.861**	53.817**	-7.90**
apr1	-0.269**	-0.357**	0.410**	0.081*	0.066**	0.687**	140.007**	-11.36**
apr2	-0.274**	-0.334**	0.401**	0.128**	0.058**	0.697**	79.677**	-10.68**
apr3	-0.169**	-0.275**	0.274**	0.108**	0.027	0.753**	71.831**	-9.99**
apr6	-0.267**	-0.212**	0.391**	0.159**	0.110**	0.650**	84.693**	-9.36**
apr7	-0.154**	-0.223**	0.222**	0.128**	0.035**	0.826**	82.007**	-8.67**
apr8	-0.217**	-0.229**	0.366**	0.113**	0.129**	0.354**	117.386**	-10.54**
apr9	-0.065**	-0.202**	0.395**	0.206**	0.038*	0.611**	138.940**	-5.93**
apr10	-0.203**	-0.305**	0.388**	0.150**	0.092**	0.624**	148.342**	-11.12**

*,** 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. cntd Panel B. LIFFE

DAY	π_{22}	γ_{22}	γ_{21}	α_{22}	α_{21}	β_{22}	F
mar2	-0.047	-0.078	-0.002	0.032**	0.028**	0.954**	0.877
mar3	-0.077**	-0.111**	0.091	0.032**	0.068*	0.884**	1.750
mar4	-0.102**	-0.169**	0.234**	0.064**	0.114*	0.741**	20.847**
mar5	-0.121*	-0.162**	0.259**	0.100**	0.064*	0.808**	10.932**
mar6	-0.132**	-0.254**	0.327**	0.174**	0.018	0.709**	33.054**
mar9	-0.081**	-0.221**	0.200*		0.166*		11.599**
mar10	-0.133**	-0.151**	0.076		0.025**	0.983**	1.806
mar11	-0.127**	-0.240**	0.242**	0.020	0.037*	0.931**	14.310**
mar12	-0.126*	-0.221**	0.286**	0.068**		0.858**	22.873**
mar13	-0.092	-0.180**	0.175*	0.014	0.077**	0.927**	11.115**
mar16	-0.122**	-0.321**	0.144*	0.031**	0.018	0.932**	11.225**
mar17	-0.125**	-0.191**	0.356**	0.096**		0.834**	17.135**
mar18	-0.101**	-0.132**	0.125*	0.062**		0.917**	4.145*
mar19	-0.127*	-0.191**	0.282**	0.013	0.095**	0.854**	25.172**
mar20	-0.121**	-0.195**	0.215**	0.008	0.041*	0.929**	13.480**
mar23	-0.121*	-0.175**	0.298**	0.001	0.072*	0.819**	25.179**
mar24	-0.151*	0.036	0.254**	0.133**	0.053	0.760**	14.967**
mar25	-0.096	-0.107	0.150	0.103*	0.363**	0.346**	5.509*
mar26	-0.131**	-0.233**	0.353**	0.030	0.151	0.569**	33.617**
mar27	-0.107*	-0.190**	0.244**	0.051	0.085*	0.803**	11.355**
mar30	-0.186**	-0.182**	0.444**	0.075*	0.220**	0.669**	46.734**
mar31	-0.117*	-0.119*	0.220**	0.057	0.299**	0.256	16.194**
apr1	-0.254**	-0.217**	0.371**	0.094*	0.245**	0.637**	27.031**
apr2	-0.136*	-0.184**	0.170*	0.053	0.230**	0.496**	5.283*
apr3	-0.166**	-0.256**	0.169**	0.062*	0.068**	0.854**	4.383*
apr6	-0.081	-0.201**	0.333**	0.135*	0.379**	0.624**	13.719**
apr7	-0.102*	-0.290**	0.331**	0.040	0.086**	0.864**	30.891**
apr8	-0.135*	-0.176**	0.220**	0.063	0.041	0.215	10.231**
apr9	-0.030	-0.057	0.069	0.099**	0.184*	0.710**	4.887*
apr10	-0.161**	-0.147**	0.259**		0.316**	0.784**	9.416**

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

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

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

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

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