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VOLATILITY TRANSMISSION AND PATTERNS IN BUND FUTURES

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Abstract

We analyze intraday volatility behavior for the Bund futures contract that is traded simultaneously at two competing exchanges. We investigate the transmission of volatility between the exchanges. We find that the lead/lag relations are restricted to a few minutes and do not reveal a dominant leader. We then analyze patterns in intraday volatility. We find that volatility behaves similarly at both exchanges; i.e., it decreases from the opening until early afternoon and increases thereafter. The same pattern is detected in explanatory variables such as traded volume and time-between-trades.

I. Introduction

The equilibrium price of a financial asset listed at several markets simultaneously is likely to be determined in all these markets jointly. Even though these different markets often consist of different traders and possibly different

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trading systems, intraday price series should be almost identical according to the no-arbitrage condition. When the price in one market exceeds that in the other market, an arbitrageur could buy the asset in one market and sell it at the same time in the other market. Hence, the arbitrageur can lock in a riskless gain, provided the difference in prices is sufficiently large to offset transaction costs.

The similarity of connected financial asset price series is subject of various studies both at the level of returns and the level of volatility. Interactions in returns are explored extensively. We focus on the interaction of the second distributional moment, volatility. The most popular approach to this issue is (bivariate) ARCH modeling. Unfortunately, for very high-frequency data this technique is not appropriate. Even though theoretically this method works, when confronted with market microstructural aspects, the validity is often empirically rejected. We propose an alternative approach that is useful for very high-frequency data.

Future price movements are difficult to predict. Volatility, on the other hand, often shows systematic patterns through time that may be predictable. This forecastability can be useful in, for example, the pricing of (futures) options. In addition to this "statistical" motivation, theoretical arguments explain our interest in volatility transmission. Stoll and Whaley (1990) and Chan, Chan, and Karolyi (1991) focus on transmissions in returns and volatilities within the context of price discovery. They argue first that if volatility in two markets varies over time in a related way, this may lead to incorrect inferences from an analysis of returns transmission. Second, if a returns analysis is inconclusive, volatility spillovers provide an alternative measure of information transmission. Third, volatility transmission may predict the arrival rate of information. All three arguments make the analysis of volatility transmission a compelling exercise.

We analyze the volatility transmission and intraday patterns of the Bund futures contract. This major derivative asset is traded simultaneously (trading hours almost coincide) at the London International Financial Futures Exchange (LIFFE)[1] and at the Deutsche Termin-Börse (DTB) in Frankfurt. For the common trading hours of LIFFE and DTB, we examine whether systematic patterns occur in the transmission of volatility. Such patterns may indicate a lead and/or lag relation. One interpretation of this phenomenon is that relevant news can originate in one market and disperse eventually to the other market (e.g., Ederington and Lee (1993)). For returns, these market interactions are researched extensively (for the Bund futures contract, e.g., Kofman and Moser (1997)). A general result is that simultaneity dominates in returns transmission, stirred by an occasional lead of either one of the two exchanges. Presumably, these occurrences are driven by news originating at the leading market. An important distinguishing characteristic between the two Bund

[1]Currently, LIFFE already has an average daily volume of about 140,000 contracts, easily exceeding 200,000 contracts when, for example, there is a Bundesbank meeting on Germany's interest rate policy.

futures markets is that one exchange (LIFFE) uses an open outcry (floor trading) system and the other uses an automated trading system. Amihud and Mendelson (1987) note that volatility dynamics are affected by the mode of operation of an exchange. Their distinction between fundamental (value) variance and observed variance is particularly relevant for our setting where the former equalizes across the two exchanges because of arbitrage. The latter, however, may be influenced by market microstructural differences driven by the choice of trading system, for example. That makes it imperative to investigate and compare the respective intraday volatility patterns at both exchanges. For a proper volatility transmission analysis, we filter the individual intraday volatility series to remove these idiosyncratic volatility patterns.

Considering the usual strength of arbitrage, we expect that differences in returns, as well as in their volatility, do not last very long. This requires us to consider volatility at very short intervals. A commonly used measure of volatility is the sample standard deviation or variance of either prices or returns. This measure can only be computed for short intervals that contain a sufficient number of prices or price changes. Given that we are interested in analyzing volatility at one- and five-minute sampling intervals, we consider the number of price changes as an alternative to sample standard deviation to test for the presence of volatility transmissions between LIFFE and DTB.

Several recent studies show a systematic daily pattern in the volatility of liquid financial asset prices. Average volatility is typically high at both beginning and end of a trading session with relatively low values in between. The high morning variance can be attributed to the resolution of uncertainty during the overnight close. Reduced trading during lunch time explains the low intermediate variance, while (for European markets) the opening of the U.S. markets explains the increasing variance in the afternoon. This so-called U-shape is detected in equity markets (e.g., Wood, McInish, and Ord (1985) and Lockwood and Linn (1990)).[2] Futures markets, however, show ambiguous results. Ederington and Lee (1993) do not find any pattern for Eurodollar, Deutschemark, and Treasury bond futures. Webb and Smith (1994), on the other hand, detect a U-shape in the volatility of Eurodollar futures. Chan, Chan, and Karolyi (1991) also find a U-shape in the variance of S&P futures returns.

In this paper we test for the presence of a U-shape pattern in Bund futures price volatility, using the procedure of Lockwood and Linn (1990). This test can also be applied to a set of variables suggested by Fletcher (1995) to explain the volatility process. These information proxy variables include bid-ask spreads, volume, and trading intensity. Jones, Kaul, and Lipson (1994) use the number of

[2]Any shape that distinguishes the evolution of intraday volatility in terms of high-low-high classifies as a U-shape. Sometimes an inverse J is detected—high in the morning and then slowly tapering off.

trades instead of trading volume. We propose an additional activity variable, time-between-trades, to capture the same information suggested in Fletcher (1995). Unlike Jones, Kaul, and Lipson, we find that trade size does matter, in addition to trade activity. We also examine the explanatory power of these proxy variables for the specific pattern in intraday volatility. For that purpose we relate the U-shape pattern to the set of proxy variables and test whether these variables fully capture this pattern.

II. Data

We apply our analysis to the dually listed Bund futures contract. The asset concerns an agreement between buyer and seller to exchange a notional 6 percent German Government Bond (DM 250,000 face value) at a fixed maturity date for cash with delivery four times a year. Since September 1988, Bund futures are traded at the London International Financial Futures Exchange (LIFFE). In November 1990, trading in Bund futures was also introduced at the Deutsche Termin-Börse (DTB) in Frankfurt. The Bund contract has become the major futures contract in European financial markets. Severe competition between the exchanges, the dominant German capital market, and the stable German interest rates all contribute to the ongoing growth of this contract. Average daily volume on LIFFE, for example, increased from 20,000 contracts in 1988 to 200,000 contracts in 1996.

The data for our analysis are obtained from the exchanges' time and sales records time-stamped to the nearest second. For convenience, we use London time (GMT) throughout our investigation. LIFFE opens at 7:30 and trades until 16:15 by open outcry (OOC). After a five-minute break, trade is resumed until 17:55 using a computerized version of open outcry, called Automated Pit Trading (APT). In Frankfurt, automated trading starts at 7:00 and ends at 16:30.

Our dataset consists of two sample periods. The first period contains all transactions from March 2, 1992, through April 10, 1992. This period coincides with the time LIFFE accused a group of major German banks of diverting trades from LIFFE to DTB to boost the latter's market share. This dataset also coincides with the one used by Kofman and Moser (1996), who focus on the dynamics at the return level. The second sample period contains all transactions from September 8, 1995, through December 20, 1995. This more recent sample allows us to analyze whether the volatility spillovers and patterns change over time, apart from an obvious increase in trading volume.

Time, volume, and trading price are known for each transaction. For LIFFE we also have bid and ask quotes for our second sample period. However, we cannot identify whether transactions are initiated by a buyer or a seller. Our analysis is not biased by variable exchange rate denominations, since Bund futures prices are quoted in percentage points.

A first analysis of the data reveals that the Bund futures market is highly liquid in the sense of high turnover. For our 1992 sample, LIFFE reports 2.5 transactions each minute with an average of 22.5 contracts per transaction, while DTB reports 1.6 transactions each minute with an average of 23.3 contracts per transaction. For the 1995 sample, LIFFE reports 4.8 transactions each minute with an average of 33.7 contracts per transaction, while DTB reports 4.4 transactions per minute with an average of 17.9 contracts per transaction. In total, LIFFE accounts for approximately 1.6 times as many transactions as DTB for the 1992 sample, and 1.2 times as many transactions for the 1995 sample. The difference in turnover is not easily explained by a difference in transaction costs. The computerized DTB has slightly lower trade execution costs, but Kofman and Moser (1997) show that this cost advantage is largely offset by an asymmetric information risk in screen trading. That explains the relatively stable distribution of market shares for both exchanges. Following the November 1991 surge in DTB activity, these volume shares stabilized at about a 35 percent DTB market share versus a 65 percent LIFFE market share for the 1992 sample. Although the number of transactions per minute on DTB is now almost similar to that on LIFFE, LIFFE has a larger share of trades resulting in a 69 percent market share in terms of total volume. Pagano and Röell (1992) note that small orders are often executed at a better price in the electronic system whereas large orders obtain a better price in the floor system.

III. Methodology

An identical financial asset trading at two markets simultaneously should exhibit similar returns series for arbitrage reasons. The high quality of information technology and the possibility of rapid international capital flows allow arbitragers to execute trades within minutes at both exchanges. Return spillovers occur either instantaneously or within a very short time. We also expect this to be the case for volatility spillovers. When new and relevant information becomes available in one market, this is probably first observed at the volatility level in that market and only a few moments later in the other market.

We analyze intertemporal volatility transmission for the Bund futures contract. To be more specific, we investigate where relevant information becomes available and whether traders in one market are reacting to changes (regardless of whether they reflect new information) in the other market.

The Bund futures contract is a highly liquid asset. For five-minute sampling intervals, the sample standard deviation can be calculated from either returns or prices. The absolute difference between two consecutive transaction prices is often equal to zero, one or two ticks, and only incidentally larger than two ticks. While we only observe a few discrete levels of possible returns, we observe many different levels of prices. We therefore prefer to follow Webb and Smith (1994) who use the sample variance of prices rather than returns. For one-minute intervals, this might be a problem if there are too few observations. Our 1992 sample, for example, typically contains only two or three transaction prices per one-minute interval. We therefore use a second volatility measure, the number of price changes, that can be applied to very short sampling intervals. A disadvantage is the loss of information on the size of the price change. This need not be an important loss, since we are dealing with series of prices that are close to the continuously measured set of transaction prices. The shorter we choose our sampling interval, the more peaked and kurtotic our empirical returns distribution becomes. Price changes typically reflect the minimum tick size, basically because trades bounce between bids and asks. Standard volatility models (e.g., ARCH) then tend to be difficult to implement (e.g., Harris (1990)). We then compare the performance of our two volatility measures.[3]

Volatility over the five-minute interval t of day d, $V_{d,t}$, is defined as the square root of the sum of the squared deviations from the average of all prevailing prices in that interval. We call this measure SDP, the standard deviation of prices. The set of prevailing prices includes the previous interval's last recorded price, since we assume that price level to be valid until the first trade occurs in interval t.[4] An expression for $V^M_{d,t}$ (M indicates the market, LIFFE or DTB) is:

$$V^M_{d,t} = \sqrt{\left(\frac{(P_{d,t} - P^{N_{d,t-1}}_{d,t-1})^2 + \sum_{i=1}^{N_{d,t}}(P_{d,t} - P^i_{d,t})^2}{N_{d,t} + 1}\right)} \qquad (1)$$

where

$P^i_{d,t}$ = the i^{th} price in interval t of day d in either of the two markets;
$N_{d,t}$ = the number of prices for interval t of day d; and
$P_{d,t}$ = the arithmetic average of all prices in interval t (including the last price in interval $t-1$ of day d).

[3]Of course, many alternative risk measures exist: the difference between an interval's high and low, the absolute return, the squared return, etc. Most of them suffer from the fact that the bid-ask spread and minimum tick size dominate the possible price range.

[4]Our sample does not contain a price at the exact time of opening a new five-minute interval. Such a price would replace the previous interval's last recorded price in equation (1).

The volatility for one-minute sampling intervals is measured by the number of price changes, $K^{M}_{d,\tau}$,[5] where τ is the time index for one-minute intervals. We call this measure NPC, the number of price changes.

Using these volatility measures, we first explore volatility transmission from one market to the other market. We then look at the intraday pattern of volatility and check whether proxies for information (such as volume and time-between-trades) exhibit an intraday pattern similar to that of volatility and whether they explain the level of volatility. For this second purpose we use the average time series over our sample of trading days since we are interested in the average intraday structure. For both purposes we take into account that bid-ask bounce and discreteness bias our volatility estimates upwardly (Harris (1990), Stoll and Whaley (1990)). We control for this bias by filtering the intraday volatility estimates before our transmission analysis.

The Bund futures contract is only traded in two markets at almost identical trading hours. It can therefore be considered a closed system, not influenced by external factors. This has the advantage that we can rely on the bivariate causality testing method of Pierce and Haugh (1977). With causality, we imply causality in the sense of Granger (1969); a variable X causes another variable Y, with respect to a given information set (including the past values of X and Y), if present Y can be better predicted when using past values of X than by not doing so. All other information contained in the past is used in either case. According to Pierce and Haugh (1977), three outcomes (not necessarily mutually exclusive) are possible; i.e., x causes y, y causes x, and instantaneous causality exists. Feedback causality is defined as the case where x causes y and y causes x. Since we have only two relevant time series, we do not face identification problems often encountered in multiple time-series analysis.

To avoid spurious correlations between the original series due to idiosyncratic characteristics (such as the daily U-shaped pattern, discreteness, and bid-ask bounce) we filter the original series:

$$u_t = F(B)\,x_t$$

$$v_t = G(B)\,y_t \tag{2}$$

where $F(B)$ and $G(B)$ are polynomial functions of the backward shift operator B, and u_t and v_t are the residual series, components of x_t and y_t, respectively, that cannot be predicted from their own pasts. The x_t reflects $V^{\text{LIFFE}}_{d,t}$ in the case of five-minute SDP series and $K^{\text{LIFFE}}_{d,\tau}$ in the case of one-minute NPC series, and y_t reflects

[5] Since the minimum tick size is one, K will be close to N. After scaling K by the number of transactions, N gives a series that is (almost) constant. Using K/N then leads to a loss of "variability" in our regressions.

$V_{d,t}^{\text{DTB}}$ and $K_{d,\tau}^{\text{DTB}}$, respectively. We mitigate the bid-ask bounce and discreteness effect by specifying filters in (2) and using the residuals. Stoll and Whaley (1990) propose an ARMA(p,q) filter of infinite order. We use a similar procedure. An alternative method is based on pseudo-equilibrium prices (Ederington and Lee (1993)).

Pierce and Haugh (1977) show that the residuals u_t and v_t are subject to a causality-preserving transformation; the linear nature of the transformation insures that u and v are causally related in the same way as x and y. They also show that the cross-correlations ($\rho_{u,v}(k)$, the cross-correlation between u_t and v_{t+k}) between the prewhitened series characterize any causality event. For example, y does not cause x if and only if $\rho_{u,v}(k) = 0 \; \forall \; k < 0$. We only need to establish that u_t and v_t are each univariate white noise series. If that is true, instantaneous causality exists if and only if $\rho_{u,v}(0) \neq 0$. The causality direction, however, cannot be detected in this case. Whether instantaneous causality exists from X to Y, from Y to X, or both cannot be ascertained from the data.

We first obtain the whitened or filtered series from the original series specified in (2). We use the Box and Jenkins (1970) approach to estimate the appropriate filters from the sample series:

$$\hat{u}_t = \hat{F}(B)\, x_t$$

$$\hat{v}_t = \hat{G}(B)\, y_t \tag{3}$$

where we find the estimated filters by estimating autoregressive moving average (ARMA) processes.

We then analyze the causality by estimating the sample residual cross-correlations:

$$\hat{r}_k = r_{\hat{u}\hat{v}}(k) = \frac{\Sigma \hat{u}_{t-k}\, \hat{v}_t}{\sqrt{\Sigma \hat{u}_t^2 \, \Sigma \hat{v}_t^2}} \tag{4}$$

where k is an integer. Under the assumption of series independence, Pierce and Haugh (1977) show that any vector of correlations such as (4) is asymptotically normally distributed:

$$\sqrt{n}\,\hat{r} \sim N(0,I) \qquad \hat{r} = (\hat{r}_{k_1}, \ldots, \hat{r}_{k_m}) \tag{5}$$

where k_i are integers, and hence that

$$n\hat{r}'\hat{r} = n \sum_{i=1}^{m} \hat{r}_{k_i}^2 \tag{6}$$

is $\chi^2(m)$ distributed under the null hypothesis of independence.

We next investigate the intraday pattern of volatility. We analyze the sample volatility in each five-minute interval, SDP, averaged over all trading days. Chan, Chan, and Karolyi (1991), for the S&P cash and futures contracts, and Webb and Smith (1994), for the Eurodollar futures contract, show that we may expect to find a U-shape in the average volatility series. In particular, high volatility in the opening minutes, decreasing until lunch and increasing after lunch until market close. We expect to find a sudden jump in volatility when the U.S. markets open in the afternoon. We test for a U-shape by splitting every day into three periods and then perform a variance analysis. Lockwood and Linn (1990) suggest the following test statistic:

$$F = \frac{\frac{1}{J-1}\sum_{j=1}^{J} n_j (V_{.j} - V_{..})^2}{\frac{1}{N-J}\sum_{j=1}^{J}\sum_{i=1}^{n_j}(V_{ij} - V_{.j})^2} \tag{7}$$

where

V_{ij} = the i^{th} observation of the SDP volatility in intraday period j;
$V_{.j}$ = the average SDP volatility over the n_j observations in period j; and
$V_{..}$ = the overall SDP mean.

Under the null hypothesis of constant volatility, this F-statistic is approximately F-distributed with 2 and $N-3$ degrees of freedom. This statistic is independent of volatility clustering for successive intervals, since we average volatility over all available trading days. When F exceeds the relevant critical value and when the V_{ij} pattern resembles a U-shape, we reject the null hypothesis that the volatility level is constant during the day in favor of a U-shape.

We also analyze the intraday patterns of volume, time-between-trades, and bid-ask spreads. We use a simple linear regression to investigate whether the U-shape in volatility can be explained by these proxy variables:

$$V_t = c + \alpha * \mathrm{VOL}_t + \beta * (1/\mathrm{TBT}_t) + \gamma * \mathrm{BAS}_t + \epsilon_t \tag{8}$$

where

V_t = the five-minute sample volatility SDP averaged over all trading days in our sample;
VOL_t = the average volume per interval;
TBT_t = the average time-between-trades per interval; and
BAS_t = the average bid-ask spread per interval.

Since we expect the empirical pattern of TBT to be a U-shape, we consider the inverse of TBT in equation (8). We can test for significant effects of these information proxy variables and for the extent the proxy variables actually explain the U-shape in volatility by calculating the F-test in equation (7) based on the residuals in (8):

$$V_t^* = V_t - [\hat{c} + \hat{\alpha}*\text{VOL}_t + \hat{\beta}*1/\text{TBT}_t + \hat{\gamma}*\text{BAS}_t] \qquad (9)$$

Market microstructure papers sometimes use a more elaborate lag structure for the explanatory variables. However, incorporating the same variable at different lags increases the risk of multicollinearity.

Finally, to investigate whether LIFFE and DTB share a common U-shape, we use the F-test on the difference between the volatility series of LIFFE and DTB.

IV. Results

Volatility Transmission

Volatility clustering is a well-known characteristic of financial asset prices. Periods of high volatility alternate with periods of low volatility. Furthermore, we expect to find high first-order autocorrelation caused by bid-ask bounce and discreteness in our series (Stoll and Whaley (1990)). These causes have little to do with informational persistence, which implies that we first have to remove this autocorrelation bias.

For convenience we estimate an AR(10) model for all volatility series to remove the dynamic structure of the individual series. Even though we apply the Box-Jenkins (1970) methodology to specify individual ARMA models for each of the series, we find that an AR(10) is sufficient to whiten all of the considered series. While fixing the lag length at ten, we consider the inefficiency of this probably overparameterized model to be less important than spurious correlations, $\hat{r}_k$, due to too-restrictive models. The residuals from these AR(10) models constitute prewhitened series for both exchanges, for which we compute cross-correlations. We restrict our analysis to the volatility series from 7:30 until the close of LIFFE-OOC at 16:15, to avoid a potential influence of a change in trading system. A positive value of the cross-correlation $\rho(V_d^{\text{DTB}}, V_d^{\text{LIFFE}})(1)$ between current volatility at LIFFE and five-minute lagged volatility at DTB is interpreted as a lead of DTB on LIFFE. Similarly, a positive value of the contemporaneous cross-correlation of DTB and LIFFE, $\rho(V_d^{\text{DTB}}, V_d^{\text{LIFFE}})(0)$, implies simultaneous movements in volatility.

The cross-correlations between the prewhitened series are given in Table 1 for the 1992 and 1995 sample. The first two columns are based on the SDP measure defined in equation (1). Columns 3 and 4, and 5 and 6 are based on the

TABLE 1. Volatility Transmission Between LIFFE and DTB.

		Cross-correlations					
		SDP (no. of price changes per five-minute interval)		NPC (standard deviation per five-minute interval)		NPC (no. of price changes per one-minute interval)	
Leader[a]	Lag	1992	1995	1992	1995	1992	1995
LIFFE	-10	-0.016	-0.033**	0.012	-0.017	-0.016	-0.011**
	-9	-0.020	-0.015	-0.022	-0.002	-0.012	-0.006
	-8	0.007	-0.001	-0.006	-0.002	0.005	-0.010
	-7	-0.010	-0.020	0.005	-0.006	-0.002	0.001
	-6	0.014	-0.015	-0.013	-0.002	0.002	0.003
	-5	0.017	0.005	0.002	0.002	0.004	0.010
	-4	-0.002	0.007	0.005	0.004	0.011	0.013**
	-3	0.014	-0.009	0.005	0.024	0.023***	0.016***
	-2	0.012	0.008	-0.009	0.022	0.047***	0.037***
	-1	0.061***	0.001	0.089***	0.082***	0.093***	0.094***
	0	0.583***	0.756***	0.526***	0.616***	0.225***	0.291***
DTB	1	0.041**	0.066***	0.088***	0.094***	0.094***	0.136***
	2	0.011	0.019	0.033	0.006	0.051***	0.059***
	3	0.023	0.020	0.033	0.020	0.021***	0.032***
	4	0.022	0.012	-0.007	0.002	0.024***	0.024***
	5	-0.010	-0.010	0.021	0.011	0.002	-0.002
	6	-0.015	-0.002	-0.016	-0.003	0.010	0.011**
	7	0.020	0.004	-0.022	0.003	0.004	-0.012**
	8	-0.007	-0.018	-0.016	-0.007	-0.004	-0.004
	9	-0.008	-0.023	-0.018	-0.007	0.002	-0.008
	10	-0.003	-0.029**	-0.010	-0.024**	0.002	-0.012**
No. of Obs.[b]		3,130	7,551	3,130	7,551	15,730	37,755

Notes: A continuous series of SDP and NPC volatility estimates is generated by stacking the daily estimates for the 1992 and 1995 samples. Autocorrelation in these series is removed with an AR(10) filter. The residuals are used to estimate (intertemporal) cross-correlations. The standard error of the cross-correlation between two series of size N is calculated as $1/\sqrt{N}$.

[a]For the top half LIFFE leads, for the bottom half DTB leads.
[b]The number of effective observations is based on the maximum cross-correlation lag (=10).

**Significant at the 5 percent level.
***Significant at the 1 percent level.

NPC series for five-minute and one-minute sampling intervals, respectively. The first four columns (five-minute sampling interval) indicate no significant leads/lags exist beyond the first interval. The causality effect seems to be larger for the NPC measure in columns 3 and 4, while the simultaneous spillover is larger for the SDP measure. Whether NPC over- or underestimates the cross-correlations remains an open issue. The main conclusions are similar for both measures. Columns 5 and 6 indicate that for one-minute intervals DTB has a four- to six-minute lead and LIFFE

1992	
March 2	Germany's Treuhand agency reports on successful selling of half of the former East German state companies.[D]
March 3	Budget and election worries prompt profit-taking behavior in the UK government bond market.[L]
March 4	Rumours on interest rate cuts are quashed by Bundesbank's decision to drain DM 2.5 billion from the market at yesterday's security repurchase tender.[D]
March 5	Expiration of Bund futures contract at LIFFE.[L] Better-than-expected unemployment and industrial production figures in Germany.[D]
March 6	Expiration of Bund futures contract at DTB.[D] High German inflation announced.[D]
March 12	Rumours on interest taxation of foreign investors denied by the Finance Ministry of Germany.[D]
March 16	Bundesbank invites banks to tender for an issue of medium term treasury notes on March 24.[D]
March 18	Rumours that Germany's prime minister will attend Bundesbank committee meeting rises traders' expectations of interest rate cuts.[D]
March 19	Meeting of Bundesbank committee decides not to cut interest rates.[D] Futures Industry Association meeting announces DTB-Bund listing at Chicago Board of Trade.[D]
March 20	DMark devalues against USDollar.[D]
March 22	Chicago Board of Trade and DTB sign agreement to cooperate by introducing Bund futures trading in Chicago.[D]
March 23	Interest rate cut rumours from Bundesbank source.[D]
March 24	LIFFE Bund trading opens strong, then collapses before afternoon stabilization.[L]
March 26	Deutsche Bank announces that inflation has peaked.[D]
March 30	Finance Ministry in Bonn reports that foreign investors regain trust in the German capital market.[D]
April 1	Bundesbank warns about wage-price spiral.[D] British investors cautious because of Labour Party's lead in opinion polls.[L]
April 2	Futures traders slightly disappointed by Bundesbank's 1991 profit.[D]
April 3	Futures exchange 'abandoned' because of weekend regional elections in Germany.[L]
April 7	Bund futures react in response to false rumour on pay settlement in German public sector.[D]
April 9	British elections.[L] Annual report Bundesbank.[D]
April 10	Tories win British elections. Relieved capital market reaction.[L]

[L]Indicates LIFFE-oriented news item.
[D]Indicates DTB-oriented news item.

Figure I. News Items Related to Bund Futures Trading.

has a three- to four-minute lead. Comparing 1992 with 1995, the results are stable. One difference, however, is the strenghtening of the simultaneous cross-correlation. More than in the past, these markets have comparable speed in processing new information.

To investigate how information affects volatility, we collect some news items from the *Financial Times* that might have some effect on the Bund futures price in 1992. We compare the news items in Figure I with the (daily) volatility cross-correlations for 1992. Once again, we use an AR(10) filter to prewhiten the

TABLE 2. VolatilityTransmission for Each Trading Day in 1992.

	Cross-correlation				Cross-correlation		
Date	DTB Leads	SIM[a]	LIFFE Leads	Date	DTB Leads	SIM[a]	LIFFE Leads
March 2	0.171***	0.0252	-0.0122	March 23	0.103**	0.139***	0.174***
3	0.148***	0.0319	0.0430	24	0.152***	0.171***	0.180***
4	0.102**	0.0133	0.0733	25	0.176***	0.323***	0.0771
5	0.137***	0.216***	0.0518	26	0.0728	0.208***	-0.0040
6	0.0818	0.322***	0.119***	27	0.0435	0.163***	0.0603
9	-0.0559	0.212***	-0.0712	30	0.215***	0.392***	0.0647
10	0.0766	0.157***	0.0744	31	0.213***	0.260***	-0.0112
11	-0.0228	0.171***	-0.0403	April 1	0.0110	0.233***	0.0381
12	0.0244	0.294***	-0.0001	2	0.125***	0.279***	0.104**
13	0.154***	0.288***	0.0849	3	0.0494	0.218***	0.0831
16	0.0380	0.136***	0.0201	6	0.138***	0.256***	0.130***
17	0.207***	0.176***	0.0889**	7	0.0390	0.325***	0.0334
18	0.0365	0.186***	0.200***	8	0.0748	0.163***	0.0791
19	-0.0195	0.259***	0.114***	9	0.208***	0.247***	0.0846
20	0.0262	0.365***	0.0936**	10	0.164***	0.238***	0.166***

Notes: The NPC volatility measure for one-minute intervals is used to estimate intraday volatility series. Autocorrelation in these series is removed with an AR(10) filter. The residuals are used to estimate (intertemporal) cross-correlation. The standard error of the cross-correlation between two series of length N is calculated as $1/\sqrt{N}$.

[a]SIM indicates simultaneous cross-correlation.

**Significant at the 5 percent level.
***Significant at the 1 percent level.

NPC volatility series. Table 2 reports the cross-correlations $\rho(K_d^{\text{DTB}}, K_d^{\text{LIFFE}})(-1)$, $\rho(K_d^{\text{DTB}}, K_d^{\text{LIFFE}})(1)$, and $\rho(K_d^{\text{DTB}}, K_d^{\text{LIFFE}})(0)$ for that series. Simultaneous correlation is significantly positive for twenty-seven days. We observe a significant one-minute lead of LIFFE on ten days and a significant DTB lead on fifteen days. On thirteen days, this significant lead is unique. We call this a pure lead.

Different interpretations of the same news item in London and Frankfurt may induce volatility transmission from London to Frankfurt and vice versa within one trading day. A pure lead of DTB can be caused by news originating in Germany and affecting the UK throughout the day. These items are classified in Figure I as DTB oriented. In a similar vein we identify LIFFE-oriented news.

Comparing the news items with the results in Table 2, we observe for five of thirteen days a potential explanation of a pure lead of the DTB. Macroeconomic news (Treuhand agency, unemployment, and industrial production figures in Germany) explains the DTB lead on March 2 and 5. Bundesbank-related news explains the DTB lead on March 4 and April 9, while the Finance Ministry report explains March 30. The fortnightly Bundesbank meetings occur on March 5 and 19, and April 2, 1992. On March 5 and April 2, DTB has a significant lead over LIFFE, but on March 19 (when the Bundesbank decided not to cut interest rates) LIFFE

TABLE 3. News Related to Daily Volatility Spillovers.

Date (1995)	News	DTB Leads	SIM[a]	LIFFE Leads
September 8	Trade Balance June	0.101**	0.366***	0.107**
September 20	M3 August	0.206***	0.275***	0.0419
September 21	Bundesbank meeting	0.124***	0.378***	0.000529
September 27	Preliminary CPI September	0.141***	0.371***	0.125***
October 5	Bundesbank meeting Unemployment September	0.202***	0.334***	0.176***
October 10	Current Account July	0.158***	0.160***	0.0455
October 13	Retail Sales August	0.131***	0.338***	0.140***
October 19	Bundesbank meeting M3 September	0.155***	0.393***	0.0822
October 20	IFO[b] Survey September	0.120***	0.291***	0.133***
November 2	Bundesbank meeting	0.176***	0.261***	0.0890**
November 3	Current Account August Trade Balance August	0.178***	0.399***	0.130***
November 7	Unemployment October	0.0843	0.188***	0.0791
November 15	Retail Sales September	0.136***	0.375***	0.00132
November 16	Bundesbank meeting	0.101**	0.143***	0.104**
November 20	IFO Survey October	0.113***	0.296***	0.0364
November 22	M3 October	0.116***	0.207***	0.0897**
November 30	Bundesbank meeting	0.137***	0.317***	0.140***
December 6	Current Account September	0.0978**	0.346***	-0.000599
December 7	Unemployment November GDP 3rd Quarter IFO November	0.0940**	0.212***	0.152***
December 13	Retail Sales October	0.170***	0.222***	0.0982**
December 14	Bundesbank meeting	0.200***	0.254***	0.0699
December 20	M3 November	0.135***	0.256***	0.0279

Notes: The NPC volatility measure for one-minute intervals is used to calculate the correlations between LIFFE and DTB (simultaneous and one-minute lead/lags).

[a]SIM indicates simultaneous cross-correlation.
[b]IFO publishes a monthly survey information on overall business sentiment. The survey is regarded as the most important indicator for overall economic activity.

**Significant at the 5 percent level.
***Significant at the 1 percent level.

leads. In other cases, the results in Table 2 are difficult to attribute to news items in Figure I. In general, macroeconomic news and Bundesbank meetings seem to explain the lead of the host country of the underlying Bund asset. We therefore restrict our daily analysis of the 1995 sample to Bundesbank meetings and macroeconomic news in Germany.

Table 3 confirms our previous conclusions. Bundesbank meetings and macroeconomic news (e.g., the IFO survey, M3, Current Account, and Retail Sales) always coincide with a significant volatility spillover from DTB to LIFFE, which is often a pure lead. Other macroeconomic variables, such as the Production and Consumer Price Indexes, Unemployment, and Trade Balance are apparently less or not important.

We conclude that simultaneity dominates and that leads/lags are not mutually exclusive on individual days, which confirms the "full-feedback" results in Chan, Chan, and Karolyi (1991).

Intraday Volatility Patterns

We next investigate whether structural patterns occur in intraday volatility. For each five-minute interval, we compute the mean of SDP volatility, $V^M_{d,t}$, over all trading days. The average SDP volatility series for LIFFE and DTB are depicted in Figures II and III, respectively.[6] Note that the average SDPs are small, illustrating the typically small price change in Bund futures.

Comparing Figures II and III, we observe that LIFFE-OOC is slightly more volatile (average volatility of 0.92) than DTB (average volatility of 0.84), and that LIFFE-APT is least volatile (average volatility of 0.73). The latter confirms that LIFFE-APT serves as a system to offset positions at the end of the day without much news-driven volatility.

We might be tempted to conclude that automated systems (DTB and LIFFE-APT) are more informationally efficient given Amihud and Mendelson's (1987) notion of identical value variance. They argue that if observed variance is not equivalent for a strictly identical asset, the exchange with the lowest observed variance is the most informationally efficient. However, that conclusion is misleading since bid-ask bounce and discreteness inflate observed variance without implying informational inefficiency. To the contrary, the market that is perceived to be informationally superior attracts more order flow. The increase in transactions only increases the bias in observed volatility of this market.

We observe a U-shape in both series. Volatility decreases until noon and rises thereafter to remain at a higher level until closing time. The peak at 13:30 coincides with the opening of the U.S. financial markets. The volatility jump at 7:30 in Figure III reflects a suspended start of DTB Bund trading. Until the opening of LIFFE, at 7:30, volatility is relatively low in Frankfurt. At 16:15, when LIFFE closes for five minutes before changing to the APT system, we observe a similar drop in DTB volatility. These facts, combined with lower volatility, lower average volume of transactions, and less transactions per minute at DTB, indicate a more active role for the LIFFE trading floor.

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[6] Figures II through VIII are based on the 1995 sample. Similar figures for the 1992 sample are available from the authors upon request.

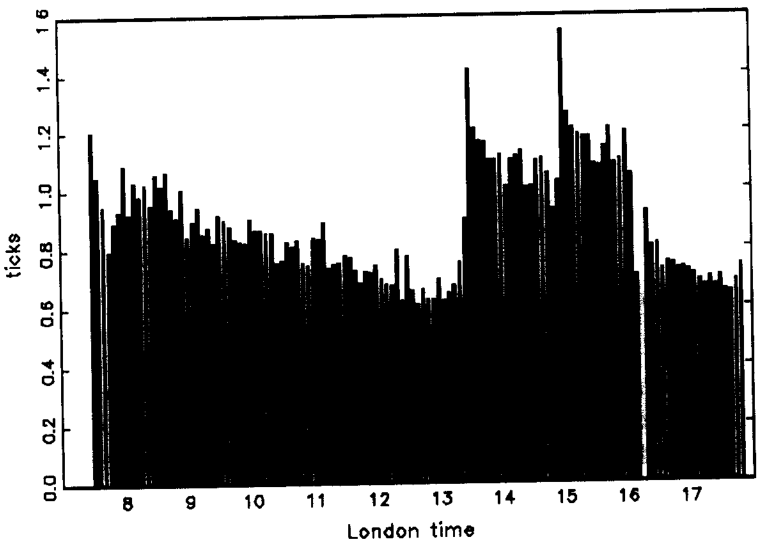

Figure II. Average Price Volatility (SDP) at LIFFE, September 8–December 20, 1995.

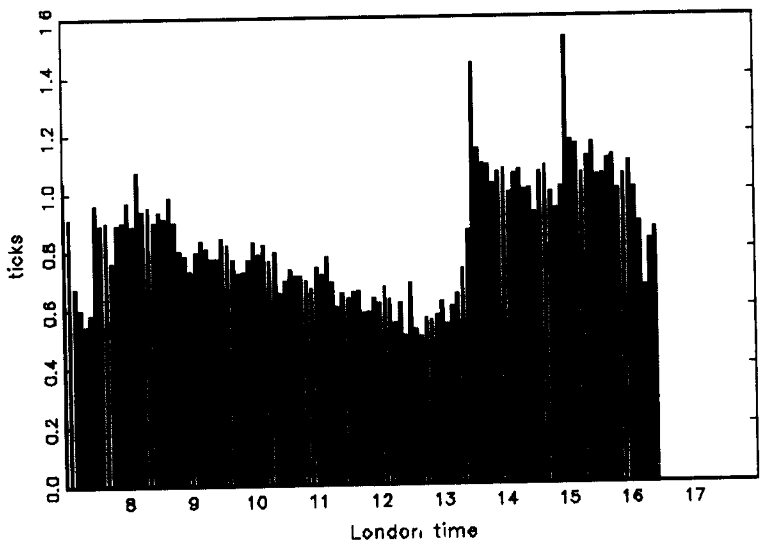

Figure III. Average Price Volatility (SDP) at DTB, September 8–December 20, 1995.

We also compute the averages of volume, time-between-trades, and (for LIFFE only) bid-ask spread. Volume is computed as the average number of contracts traded, time-between-trades as the average time between transactions, and the bid-ask spread as the difference between the last observed bid and ask quote.

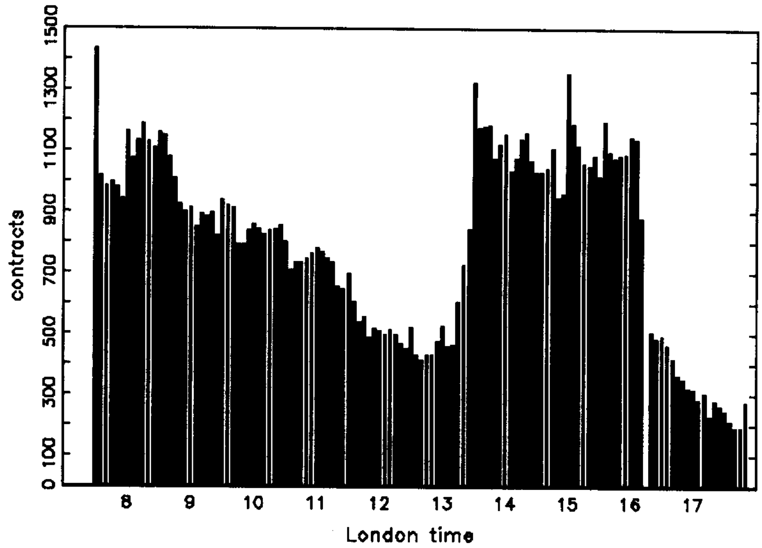

Figure IV. Average Number of Contracts (VOL) at LIFFE, September 8–December 20, 1995.

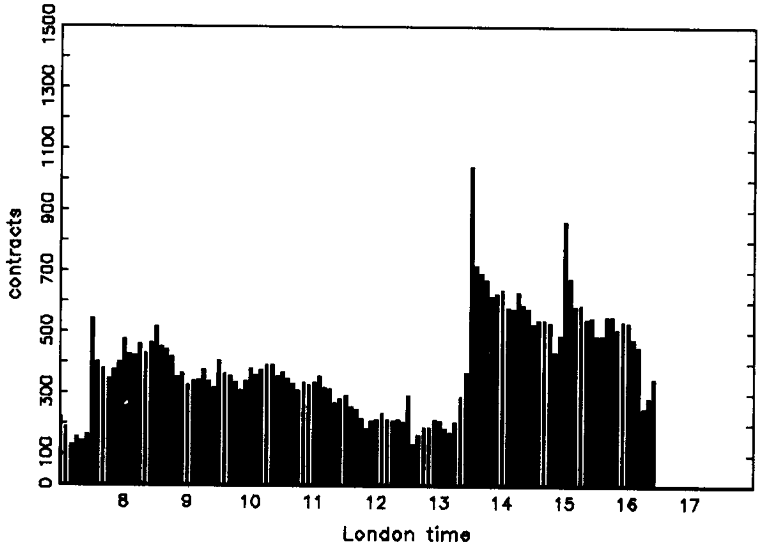

Figure V. Average Number of Contracts (VOL) at DTB, September 8–December 20, 1995.

We consider (as for SDP) five-minute sampling intervals. The averages over all trading days for those variables are given in Figures IV through VIII.

We observe a (inverse) U-shape in these series that is similar to the pattern detected in average SDP volatility. Comparing the 1995 sample with the 1992 sample, volume increases and time-between-trades decreases.

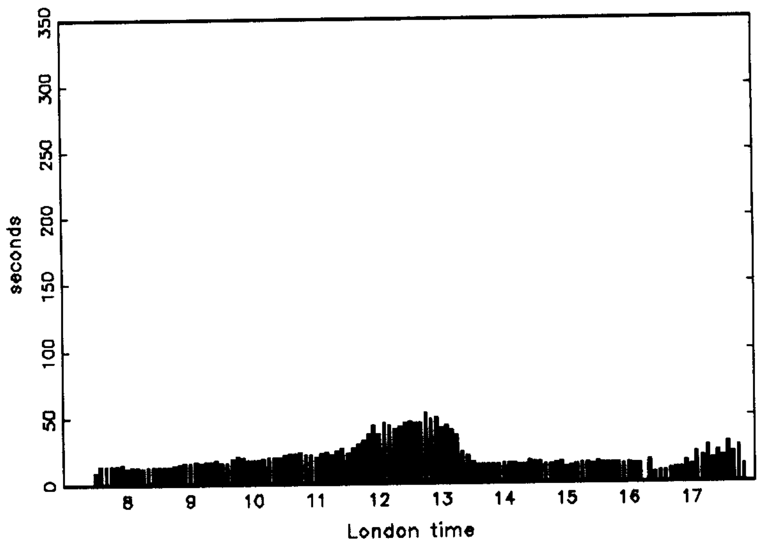

Figure VI. Average Time Between Trades (TBT) at LIFFE, September 8–December 20, 1995.

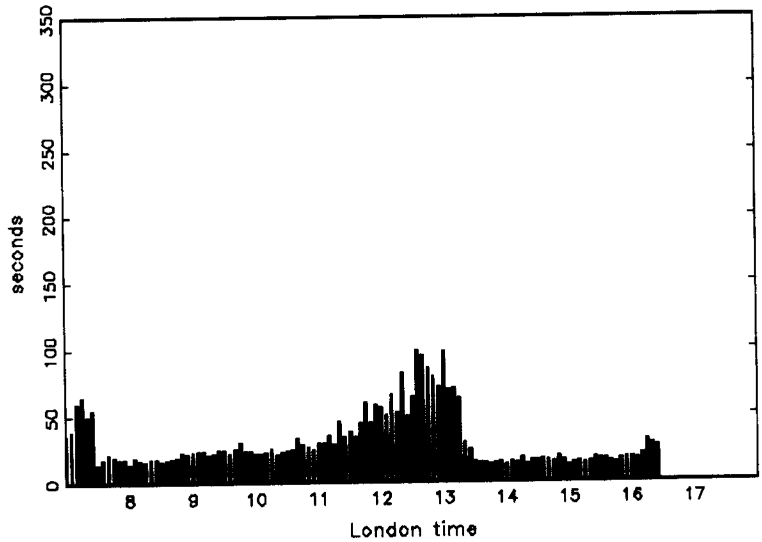

Figure VII. Average Time Between Trades (TBT) at DTB, September 8–December 20, 1995.

To formally check whether volume, time-between-trades, and bid-ask spreads can explain the U-shape pattern in the average SDP volatility series, we estimate equation (8). Our dependent variable is average SDP volatility for five-minute intervals. Volume and time-between-trades are the explanatory variables, and the bid-ask spread is an additional variable for LIFFE.

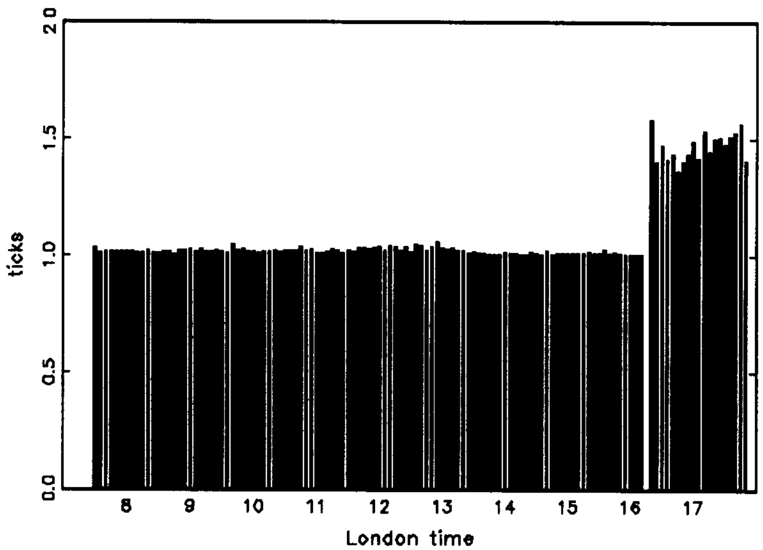

Figure VIII. Average Bid-Ask Spread (BAS) at LIFFE, September 8–December 20, 1995.

The t-ratios in Table 4 indicate that the bid-ask spread is significantly negatively related to current volatility. The profusion of competing market makers and a very liquid market force the bid-ask spread at LIFFE to its minimum one-tick price move. During lunch (when market makers prefer not to trade), the bid-ask spread is often quoted at two ticks.

Volume and the inverse of time-between-trades also individually influence volatility. This contrasts with the results in Jones, Kaul, and Lipson (1994), where no relation exists between trade size and volatility. Trade size and trade activity together explain 86 percent to 92 percent of the pattern in volatility. However, the explanatory power of time-between-trades in addition to volume is small. The high correlation between volume and the inverse of time-between-trades occurs because these reflect the same variable if the volume per trade is constant. Although individually significant, the bid-ask spread for the 1995 sample offers no contribution after including volume and the inverse of time-between-trades. We conclude from the regression results that volatility is best explained by volume.

To test for the apparent U-shape, we adopt the following procedure. We support a U-shape (1) when the F-statistic in equation (7) rejects the null hypothesis of a constant mean and (2) when we find high averages at the beginning and end of the day compared with a lower average around noon. As footnote 2 indicates, the F-test does not test for a smooth U-shape, but merely for nonconstant variance in the sense of high-low-high.

The null hypotheses of constant average volatility is rejected at the 1 percent level for both exchanges (in Table 5, see rows 1 and 4 for 1992 and rows

TABLE 4. Volatility (V) Pattern Explained by the Patterns in Volume (VOL), Bid-Ask Spread (BAS), and the Inverse of Time-Between-Trades (1/TBT).

		Explanatory Variables				
Dependent Variable	Parameter Restrictions[a]	constant	VOL	1/TBT	BAS	R^2
Panel A. 1992 Sample						
V^{LIFFE}	$\beta = 0$	0.370	0.00119	—		0.69
		(11.9)[b]	(10.6)			
V^{LIFFE}	$\alpha = 0$	0.505	—	9.63		0.57
		(14.9)		(7.78)		
V^{LIFFE}	—	0.384	0.00093	2.80		0.70
		(12.3)	(5.40)	(2.56)		
V^{DTB}	$\beta = 0$	0.242	0.00165	—		0.73
		(12.3)	(14.3)			
V^{DTB}	$\alpha = 0$	0.347	—	18.1		0.51
		(8.57)		(6.32)		
V^{DTB}	—	0.235	0.00135	5.50		0.75
		(15.2)	(11.6)	(2.64)		
Panel B. 1995 Sample						
V^{LIFFE}	$\beta = \gamma = 0$	0.321	0.00068	—	—	0.83
		(6.52)	(10.6)			
V^{LIFFE}	$\alpha = \gamma = 0$	0.486	—	7.66	—	0.68
		(11.7)		(7.43)		
V^{LIFFE}	$\alpha = \beta = 0$	8.26	—	—	-7.29	0.35
		(4.79)			(-4.27)	
V^{LIFFE}	$\gamma = 0$	0.244	0.00119	-6.59	—	0.86
		(6.13)	(11.1)	(-5.60)		
V^{LIFFE}	—	0.687	0.00119	-6.80	-0.427	0.86
		(1.14)	(10.6)	(-5.70)	(-0.76)	
V^{DTB}	$\beta = 0$	0.356	0.00122	—		0.90
		(9.19)	(11.2)			
V^{DTB}	$\alpha = 0$	0.428	—	8.99		0.82
		(17.4)		(14.6)		
V^{DTB}	—	0.356	0.00091	2.64		0.92
		(12.2)	(7.50)	(4.52)		

[a]This column indicates which parameters in

$$V_t = \text{constant} + \alpha^* \text{VOL}_t + \beta^*(1/\text{TBT}_t) + \gamma^* \text{BAS}_t + \varepsilon_t$$

are set to zero. The "—" entries indicate the unrestricted regression.
[b]The t-values are given in parentheses and are based on Newey and West (1987) standard errors.

1 and 5 for 1995). We investigate whether the U-shape on both exchanges is caused by a common feature by analyzing a series that subtracts LIFFE's volatility from DTB's volatility (ΔV). We find that constant volatility cannot be rejected at the 10 percent level for 1992, which indicates that DTB and LIFFE have similar U-shapes. For our 1995 sample we no longer find a U-shape, even though volatility is not

TABLE 5. Variance Analysis of the Patterns in Volatility (V), Volume (VOL), Bid-Ask Spread (BAS), and the Inverse of Time-Between-Trades (1/TBT).

		Means over Time[a]			
	Variable	Morning	Fixing	Afternoon	F^{b}
Panel A. 1992 Sample					
LIFFE	V	0.721 (0.124)	0.554 (0.0939)	0.848 (0.0844)	53.19*
	VOL	304 (80)	164 (43)	381 (65)	70.22*
	1/TBT	0.0238 (0.0118)	0.00939 (0.00336)	0.0304 (0.00673)	39.07*
DTB	V	0.572 (0.0935)	0.395 (0.0681)	0.688 (0.0816)	83.62*
	VOL	204 (47)	108 (31)	252 (55)	66.94*
	1/TBT	0.0115 (0.00402)	0.00645 (0.00222)	0.0172 (0.00386)	62.40*
LIFFE-DTB	ΔV	0.149 (0.0620)	0.159 (0.0705)	0.159 (0.0567)	0.36
Residual series of Table 4:[c]					
$V^{*,\text{LIFFE}}$	$\beta = 0$	-0.0114 (0.0831)	-0.0111 (0.0616)	0.0247 (0.0964)	2.10
$V^{*,\text{LIFFE}}$	$\alpha = 0$	-0.0139 (0.0898)	-0.0412 (0.0790)	0.0501 (0.105)	7.75*
$V^{*,\text{LIFFE}}$	—	-0.0128 (0.0780)	-0.00873 (0.0637)	0.0250 (0.0957)	2.30
$V^{*,\text{DTB}}$	$\beta = 0$	-0.00781 (0.0672)	-0.0256 (0.0567)	0.0230 (0.0765)	5.19*
$V^{*,\text{DTB}}$	$\alpha = 0$	0.0150 (0.0821)	-0.0692 (0.0619)	0.0285 (0.109)	9.87*
$V^{*,\text{DTB}}$	—	-0.00230 (0.0648)	-0.0209 (0.0547)	0.0185 (0.0769)	2.46
Panel B. 1995 Sample					
LIFFE	V	0.894 (0.104)	0.704 (0.0699)	1.13 (0.117)	128.13*
	VOL	911 (164)	527 (103)	1114 (90)	139.64*
	1/TBT	0.0627 (0.0157)	0.0276 (0.00831)	0.0713 (0.00528)	105.94*
	BAS	1.01 (0.0165)	1.02 (0.0128)	0.999 (0.00673)	20.16
DTB	V	0.810 (0.103)	0.618 (0.0794)	1.08 (0.124)	141.91*
	VOL	373 (56)	221 (51)	586 (117)	153.71*
	1/TBT	0.0472 (0.0115)	0.0187 (0.00791)	0.676 (0.00883)	167.12*
LIFFE-DTB	ΔV	0.0843 (0.0472)	0.0862 (0.0431)	0.0516 (0.0378)	6.64

(Continued)

TABLE 5. Continued.

	Variable	Means over Time[a] Morning	Fixing	Afternoon	F^{b}
Panel B. 1995 Sample					
Residual series of Table 4:[c]					
$V^{*,LIFFE}$	$\beta = \gamma = 0$	-0.0479	0.0230	0.0529	25.37
		(0.0547)	(0.0477)	(0.0866)	
$V^{*,LIFFE}$	$\alpha = \gamma = 0$	-0.0726	0.00631	0.101	50.95
		(0.0609)	(0.0497)	(0.106)	
$V^{*,LIFFE}$	$\alpha = \beta = 0$	-0.0424	-0.121	0.149	47.66*
		(0.114)	(0.0799)	(0.124)	
$V^{*,LIFFE}$	$\gamma = 0$	-0.0249	0.0112	0.0281	6.56
		(0.0550)	(0.0541)	(0.0878)	
$V^{*,LIFFE}$	—	-0.0243	0.0105	0.0278	6.31
		(0.0551)	(0.0530)	(0.0882)	
$V^{*,DTB}$	$\beta = 0$	-0.00221	-0.00888	0.00968	0.65
		(0.0582)	(0.0404)	(0.0812)	
$V^{*,DTB}$	$\alpha = 0$	-0.0423	0.0213	0.0461	14.04
		(0.0549)	(0.0554)	(0.111)	
$V^{*,DTB}$	—	-0.0123	0.00954	0.0110	2.01
		(0.0515)	(0.0413)	(0.0744)	

[a]Trading hours are split into Morning (7:30–11:30, 48 observations), Fixing (11:30–13:30, 24 observations), and Afternoon (13:30–16:15, 33 observations).
[B]Value of the F-test in equation (7), with 2 and 103 degrees of freedom. The null hypothesis is constant variance, rejection of which supports a U-shape if F exceeds 4.85 and the mean of Fixing is less than the mean of Morning and Afternoon. These cases are indicated by *.
[C]$V_t^* = V_t - [\hat{c} + \hat{\alpha} * \text{VOL}_t + \hat{\beta} * 1/\text{TBT}_t + \hat{\gamma} * \text{BAS}_t]$.

constant. Afternoon volatility (after the U.S. markets open) at DTB is almost equal to LIFFE's volatility. Morning and noon volatility is still slightly less.

Next, we analyze the proxy variables for information transmission. The results are in Table 5. Volume of trade has a U-shape similar to the pattern in the average SDP volatility series, according to Figures IV and V. Our U-shape test corroborates the visual evidence (see Panel A for 1992 and Panel B for 1995). Time-between-trades has an inverse U-shape, according to Figures VI and VII. The regression results for 1/TBT reject the constant volatility null hypothesis. To the contrary, the bid-ask spread seems flat, which is confirmed in Table 5.

Finally, we examine the explanatory power of the regressions in Table 4 by using our U-shape test. If the explanatory variables and the volatility measure share a common U-shape, the residual series of these regressions should no longer contain a structural U-shape. The second half of the 1992 and 1995 results in Table 5 gives the results. The lines labeled "—" indicate the results for the unrestricted model. Including all explanatory variables removes every sign of a U-shape. However, it may not be necessary to include all of them to capture the U-shape in the average SDP volatility series. In Table 5, for example, we observe that using volume as the only regressor ($\beta = 0$ and $\beta = \gamma = 0$ for LIFFE for 1992 and 1995, respectively, and $\beta = 0$ for DTB) is sufficient to remove the U-shape except for the DTB in 1992. Restricting the model to the inverse of time-between-trades ($\alpha = 0$ and $\alpha = \gamma = 0$ for LIFFE for 1992 and 1995, respectively, and $\alpha = 0$ for DTB) does not capture the U-shape in 1992. It does remove the U-shape in 1995, but retains nonconstant volatility. The bid-ask spread (restriction $\alpha = \beta = 0$ in Table 5) does not capture the U-shape.

V. Conclusions

We analyze two aspects of intraday Bund futures volatility: transmission of volatility between LIFFE and DTB and a common U-shape in their intraday levels of volatility. The empirical investigation is based on intraday transaction prices for samples from 1992 and 1995.

For five-minute intervals we find a sufficient number of trades at both LIFFE and DTB to use standard deviations as a measure of volatility. The intraday volatility series are significantly autocorrelated, which is caused by bid-ask bounce and discreteness biases in high-frequency data. We therefore prewhiten the series using an ARMA filter. The unbiased five-minute cross-correlations indicate strong simultaneity and absence of a significant lead of either exchange. We cannot use the standard deviation as a measure of volatility for one-minute intervals because of infrequent trading. Instead, we use the number of price changes per interval. The unbiased one-minute cross-correlations still indicate simultaneity, but we also find leads/lags in both directions. Hence, we find no clear structural dynamics from one exchange to the other. These findings apply intraday as well as interday, which may be explained because leads/lags depend upon the origin of important news. In particular the fortnightly Bundesbank meetings and German macroeconomic news explain the leads of the DTB. However, exceptions remain that are not so easily explained.

In the second part of our analysis,we investigate the informational efficiency differences between LIFFE, using a floor trading system, and DTB, using an electronic trading system. We find evidence of a U-shape for intraday volatility as well as for a set of explanatory variables. We also find no significant difference between the volatility U-shapes at LIFFE and DTB. We find no support for the alleged informational advantage of automated trading systems.

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