The Relative Importance of Information, Inventory and Price Clustering for STIR Futures Pre- and Post-EMU

Abstract

This paper applies an established bid-ask spread decomposition model to short-term interest rate (STIR) futures to assess the impact of both the migration from floor to electronic trading and European Monetary Union (EMU). Additionally, the paper presents and tests a modified decomposition model which is specifically adapted to the features of order-driven markets. The latter model provides much improved performance. Price clustering is introduced as a new explanatory factor within this framework and is shown to be vitally important in understanding the bid-ask spread and price determination.

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1 Introduction

Using a trade indicator model specifically adapted to an order-driven market setting, this paper quantifies the respective contributions of asymmetric information, inventory and, uniquely, price clustering in short-term interest rate (STIR) futures price formation and bid-ask spreads. Whereas trade indicator models have been used primarily to identify the components of the bid-ask spread in the literature (e.g. Glosten and Harris (1988), Huang and Stoll (1997)), they can also be used to explain the drivers of asset prices (e.g. Madhavan et al (1997)) due to the close interdependence between price increments and bid-ask spreads in theoretical work (e.g. Kyle (1985), Glosten and Harris (1988), Harris (1994)).

The seminal trade indicator model of Glosten and Harris (1988) uses the trade indicator sequence to separate price changes into a "transitory" component comprising order processing and inventory management costs and an "adverse selection" component associated with permanent price shifts and informed trading. Madhavan et al (1997) and Huang and Stoll (1997) extend the analysis to intra-day NYSE data to study the changing structure of the bid-ask spread over the course of the day, though they arrive at surprisingly different conclusions. Madhavan et al (1997) find that asymmetric information comprises between 36% and 51% of the bid-ask spread, whereas Huang and Stoll (1997) find order-processing is responsible for about 90% of the bid-ask spread on average for stocks, within a range of 97% down to 57%. In a more elaborate version of their model, the latter study isolates the asymmetric information component at 9.6% of the spread on average, within a range between 1.4% and 22%. However, most of the existing research using these models focuses on equities. Given previous research and stylised facts about futures markets, one would expect the bid-ask spread for STIR futures to have a quite different bid-ask composition from that of equities.

Schwager (1984) notes that technical analysis is more widely accepted and practiced in futures markets than in equity markets. Further, the relative absence of price clustering, combined with near stationary intra-day bid-ask spreads for STIR futures observed in a separate study (McGroarty (2003)), suggests that the tick size should prove to be an important explanatory factor for these markets.

A major difference between the LIFFE STIR futures market and the NYSE equity market is the absence of market makers on the former market. Market makers, or "specialists", are a very important feature of the structure of the NYSE. While they sometimes match incoming market orders with existing limit orders, they also frequently step up directly as the counterparty for a trade. By contrast, the "scalpers" on LIFFE futures markets do not seem to risk their own capital to any similar extent. This is borne out by Manaster and Mann's (1996) finding that the average S&P500 index futures trader could reduce their inventory holdings by 50% in a single trade, probably because, as Kuserk and Locke (1993) note, scalpers tend to trade often and in small amounts. The capital risk taken by NYSE specialists takes much longer to dissipate. Both Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993) found that it takes NYSE specialists a full week to achieve a 50% reduction in inventory. This leads us to conclude that futures markets are more order-driven than the NYSE. As such, we expect that the inventory management component of the bid-ask spread should be less important in futures markets than was found in equity market studies.

Our study spans a period which includes both European currency convergence (i.e. EMU) and a migration from floor based to electronic trading. While two of the four instruments studied here are not directly changed by EMU, the magnitude of this event may well change the dynamics of the overall market. Similarly, the switch to electronic trading also has the potential to alter the established patterns and relationships in these markets. Indeed, Pirrong (1996) predicted that the switch from floor to electronic trading should lower order processing costs in LIFFE futures markets and this should reduce bid-ask spreads.

The remainder of the paper is organised as follows. Section 2 reviews the established theoretical model for bid-ask spread decomposition. Section 3 presents an original modified trade indicator model which reflects the order driven nature of the futures markets under investigation in this paper. Section 4 describes the data and methodology, Section 5 presents the empirical results and Section 6 concludes.

2. Theoretical Background:
The Huang and Stoll Trade Indicator Model

Trade indicator models relate price changes to the "side" of trades, i.e. whether a given trade is transacted near the prevailing bid quote or the prevailing ask quote. Huang and Stoll's (1997) form of the model is, perhaps, the most general and we follow their notation here. In this model, the trade indicator variable, denoted as *Qt*, can take on only three distinct values, +1 when the transaction is initiated by the buyer (i.e. where the transaction price is above the mid-quote), -1 when the transaction is initiated by the seller (i.e. where the transaction price is below the mid-quote) and 0 where neither party can be identified as the initiator (i.e. where the transaction price exactly equals the mid-quote). The prevailing bid and ask quotes, which make up the mid-quote, are defined as those which pre-exist each trade and must be no more than one minute old.

Equation (1) is the basic Huang and Stoll (1997) model, where they identify the "residual" order processing component from the combined adverse selection and inventory management components.

(1) $$\Delta P_t = \tfrac{S}{2}(Q_t - Q_{t-1}) + \lambda \tfrac{S}{2} Q_{t-1} + e_t$$

Here, the left hand side variable is the change in traded price, while on the right hand side, the *S/2* is the constant half-spread and λ represents the combined adverse selection and inventory management components. The error term combines public information releases which change prices and deviations in the bid-ask spread. The second Huang and Stoll (1997) model adds an additional lag of the trade indicator variable to the above equation as follows:

(2) $$\Delta P_t = \tfrac{S}{2} Q_t + (\alpha + \beta - 1)\tfrac{S}{2} Q_{t-1} - \alpha \tfrac{S}{2}(1 - 2\pi) Q_{t-2} + e_t$$

(α plus β) equals λ in the previous equation. *(1-2π)* indicates the conditional expectation of *Qt-1* given *Qt-2*, where π is the probability that a trade is of the opposite sign to the previous one. The second model also requires that *(1-2π)* be simultaneously estimated along with the extended regression equation, using (3).

$$(3) \qquad Q_t = (1-2\pi)Q_{t-1} + u_t$$

As Huang and Stoll (1997) explain, three separate but co-existing variables linked to price underpin these models. These are: 1) the fundamental valuation, *Vt*, 2) the mid-quote value between the bid and the ask, *Mt*, and 3) the transaction price, *Pt*.

$$(4) \qquad V_t = V_{t-1} + \alpha \tfrac{S}{2} Q_{t-1} + \varepsilon_t$$

Order flow drives the fundamental value by equation (4), (e.g. Glosten and Milgrom (1985)) reflecting the influence of both informed trading, α, and the random release of public information, ε_t. Accumulated market maker inventory (e.g. Huang and Stoll (1997)) determines the mid-quote as (5).

$$(5) \qquad M_t = V_t + \beta \tfrac{S}{2} \sum_{i=1}^{t-1} Q_i$$

And, finally, combining the above, transaction price is given by (6).

$$(6) \qquad P_t = V_t + \beta \tfrac{S}{2} \sum_{i=1}^{t-1} Q_i + \tfrac{S}{2} Q_t + \eta_t$$

Taking the first difference of equation (6) allows the change in price to be related to the sign indicator sequence of past trades, as presented in equation (1).

Although equations (1) and (2) above appear very similar in structure, the second model represents a major shift. It actually embodies a blend of the two separate traditions of return decomposition models. The new term π denotes the probability that each successive trade will be of the opposite sign to its predecessor. This uses the serial correlation of the trade flow to reveal the components of the bid-ask spread. In other words, it infers the bid-ask spread from bid-ask bounce. However, the original covariance model (Roll (1984)) is valid only where the bid-ask spread entirely consists of order processing costs, i.e. it can not accommodate either inventory cost or adverse selection risk costs. Choi, Salandro and Shastri (1988) expand the covariance model framework to allow $\pi \neq ½$. George, Kaul and Nimalendran (1991) develop a covariance model which permits informed trading, where they find that time variation in the price change is an important factor in computing the traded bid-ask spread. Adjusting for the latter shows the adverse selection component to be smaller than had been claimed previously. Covariance models depend on the probabilities of change in trade direction, while trade indicator models depend only on the trade direction of incoming orders.

Huang and Stoll (1997) also introduce a trade size dimension into their analysis. They develop a cumbersome model around three different trade size classifications. In our analysis, we implement a simpler two trade size model, equation (7), which embodies the same spirit.

$$
\begin{aligned}
\Delta P_t &= \frac{S_s}{2} Q_{s,t} + \frac{S_l}{2} Q_{l,t} \\
&+ (\alpha_{ss} + \beta_{ss} - 1) \frac{S_s}{2} Q_{s,t-1} - \alpha_{ss} \frac{S_s}{2} (1 - 2\pi_{ss}) Q_{s,t-2} \\
(7) \qquad &+ (\alpha_{sl} + \beta_{sl} - 1) \frac{S_s}{2} Q_{s,t-1} - \alpha_{sl} \frac{S_s}{2} (1 - 2\pi_{sl}) Q_{l,t-2} \\
&+ (\alpha_{ls} + \beta_{ls} - 1) \frac{S_l}{2} Q_{l,t-1} - \alpha_{ls} \frac{S_l}{2} (1 - 2\pi_{ls}) Q_{s,t-2} \\
&+ (\alpha_{ll} + \beta_{ll} - 1) \frac{S_l}{2} Q_{l,t-1} - \alpha_{ll} \frac{S_l}{2} (1 - 2\pi_{ll}) Q_{l,t-2} + e_t
\end{aligned}
$$

The subscripts s and l in equation (7) denote small and large trades respectively. The double subscripts on the α and β coefficients enable us to track how a trade of a particular size relates to the size of its predecessor. For example, an "*ss*" subscript is used where a small trade follows a small trade, while an "*ls*" subscript is used when a large trade follows a small trade.

3. A New Modified Model

The negative serial correlation restriction, $\pi>0.5$, is the only element of the Huang and Stoll (1997) model that imposes transitory behaviour on the inventory component of the bid-ask spread. The authors justify this restriction by acknowledging the need for market makers to "recover inventory holding costs from trade and quote reversals". In order-driven markets, this need does not exist, as there are no exogenous liquidity providing market makers who risk their own capital to create a market and who require compensation for doing so. Even in quote-driven futures markets, "scalpers", who are usually described as futures market makers, have only relatively small and short-lived inventory exposure. Combined with the fact they are not obliged to provide two-way quotes, this suggests that scalpers are probably more accurately described as "brokers" than as market "makers", where the latter term conveys the meaning of someone who puts up risk capital. Hence, we propose to relax the $\pi>0.5$ assumption for our instruments and sample periods. Positive serial correlation in prices may be expected due to market behaviour such as stop loss orders linked to hedging exotic derivatives (Osler (2005)), dynamic hedging by risk managers, and chart following activity (Osler (2003)).

Lyons (2001) suggests that, in the trade indicator model, α should fully capture informed trading, whether it is associated with future fundamentals or with future accumulated inventory, while β captures only transitory inventory effects. This conclusion is predicated on the belief that α and β are perfectly aligned with permanent and transitory price effects respectively. This alignment does not allow inventory itself to accumulate or to have a permanent impact on price. However, if we relax the restriction (i.e. $\pi>0.5$) that inventory must be transitory, then both α and β can be associated with permanent price shifts. This permits accumulated inventory to have a permanent influence on price. Furthermore, because order-driven markets have no market makers, at least in the conventional sense, then transitory inventory price effects should not exist. In other words, in an order-driven market, if β does not reflect permanent price shifts, then it should be zero.

In the absence of market makers, the question arises as to whether the description of the factor that we call inventory is accurate. It is neither transitory, nor does it reflect a risk premium for short term capital risk. However, it is unrelated to fundamental information and it does require price concessions for the market to absorb it. We persist with the label inventory but interpret the terms as "pseudo-inventory" in this sense.

The Huang and Stoll (1997) model ascribes the residual bid-ask spread (price move), when information and inventory are accounted for, (i.e. 1-α-β), as order processing. In relation to the electronic part of our study period, there is no evidence that limit order traders require any more infrastructure or need to pay any more processing costs in the STIR futures market than market order traders do. In an order-driven market, the order processing explanation seems out of place. However, one factor that has been shown to be important for bid-ask spreads and price innovations is price clustering. McGroarty (2003) examined the distribution of trading volume across the final digits of trade prices. Surprisingly, he found this distribution to be nearly uniform for LIFFE STIR futures contracts. This is very much at odds with the price-final-digit distribution found in other financial markets and is consistent with the idea that the minimum price increment (i.e. the minimum tick) is set too large in the STIR futures market. McGroarty (2003) reinforces this suggestion with direct evidence that the average per-second bid-ask spread is heavily clustered around the minimum tick level for all contracts. This price clustering behaviour is just as evident when trading is floor-based as when it is electronic. Based on this, we feel that it is more appropriate to classify the residual component of our bid-ask spread model as price clustering than as order processing.

In market-maker-less order-driven markets, liquidity, defined as limit orders against which market orders can be executed, is endogenous. It is negatively related to the bid-ask spread and positively related to the risk of non-execution. Cohen, Maier, Schwartz and Whitcomb (1981) show that more limit orders will be submitted when bid-ask spreads are wide and when the risk of non-execution is low. This also implies that the bid-ask spread is endogenous because there are no market makers. Too narrow a bid-ask spread will elicit excess market orders which will widen the bid-ask spread. Too wide a bid-ask spread will draw in more keenly priced limit orders, narrowing the bid-ask spread. This means that the exogenous factor determining both liquidity and the bid-ask spread is the risk of non-execution. The latter is negatively related to volume and positively related to volatility. In short, in an order-driven market, non-execution of orders is unlikely when volume is high and volatility is low. Parlour (1998) finds that greater depth at the best price also increases the risk of non-execution because there is a risk that a new limit order will be crowded out. Confirming the link between bid-ask spreads and non-execution risk, Foucault, Kadan and Kandel (2001) find that bid-ask spreads and times-to-execution are jointly determined in equilibrium. However these papers, like other key papers in the order-driven market microstructure literature, including Rock (1990), Glosten (1994) and Seppi (1997) rely on a crucial but questionable assumption. They all assume that informed traders would choose to submit market orders in preference to limit orders.

Experimental work by Bloomfield, O'Hara and Saar (2005) finds that informed traders are more likely to submit limit orders than market orders. The authors argue that this is because only informed traders know the true value of the underlying asset and they can extract profit using this knowledge to sell high and buy low around the true value. This insight completely redefines one of the key fundamentals of the trade indicator model, the determination of fundamental value, *V*. If informed traders are setting prices, the notion of the uninformed market maker learning by "vote-counting" no longer applies. Instead, the evolution to *V* would be solely determined by public information shocks, ε:

(8) $$V_t = V_{t-1} + \varepsilon_t$$

In an order-driven market context, the definition of the mid-quote, *M*, in equation (5) is misleading, since it contains the implied suggestion that price-setting market makers adjust their mid-quote to accommodate inventory imbalances. This cannot happen in order-driven markets since there are no market makers. However, there is no dispute that aggregate inventory imbalances will disturb *V*, insofar as downward sloping aggregate demand curves require price concessions for the excess to be held. As such, an interim variable representing the disturbed value of *V* seems more consistent with the mechanisms of order-driven markets. We use the term V^* to represent *V* disturbed by an inventory imbalance.

$$(9) \qquad V_t^* = V_t + \beta \tfrac{S}{2} \sum_{i=1}^{t-1} Q_i$$

The mid-quote, *M*, can now be defined as a function of *V**. However, given the insight of Bloomfield et al (2005) that informed traders submit limit orders in order-driven markets, informed traders must set *M*. The information they release can be captured by the following relationship for the mid-quote:

$$(10) \qquad M_t = V_t^* - \alpha \tfrac{S}{2} Q_t$$

Previously, in the quote-driven model, *Qt* acted as a vote counter, registering aggressive market order trading from informed traders. In an order-driven market trade indicator model, *Qt* is the first opportunity to record the information released at *Mt* in the trade flow. In order-driven regimes, liquidity based trading endowments are exogenous. The choice for every trader is whether to submit a limit order or a market order. Using the Bloomfield et al (2005) insight, what was aggressive buying or selling by an informed trader in a quote-driven context, will translate to the submission of an aggressive limit order. This will narrow the existing bid-ask spread and entice a trader on the opposite side to submit a market order in preference to a limit order. For this reason an upward price revision will trigger a sell, thus producing a negative relationship between *Mt* and *Qt*.

These new fundamental relationships produce the following price equation:

$$\begin{aligned} & P_t = M_t + \tfrac{S}{2} Q_t + \eta_t \\ (11) \qquad & = V_t^* - \alpha \tfrac{S}{2} Q_t + \tfrac{S}{2} Q_t + \eta_t \\ & = V_t + \beta \tfrac{S}{2} \sum_{i=1}^{t-1} Q_i - \alpha \tfrac{S}{2} Q_t + \tfrac{S}{2} Q_t + \eta_t \end{aligned}$$

This results in a price change equation that is identical to the original one in every detail but one:

$$(12)\qquad \begin{aligned}\Delta P_t &= \beta \tfrac{S}{2} Q_{t-1} - \alpha \tfrac{S}{2} Q_t + \alpha \tfrac{S}{2} Q_{t-1} + \tfrac{S}{2} Q_t - \tfrac{S}{2} Q_{t-1} + e_t \\ &= (1-\alpha)\tfrac{S}{2} Q_t + (\alpha+\beta-1)\tfrac{S}{2} Q_{t-1} + e_t\end{aligned}$$

Now, order flow relating to *Pt+1* is a component of *Qt* and is revealed by -*α*.

Equation (12) does not require *π* to identify *α*. However, there are still three parameters (*α, β* and *S*) to be estimated and only two explanatory variables (*Qt* and *Qt-1*). Given that there are quote prices available for the STIR futures data analysed in this paper, we employ the quoted bid-ask spread time series in place of the parameter *S* in the modified trade indicator model. The quoted bid-ask spread is derived from the nearest preceding bid and ask prices, if both of these are under two minutes old. If the nearest bid or ask is older than that, the bid-ask spread is left blank.

Trade indicator models relate the price (return) on the left to demand (*Q*) on the right. Quote revision and trade execution (= vote counting) are only two channels through which inventory and information can influence price. In quote driven markets, inventory drives the mid-quote and information is revealed through executed trades. In an order driven market, this is reversed. Information drives the mid-quote, while inventory impacts price via trade execution. The essential point here is that, even though inventory and information swap channels, equation (12) shows that the underlying relationships that inventory and information have with price are preserved.

On reflection, it seems intuitive that informed trading should feed through to *Qt*. After all, why should order flow linked to *Pt+1* have any different relationship with *Qt* than order flow linked to *Pt* had with *Qt-1*? Also, the absence of *α* from the coefficient of *Qt* in the original quote-driven model can be traced back to the Glosten and Milgrom (1985) assumption of regret-free quoted prices. If market makers condition their bid and ask prices on the possibility of a trader being informed, in either direction, there can be no role for *α* at time *t*. However, the idea of regret-free prices relies on several critical assumptions. If trade size is variable and price signals are uncertain, as Easley and O'Hara (1987) assume they are, then the regret-free assumption cannot hold. Furthermore, regret-free prices presuppose that the market maker is someone who could experience long-term capital exposure and finds unloading inventory difficult.

While this is evidently true of equity market makers, it is not a good description of the observed very rapid inventory turnover of futures market 'makers', even in quote-driven futures markets as evidenced by Manaster and Mann (1996). This notion of a market maker who can widen his bid-ask spread in the face of a surfacing adverse selection risk also hinges on the assumption of monopoly power. If bid-ask spreads are kept tight by competition, if market makers do not all perceive the same risk at the same time, or if the market is so liquid that unwanted positions are quick and easy to offload, it is possible to see how the bid-ask spread would not need to be regret-free. If the regret-free assumption is dropped then the modified trade indicator model is more appropriate than the original. We relax the regret-free quotes assumption for our analysis and use the modified trade indicator model.

Bloomfield et al (2005) found that informed traders prefer to place limit orders most of the time. However, they also found that when price deviates greatly from fair value, informed traders favour market orders. This finding confirms earlier predictions of Angel (1994) and Harris (1998). The modified trade indicator model accounts for informed trading in the same way, regardless of whether it is transmitted through limit orders or market orders. Thus, α may be generally interpreted as a measure of predictability and also of informed trader profitability. Similarly, β will still encapsulate the impact of inventory. Finally, the interpretation of residual, $(1-\alpha-\beta)$, fits better with the price clustering explanation than with order processing.

4. Data and Estimation Methodology

The data used to analyse the components of the bid-ask spread and the drivers of price consist of four years of STIR tick data (front month only) from Euronext-LIFFE, from 1st January 1997 to 31st December 2000. The data is time-stamped to the nearest second, and both quote and trade price data are used. The futures contracts used are Euribor/Euromark, Euroswiss and Short Sterling.

The sample period is divided into four separate time blocks with the following 3 breaks: 1) a change in the Euromark minimum tick size from 1 to 0.5, 2) EMU and 3) a transition from floor to electronic trading. Electronic trading was introduced to all contracts and so the motivation for this break requires no further explanation.

However, the first two breaks do not affect all contracts and may appear puzzling. The data for all contracts is split at the euro inception data simply because this is a huge event in global macro-economy which has the potential to affect international capital flows and portfolio compositions. As such, it is possible that financial instruments which are not denominated in euro could experience substantial side effects. The Euromark tick size change break is applied to all instruments simply so that contracts may be compared over the same time horizons.

Note that the period from 23rd August 1999 to 20th September 1999 is excluded from the analysis because these represent transition weeks, during which the STIR instruments used here migrated from floor to electronic trading.

Each STIR trade price is assigned a side by comparing with the nearest preceding bid and ask prices within the same day. The trade indicator variable, *Qt*, equals +1 when it is between the ask and the mid-quote, -1 when it is between the mid-quote and the bid and 0 when the trade price exactly equals the mid-quote, as prescribed in the Huang and Stoll (1997) model.

The change in trade price variable, *ΔPt*, is defined as *Pt – Pt-1*, where *Pt* is the transaction price and where successive prices occur within contiguous trading periods. The latter is defined as the trading day, to avoid problems with overnight periods and contract rollovers.

Both Huang and Stoll (1997) and Madhavan, Richardson and Roomans (1997) utilise the Hansen (1982) Generalised Method of Moments (GMM). We follow closely the methodology of the former. Both studies choose this method because its very weak distributional assumptions make it good at capturing unspecified errors.

The basic trade indicator ('stage one') model is implemented in the GMM structure by the expression:

$$f(x_t, \omega) = \begin{bmatrix} e_t Q_t \\ e_t Q_{t-1} \end{bmatrix}$$

where ω = [S λ]' is the vector of parameters. The orthogonality conditions are therefore expressed as $E[f(xt,\omega)] = 0$.

The GMM procedure minimises the quadratic function

$$J_{\mathrm{T}}(\omega) = g_{\mathrm{T}}(\omega)' Z_{\mathrm{T}} g_{\mathrm{T}}(\omega)$$

where $gT(\omega)$ is the sample mean of $f(xt,\omega t)$ and ZT is the sample symmetric weighting matrix. Hansen (1982) shows that, under weak regularity conditions, the GMM estimator $\hat{\omega}$T is consistent and

$$\sqrt{T}(\hat{\omega}_{\mathrm{T}} - \omega_0) \rightarrow N(0, \Omega)$$

where

$$\Omega = (D'_0 Z_0^{-1} D_o)^{-1}$$

$$D_0 = E\left[\frac{\partial f(x,\omega)}{\partial \omega}\right]$$

$$Z_0 = E[f(x_t,\omega) f(x_t,\omega)']$$

The stage one original model and the modified trade indicator model are both exactly identified using this method.

For the stage two model, the methodology is the same, except that the $f(xt,\omega)$ vector is now expressed as

$$f(x_t,\omega) = \begin{bmatrix} e_t Q_t \\ e_t Q_{t-1} \\ e_t Q_{t-2} \\ u_t Q_{t-1} \end{bmatrix}$$

where $\omega=[S\ \alpha\ \beta\ \pi]'$ is the vector of parameters of interest. The second stage model is also exactly identified, since the number of orthogonality conditions again equals the number of parameters to be estimated.

The modified trade indicator model reverts to the first set of (two) orthogonality conditions but the parameter vector now becomes $\omega = [\alpha\ \beta]'$, as S is supplied as a independent variable.

5. Empirical Results

5(a) Huang and Stoll Model Results

Table I presents the results for the Huang and Stoll (1997) model. In the stage one model, λ represents the combined adverse selection and inventory management bid-ask spread components. The analysis reveals very low λ values. In other words, under the Huang and Stoll (1997) / Glosten and Harris (1988) model, price clustering comprises the bulk of the bid-ask spread for STIR futures contracts.

The biggest single contributor to the change in STIR bid-ask spreads was the change in minimum tick size of the Euromark future. This event caused Euromark bid-ask spreads to narrow by 50%. At the same time, the order-processing portion of this bid-ask spread fell from 90% to 76%. Narrower bid-ask spreads may have permitted greater levels of inventory management and/or greater exploitation of informed trading. However, it is impossible to be conclusive on this because expectations about the new European currency would also have had a big influence on investment strategies around this time. Alongside that, Europe's futures exchanges were competing with each other to dominate the emerging pan-European business.

At stages two and three, the model blows apart. The negative α values of the stage 2 models are very hard to interpret in any meaningful way. They imply the existence of "anti-informed" traders. These are traders who are not just uninformed but persistently find themselves wrong-footed about the direction of the next trade. It strains credulity to think that such agents would not eventually do the exact opposite of what their models or instincts were telling them to do. In the stage 3 models, the α values remain negative but now grow in magnitude to more than the entire value of subsequent trades in many cases. In the context of conventional bid-ask spread models, this is so absurd as to be uninterpretable. Furthermore, the π values for these raw (i.e. not aggregated) trades are always below 0.5. This implies that transaction prices exhibit positive serial correlation. In other words, these models show prices to be inherently divergent rather than mean-reverting. Finally, any remaining confidence that we may have had in these two forms of the model was eroded by the finding that many of the t-statistics were below the 95% critical value level.

Table II presents the Huang and Stoll (1997) results when trades are aggregated together. In line with the original Huang and Stoll (1997) study, in the case of our floor-based STIR futures trade data, we aggregate sequential trades of the same side and price when these occur within a contiguous two minute time segment. This should re-combine any broken-up large deals that were pre-negotiated in an upstairs market. For order-driven STIR trades, we aggregate trades which occurred at the same second, side and price. The rationale behind this is that, in an order-driven market, a market order can take out a number of existing limit orders. On the other hand, if the trader feared that his trade was too large to go through without moving the price, he would be more likely to place a number of limit orders.

Aggregating trades in the order-driven setting makes little difference to the results. Aggregation in the quote-driven market drives π over 0.5, while the values of α remain stubbornly negative and the magnitudes of both α and β become even more extreme, particularly in the expanded models. Like the results from Table I, the results from Table II are nonsensical. The trade indicator model in its original form fails to produce any meaningful results for the STIR futures data.

5(b) Modified Model Results

Table III presents the results from the modified trade indicator model. The first thing to note is that α and β now behave as the theory predicts. In contrast to the results for the original model, α is positive in every case, and the sum of α and β is always less than 1. Also, all t-statistics are well above the 95% critical value.

Part B of Table III reveals the percentage components of the bid-ask spread / price innovation for STIR futures. Part C of Table III shows the component percentages from part B multiplied by the average bid-ask spreads from Part A, which reveal the actual bid-ask spread components in amounts. In part D, the change in the bid-ask spreads from part C is shown. (Note that the EUR/DEM conversion exchange rate is applied to all cases where EUR denominated amounts are compared to DEM denominated amounts.)

The advent of electronic trading caused a big change in the respective sizes of the information and inventory bid-ask spread components. The inventory component fell sharply, from 21% to 7% on average, which may indicate that scalpers did engage in some inventory management, while limit order traders, who actually want the position resulting from a trade, have no such activities at all. When the data is grouped into pre-EMU versus post-EMU, the average inventory percentages are 20% and 15% respectively for pre-EMU and post-EMU. The average size of the information component grows from 28% to 39% as trading migrates from floor to electronic. This contrasts with corresponding α values of 29% and 32% when the data are grouped as pre and post-EMU.

Price clustering is by far the largest component of STIR futures bid-ask spreads, accounting for more than half in most cases. The fall in this component from 69% to 57% when the Euromark minimum tick size was halved is particularly telling. The breakdown in part D reveals that this equates to a 59% fall in the value of the price clustering component itself.

6. Conclusions

Results from a modified trade indicator model show that asymmetric information consistently accounts for only around 30% of price innovations and of bid-ask spreads in the STIR futures markets studied. In every case, the residual price clustering component is by far the most substantial. However, the inventory component is often significant. If often accounted for one quarter of the bid-ask spread when trading was floor based, while its value is substantially reduced in the electronic trading data.

The modified trade indicator model proved more appropriate for the STIR futures market than the original model. The latter produced wildly implausible results. The principal reason for these extreme results proved to be a key assumption in quote-driven market microstructure models, namely, that bid-ask bounce, induced by inventory, should cause prices to revert to the mean. However, this feature assumes that the underlying market structure is quote-driven. Order-driven markets like the LIFFE STIR futures market work differently. New theory from Bloomfield et al (2005), which takes account of this difference, enabled us to develop our modified trade indicator model. Our model produced reasonable results for all contracts and time periods. Support for the key idea that informed traders are more likely to submit limit orders than market orders is now starting to come through in the literature. A recent microstructure theory paper, Goettler, Parlour and Rajan (2005), which assumes an order-driven market structure, concedes this very point.

The dominance of price continuations over price reversals in all cases suggests that the inventory component has a lasting impact on price. This contradicts the conventional notion that lasting price perturbations can only arise from the information component of the bid-ask spread. It suggests that the market requires price concessions in order to absorb inventory and that price does not immediately recover from the new concessionary levels. However, a fuller explanation for these observations requires further research.

Aside from the Euribor, STIR futures bid-ask spreads and prices do not seem to have experienced any particular perturbation directly from EMU. However, the indirect role of currency convergence in nudging futures markets towards electronic trading in a competitive, multi-national but single currency marketplace cannot be dismissed.

The price clustering bid-ask spread component shows remarkably little variation in its percentage contribution over the whole period studied. This component alone appears to constitute the major part of the STIR futures bid-ask spreads. One implication of this conclusion is that it is very hard to envisage any means by which bid-ask spreads could be lowered in these markets, short of a policy shift to a lower tick size.

Tables

	Short Sterling			
Time Period	01/01/97 - 19/01/98	20/01/98 - 31/12/98	01/01/99 - 22/08/99	20/09/99 - 31/12/00
No. of Obs.	23,160	22,986	14,935	67,689
(A) Stage 1 model				
λ	24%	30%	32%	8%
S.E.(λ)	(0.0124)	(0.0109)	(0.0138)	(0.0039)
(1-λ)	76%	70%	68%	92%
S	0.6824	0.6647	0.7333	0.6161
S.E.(S)	(0.0105)	(0.013)	(0.0114)	(0.0067)
(B) Stage 2 model				
α	-39%	-52%	-62%	-26%
S.E.(α)	(0.0458)	(0.0799)	(0.0817)	(0.0138)
β	61%	80%	91%	25%
S.E.(β)	(0.0465)	(0.0797)	(0.074)	(0.0097)
(1-α-β)	78%	72%	70%	101%
S	0.6765	0.6590	0.7272	0.6007
S.E.(S)	(0.0103)	(0.0133)	(0.0114)	(0.0066)
π	0.3859	0.4005	0.4184	0.2282
S.E.(π)	(0.0015)	(0.0015)	(0.0018)	(0.0013)
(C) Stage 3 model				
α(ll)	-48%	-79%	-95%	-6%
S.E.(α(ll))	(0.1061)	(0.2152)	(0.2675)	(4.5712)
α(ls)	-15%	-90%	-92%	-55%
S.E.(α(ls))	(0.2896)	(0.3366)	(0.4843)	(1.1999)
α(sl)	-234%	-216%	-144%	-35%
S.E.(α(sl))	(0.4575)	(0.3357)	(0.4956)	(0.3703)
α(ss)	-82%	-111%	-148%	-31%
S.E.(α(ss))	(0.1767)	(0.3641)	(0.2687)	(0.0675)
β(ll)	63%	102%	115%	26%
S.E.(β(ll))	(0.1149)	(0.2281)	(0.2512)	(3.8738)
β(ls)	30%	102%	110%	69%
S.E.(β(ls))	(0.2837)	(0.328)	(0.4778)	(1.0294)
β(sl)	263%	251%	183%	40%
S.E.(β(sl))	(0.4555)	(0.3377)	(0.477)	(0.2875)
β(ss)	114%	146%	184%	31%
S.E.(β(ss))	(0.1709)	(0.3706)	(0.2595)	(0.0134)
S(l)	0.5807	0.4997	0.5622	0.5402
S.E.(S(l))	(0.0159)	(0.0129)	(0.0161)	(0.1158)
S(s)	0.7535	0.7342	0.7876	0.6084
S.E.(S(s))	(0.0116)	(0.0168)	(0.0133)	(0.005)
π(ll)	0.3873	0.4036	0.4208	0.4071
S.E.(π(ll))	(0.0002)	(0)	(0)	(0)
π(ls)	0.4567	0.4579	0.4668	0.4340
S.E.(π(ls))	(0.0001)	(0)	(0)	(0)
π(sl)	0.4707	0.4565	0.4546	0.3070
S.E.(π(sl))	(0.0001)	(0)	(0.0002)	(0.0021)
π(ss)	0.4559	0.4652	0.4689	0.2997
S.E.(π(ss))	(0.0001)	(0.0001)	(0.0002)	(0.0042)

Table I(i). The Huang and Stoll(1997) model results for the Short Sterling contract.

	Euroswiss			
Time Period	01/01/97 - 19/01/98	20/01/98 - 31/12/98	01/01/99 - 22/08/99	20/09/99 - 31/12/00
No. of Obs.	30,320	38,268	18,080	35,875
(A) Stage 1 model				
λ	44%	40%	35%	24%
S.E.(λ)	*(0.0092)*	*(0.007)*	*(0.0189)*	*(0.0134)*
(1-λ)	56%	60%	65%	76%
S	0.6891	0.7666	0.7256	0.6452
S.E.(S)	*(0.0102)*	*(0.0073)*	*(0.032)*	*(0.01)*
(B) Stage 2 model				
α	-23%	-22%	-31%	-36%
S.E.(α)	*(0.0387)*	*(0.0301)*	*(0.0525)*	*(0.0445)*
β	64%	61%	64%	57%
S.E.(β)	*(0.0365)*	*(0.0274)*	*(0.0491)*	*(0.0408)*
(1-α-β)	58%	62%	67%	80%
S	0.6878	0.7633	0.7192	0.6378
S.E.(S)	*(0.0103)*	*(0.0073)*	*(0.0316)*	*(0.0101)*
π	0.3514	0.3653	0.3662	0.3432
S.E.(π)	*(0.0014)*	*(0.0012)*	*(0.0018)*	*(0.0013)*
(C) Stage 3 model				
α(ll)	-24%	-50%	-42%	15%
S.E.(α(ll))	*(0.0741)*	*(0.0952)*	*(0.1474)*	*(0.3624)*
α(ls)	-26%	-42%	-98%	-7%
S.E.(α(ls))	*(0.2107)*	*(0.198)*	*(0.4473)*	*(0.3051)*
α(sl)	-53%	-36%	-21%	-53%
S.E.(α(sl))	*(0.4944)*	*(0.16)*	*(1.021)*	*(0.1971)*
α(ss)	-35%	8%	-65%	-34%
S.E.(α(ss))	*(0.1842)*	*(0.1036)*	*(0.6286)*	*(0.0824)*
β(ll)	72%	95%	85%	27%
S.E.(β(ll))	*(0.0752)*	*(0.0935)*	*(0.1464)*	*(0.3697)*
β(ls)	77%	89%	129%	53%
S.E.(β(ls))	*(0.2045)*	*(0.192)*	*(0.4114)*	*(0.3043)*
β(sl)	89%	73%	56%	80%
S.E.(β(sl))	*(0.4846)*	*(0.1576)*	*(1.042)*	*(0.1749)*
β(ss)	80%	35%	104%	53%
S.E.(β(ss))	*(0.1787)*	*(0.101)*	*(0.6074)*	*(0.0764)*
S(l)	0.6056	0.6039	0.4883	0.6079
S.E.(S(l))	*(0.0101)*	*(0.0101)*	*(0.0144)*	*(0.0143)*
S(s)	0.8112	0.8693	0.8840	0.6348
S.E.(S(s))	*(0.0182)*	*(0.0089)*	*(0.0476)*	*(0.0119)*
π(ll)	0.3683	0.3882	0.3720	0.4344
S.E.(π(ll))	*(0)*	*(0)*	*(0)*	*(0)*
π(ls)	0.4369	0.4463	0.4423	0.4602
S.E.(π(ls))	*(0)*	*(0)*	*(0)*	*(0)*
π(sl)	0.4690	0.4392	0.4487	0.3951
S.E.(π(sl))	*(0)*	*(0)*	*(0.0001)*	*(0.0095)*
π(ss)	0.4377	0.4512	0.4642	0.3727
S.E.(π(ss))	*(0)*	*(0)*	*(0.0001)*	*(0.0001)*

Table I(ii). Huang and Stoll(1997) model results for the Euroswiss contract.

	Euromark		Euribor	
Time Period	01/01/97 - 19/01/98	20/01/98 - 31/12/98	01/01/99 - 22/08/99	20/09/99 - 31/12/00
No. of Obs.	23,605	29,934	16,462	195,309
(A) Stage 1 model				
λ	10%	24%	26%	8%
S.E.(λ)	*(0.0069)*	*(0.0106)*	*(0.0119)*	*(0.0023)*
(1-λ)	90%	76%	74%	92%
S	0.7545	0.3666	0.3961	0.3494
S.E.(S)	*(0.0085)*	*(0.0044)*	*(0.0052)*	*(0.0017)*
(B) Stage 2 model				
α	-37%	-57%	-64%	-35%
S.E.(α)	*(0.0237)*	*(0.0485)*	*(0.0886)*	*(0.0087)*
β	42%	77%	89%	33%
S.E.(β)	*(0.0237)*	*(0.0436)*	*(0.0812)*	*(0.0067)*
(1-α-β)	94%	79%	75%	102%
S	0.7429	0.3625	0.3930	0.3385
S.E.(S)	*(0.0082)*	*(0.0043)*	*(0.0051)*	*(0.0017)*
π	0.3567	0.3926	0.4282	0.2604
S.E.(π)	*(0.0017)*	*(0.0014)*	*(0.0017)*	*(0.0007)*
(C) Stage 3 model				
α(ll)	-19%	-48%	-37%	-51%
S.E.(α(ll))	*(0.0855)*	*(0.0898)*	*(0.1463)*	*(0.0566)*
α(ls)	-36%	-36%	-115%	-91%
S.E.(α(ls))	*(0.1956)*	*(0.5219)*	*(0.7823)*	*(0.099)*
α(sl)	-141%	-319%	-274%	-51%
S.E.(α(sl))	*(0.1229)*	*(0.3713)*	*(0.5447)*	*(0.0272)*
α(ss)	-93%	-144%	-319%	-35%
S.E.(α(ss))	*(0.0839)*	*(0.1765)*	*(0.8223)*	*(0.0106)*
β(ll)	22%	68%	67%	65%
S.E.(β(ll))	*(0.0748)*	*(0.083)*	*(0.1347)*	*(0.049)*
β(ls)	32%	49%	135%	103%
S.E.(β(ls))	*(0.1997)*	*(0.4806)*	*(0.7442)*	*(0.0897)*
β(sl)	153%	347%	304%	57%
S.E.(β(sl))	*(0.1227)*	*(0.3647)*	*(0.549)*	*(0.0284)*
β(ss)	106%	173%	350%	38%
S.E.(β(ss))	*(0.0822)*	*(0.1785)*	*(0.8116)*	*(0.0126)*
S(l)	0.6334	0.2887	0.3214	0.3035
S.E.(S(l))	*(0.0109)*	*(0.0055)*	*(0.0082)*	*(0.0018)*
S(s)	0.7901	0.4031	0.4349	0.3439
S.E.(S(s))	*(0.0091)*	*(0.0055)*	*(0.0055)*	*(0.0014)*
π(ll)	0.3787	0.3915	0.4058	0.4080
S.E.(π(ll))	*(0)*	*(0.0001)*	*(0.0001)*	*(0)*
π(ls)	0.4423	0.4520	0.4686	0.4406
S.E.(π(ls))	*(0)*	*(0)*	*(0)*	*(0)*
π(sl)	0.4318	0.4667	0.4764	0.3395
S.E.(π(sl))	*(0)*	*(0)*	*(0)*	*(0.0014)*
π(ss)	0.4450	0.4629	0.4894	0.3247
S.E.(π(ss))	*(0)*	*(0)*	*(0)*	*(0)*

Table I(iii). Huang and Stoll(1997) model results for the Euromark/Euribor contract.

Table I. The results from the original Huang and Stoll(1997) model for the Short Sterling, Euroswiss and Euromark/Euribor futures contracts.

α=adverse selection component

β=inventory component

$(1-\alpha-\beta)$=price clustering component

$\lambda=\alpha+\beta$

S=bid-ask spread

π=probability of reversal

	Short Sterling			
Time Period	01/01/97 - 19/01/98	20/01/98 - 31/12/98	01/01/99 - 22/08/99	20/09/99 - 31/12/00
No. of Obs.	15,623	19,749	8,983	63,146
(A) Stage 1 model				
λ	103%	110%	111%	7%
S.E.(λ)	*(0.0264)*	*(0.0187)*	*(0.0242)*	*(0.0036)*
$(1-\lambda)$	-3%	-10%	-11%	93%
S	1.2364	1.2618	1.3933	0.6249
S.E.(S)	*(0.0346)*	*(0.0244)*	*(0.0368)*	*(0.0067)*
(B) Stage 2 model				
α	-21%	-27%	-24%	-29%
S.E.(α)	*(0.0189)*	*(0.0515)*	*(0.0199)*	*(0.0134)*
β	113%	126%	123%	26%
S.E.(β)	*(0.0307)*	*(0.0277)*	*(0.0248)*	*(0.0095)*
$(1-\alpha-\beta)$	7%	1%	0%	103%
S	1.2530	1.2919	1.4022	0.6069
S.E.(S)	*(0.035)*	*(0.0274)*	*(0.0345)*	*(0.0066)*
π	0.8599	0.8557	0.8581	0.2253
S.E.(π)	*(0.0027)*	*(0.0027)*	*(0.0031)*	*(0.0013)*
(C) Stage 3 model				
α(ll)	-36%	-30%	-32%	-12%
S.E.(α(ll))	*(0.0448)*	*(0.1328)*	*(0.0717)*	*(0.2444)*
α(ls)	-30%	-46%	-53%	-61%
S.E.(α(ls))	*(0.0964)*	*(0.0891)*	*(0.0997)*	*(0.133)*
α(sl)	-215%	-132%	-121%	-40%
S.E.(α(sl))	*(0.1909)*	*(0.1094)*	*(0.096)*	*(0.0424)*
α(ss)	-74%	-131%	-51%	-32%
S.E.(α(ss))	*(0.1219)*	*(0.7524)*	*(0.1164)*	*(0.0231)*
β(ll)	127%	144%	147%	28%
S.E.(β(ll))	*(0.0497)*	*(0.0831)*	*(0.0536)*	*(0.2062)*
β(ls)	137%	154%	154%	73%
S.E.(β(ls))	*(0.0677)*	*(0.0608)*	*(0.0628)*	*(0.1292)*
β(sl)	281%	207%	203%	45%
S.E.(β(sl))	*(0.1718)*	*(0.0985)*	*(0.0947)*	*(0.0375)*
β(ss)	145%	189%	129%	33%
S.E.(β(ss))	*(0.1196)*	*(0.5413)*	*(0.1174)*	*(0.0168)*
S(l)	1.1757	1.2055	1.3222	0.5380
S.E.(S(l))	*(0.0388)*	*(0.0238)*	*(0.0312)*	*(0.0097)*
S(s)	1.3158	1.3393	1.4348	0.6132
S.E.(S(s))	*(0.0366)*	*(0.0489)*	*(0.0453)*	*(0.0063)*
π(ll)	0.7692	0.7192	0.6948	0.4049
S.E.(π(ll))	*(0.0003)*	*(0)*	*(0.0002)*	*(0)*
π(ls)	0.7223	0.7182	0.7256	0.4336
S.E.(π(ls))	*(0.0002)*	*(0.0001)*	*(0.0002)*	*(0)*
π(sl)	0.5732	0.6055	0.6227	0.3356
S.E.(π(sl))	*(0.0001)*	*(0)*	*(0.0001)*	*(0)*
π(ss)	0.6458	0.6501	0.6528	0.2959
S.E.(π(ss))	*(0.0001)*	*(0.0001)*	*(0.0002)*	*(0)*

Table II(i). The Huang and Stoll(1997) model with aggregated trades: Short Sterling.

	Euroswiss			
Time Period	01/01/97 - 19/01/98	20/01/98 - 31/12/98	01/01/99 - 22/08/99	20/09/99 - 31/12/00
No. of Obs.	11,146	11,451	7,686	32,717
(A) Stage 1 model				
λ	112%	109%	109%	20%
S.E.(λ)	*(0.0116)*	*(0.0096)*	*(0.0303)*	*(0.0132)*
(1-λ)	-12%	-9%	-9%	80%
S	1.2238	1.3420	1.3201	0.6524
S.E.(S)	*(0.0161)*	*(0.0127)*	*(0.0396)*	*(0.0102)*
(B) Stage 2 model				
α	-33%	-38%	-27%	-45%
S.E.(α)	*(0.0296)*	*(0.0165)*	*(0.0494)*	*(0.0413)*
β	139%	138%	128%	61%
S.E.(β)	*(0.0268)*	*(0.0159)*	*(0.0605)*	*(0.0391)*
(1-α-β)	-6%	0%	-1%	85%
S	1.2342	1.3488	1.3195	0.6430
S.E.(S)	*(0.0161)*	*(0.0124)*	*(0.0383)*	*(0.0102)*
π	0.7274	0.7491	0.7861	0.3381
S.E.(π)	*(0.0022)*	*(0.0019)*	*(0.003)*	*(0.0013)*
(C) Stage 3 model				
α(ll)	-34%	-45%	-23%	27%
S.E.(α(ll))	*(0.0544)*	*(0.0389)*	*(0.0959)*	*(0.3272)*
α(ls)	-38%	-22%	-11%	-5%
S.E.(α(ls))	*(0.0792)*	*(0.0492)*	*(0.0752)*	*(0.2935)*
α(sl)	-532%	-447%	-284%	-71%
S.E.(α(sl))	*(0.6197)*	*(0.2307)*	*(0.6742)*	*(0.1821)*
α(ss)	-217%	-105%	-118%	-41%
S.E.(α(ss))	*(0.3524)*	*(0.1018)*	*(0.1509)*	*(0.0776)*
β(ll)	146%	157%	140%	12%
S.E.(β(ll))	*(0.0455)*	*(0.0339)*	*(0.1136)*	*(0.3473)*
β(ls)	154%	143%	135%	48%
S.E.(β(ls))	*(0.0611)*	*(0.0372)*	*(0.0685)*	*(0.2926)*
β(sl)	601%	517%	345%	95%
S.E.(β(sl))	*(0.6161)*	*(0.2267)*	*(0.6919)*	*(0.1609)*
β(ss)	279%	183%	188%	58%
S.E.(β(ss))	*(0.3226)*	*(0.0917)*	*(0.131)*	*(0.0715)*
S(l)	1.1758	1.2519	1.1098	0.5994
S.E.(S(l))	*(0.0174)*	*(0.0164)*	*(0.0411)*	*(0.0142)*
S(s)	1.3177	1.3974	1.4865	0.6425
S.E.(S(s))	*(0.0329)*	*(0.016)*	*(0.1098)*	*(0.0119)*
π(ll)	0.6962	0.6771	0.6994	0.4316
S.E.(π(ll))	*(0)*	*(0)*	*(0.0001)*	*(0)*
π(ls)	0.7025	0.7126	0.7415	0.4581
S.E.(π(ls))	*(0)*	*(0.0001)*	*(0.0001)*	*(0)*
π(sl)	0.5254	0.5341	0.5528	0.3908
S.E.(π(sl))	*(0)*	*(0)*	*(0.0001)*	*(0)*
π(ss)	0.5752	0.6074	0.6131	0.3666
S.E.(π(ss))	*(0)*	*(0.0002)*	*(0.0001)*	*(0.0001)*

Table II(ii): Huang and Stoll(1997) model with aggregated trades: Euroswiss.

	Euromark		Euribor	
Time Period	01/01/97 - 19/01/98	20/01/98 - 31/12/98	01/01/99 - 22/08/99	20/09/99 - 31/12/00
No. of Obs.	9,727	14,444	8,740	180,388
(A) Stage 1 model				
λ	86%	105%	99%	7%
S.E.(λ)	*(0.0352)*	*(0.0229)*	*(0.0221)*	*(0.0022)*
(1-λ)	14%	-5%	1%	93%
S	1.2642	0.6780	0.6787	0.3528
S.E.(S)	*(0.0391)*	*(0.0166)*	*(0.0142)*	*(0.0017)*
(B) Stage 2 model				
α	-8%	-14%	-13%	-37%
S.E.(α)	*(0.0203)*	*(0.0236)*	*(0.0198)*	*(0.0087)*
β	84%	111%	105%	34%
S.E.(β)	*(0.0384)*	*(0.0234)*	*(0.0277)*	*(0.0066)*
(1-α-β)	24%	3%	8%	103%
S	1.2484	0.6788	0.6868	0.3408
S.E.(S)	*(0.0383)*	*(0.0163)*	*(0.0143)*	*(0.0017)*
π	0.9325	0.8748	0.8566	0.2589
S.E.(π)	*(0.0021)*	*(0.0023)*	*(0.003)*	*(0.0007)*
(C) Stage 3 model				
α(ll)	-32%	-18%	-22%	-52%
S.E.(α(ll))	*(0.0606)*	*(0.0415)*	*(0.0582)*	*(0.0707)*
α(ls)	-14%	-33%	-19%	-92%
S.E.(α(ls))	*(0.1027)*	*(0.0761)*	*(0.0953)*	*(0.1238)*
α(sl)	-70%	-136%	-141%	-52%
S.E.(α(sl))	*(0.1502)*	*(0.1438)*	*(0.1346)*	*(0.034)*
α(ss)	-31%	-25%	-59%	-35%
S.E.(α(ss))	*(0.1171)*	*(0.3619)*	*(0.1151)*	*(0.0133)*
β(ll)	113%	127%	121%	64%
S.E.(β(ll))	*(0.0629)*	*(0.0328)*	*(0.0458)*	*(0.0613)*
β(ls)	101%	133%	120%	102%
S.E.(β(ls))	*(0.0632)*	*(0.0648)*	*(0.0768)*	*(0.1121)*
β(sl)	123%	197%	200%	59%
S.E.(β(sl))	*(0.1225)*	*(0.127)*	*(0.1162)*	*(0.0355)*
β(ss)	90%	100%	126%	38%
S.E.(β(ss))	*(0.0933)*	*(0.2572)*	*(0.1245)*	*(0.0108)*
S(l)	1.1223	0.6220	0.6189	0.3021
S.E.(S(l))	*(0.0343)*	*(0.0177)*	*(0.0171)*	*(0.0022)*
S(s)	1.3709	0.7085	0.7208	0.3453
S.E.(S(s))	*(0.0435)*	*(0.0143)*	*(0.0134)*	*(0.0018)*
π(ll)	0.7508	0.7398	0.7318	0.4062
S.E.(π(ll))	*(0.0002)*	*(0.0001)*	*(0.0001)*	*(0)*
π(ls)	0.7641	0.7503	0.7365	0.4400
S.E.(π(ls))	*(0.0002)*	*(0.0001)*	*(0.0001)*	*(0)*
π(sl)	0.6423	0.6095	0.5980	0.3547
S.E.(π(sl))	*(0.0001)*	*(0.0001)*	*(0.0001)*	*(0)*
π(ss)	0.6711	0.6443	0.6559	0.3219
S.E.(π(ss))	*(0.0002)*	*(0.0001)*	*(0.0001)*	*(0)*

Table II(iii): Huang and Stoll(1997) model with aggregated trades: Euromark/Euribor.

Table II: The results from the Huang and Stoll (1997) model, with trades aggregated where they may be components of a single large trade.
α=adverse selection component
β=inventory component
$(1-\alpha-\beta)$=price clustering component
$\lambda=\alpha+\beta$
S=bid-ask spread
π=probability of reversal

	Short Sterling			
Time Period	**01/01/97 - 19/01/98**	**20/01/98 - 31/12/98**	**01/01/99 - 22/08/99**	**23/08/99 - 31/12/00**
No. of Obs.	23,160	22,986	14,935	67,689
(A) Summary Statistics				
Av. Spread	0.9693	0.9680	0.9815	1.0228
Av. Daily Volume	15,316	22,218	23,008	17,434
(B) % Breakdown of Bid-Ask Spread (with Standard Errors)				
α	31%	33%	26%	39%
S.E.(α)	*(0.0106)*	*(0.0132)*	*(0.0117)*	*(0.0067)*
β	16%	20%	23%	5%
S.E.(β)	*(0.0097)*	*(0.008)*	*(0.0121)*	*(0.0022)*
(1-α-β)	52%	47%	51%	56%
(C) The Components of the Average Quoted Spread				
α	0.3036	0.3191	0.2593	0.3998
β	0.1569	0.1937	0.2229	0.0464
(1-α-β)	0.5088	0.4552	0.4993	0.5766
(D) % Change in the Components of the Average Quoted Spread				
α		5%	-19%	54%
β		23%	15%	-79%
(1-α-β)		-11%	10%	15%

Table III(i): The components of the Short Sterling bid-ask spread.

	Euroswiss			
Time Period	**01/01/97 - 19/01/98**	**20/01/98 - 31/12/98**	**01/01/99 - 22/08/99**	**23/08/99 - 31/12/00**
No. of Obs.	30,320	38,268	18,080	35,875
(A) Summary Statistics				
Av. Spread	1.0262	1.0172	0.9986	1.2083
Av. Daily Volume	7,507	12,322	11,284	7,808
(B) % Breakdown of Bid-Ask Spread (with Standard Errors)				
α	33%	25%	28%	45%
S.E.(α)	*(0.0099)*	*(0.0071)*	*(0.0319)*	*(0.0084)*
β	29%	30%	25%	12%
S.E.(β)	*(0.0069)*	*(0.006)*	*(0.0098)*	*(0.0079)*
(1-α-β)	38%	45%	47%	43%
(C) The Components of the Average Quoted Spread				
α	0.3410	0.2501	0.2799	0.5464
β	0.2987	0.3064	0.2488	0.1413
(1-α-β)	0.3865	0.4606	0.4699	0.5205
(D) % Change in the Components of the Average Quoted Spread				
α		-27%	12%	95%
β		3%	-19%	-43%
(1-α-β)		19%	2%	11%

Table III(ii): The components of the Euroswiss bid-ask spread.

	Euromark		Euribor	
Time Period	01/01/97 - 19/01/98	20/01/98 - 31/12/98	01/01/99 - 22/08/99	23/08/99 - 31/12/00
No. of Obs.	23,605	29,934	16,462	195,309
(A) Summary Statistics				
Av. Spread	0.9841	0.4907	0.4859	0.5195
Av. Daily Volume	27,458	45,087	28,186	50,373
(B) % Breakdown of Bid-Ask Spread (with Standard Errors)				
α	24%	27%	21%	32%
S.E.(α)	(0.0086)	(0.0085)	(0.0103)	(0.0033)
β	7%	16%	20%	5%
S.E.(β)	(0.0054)	(0.0088)	(0.0105)	(0.0015)
(1-α-β)	69%	57%	59%	62%
(C) The Components of the Average Quoted Spread				
α	0.2392	0.1311	0.1009	0.1682
β	0.0672	0.0803	0.0961	0.0268
(1-α-β)	0.6777	0.2794	0.2889	0.3245
(D) % Change in the Components of the Average Quoted Spread				
α		-45%	51%	67%
β		19%	134%	-72%
(1-α-β)		-59%	102%	12%

Table III(iii): The components of the Euromark/Euribor bid-ask spread.

Table III: The components of the bid-ask spread for the Short Sterling, Euroswiss and Euromark/Euribor futures contracts, computed using the Modified Model
All inter-temporal comparisons of the Euribor with the Euromark futures contract have been adjusted by the fixed EUR/DEM conversion rate of 1.95583.
α=adverse selection component
β=inventory component
(1-α-β)=price clustering component

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