

The Components of Electronic Order-Driven Spot FX Bid-Ask Spreads Pre- and Post-EMU

Frank McGroarty¹, Owain ap Gwilym² and Stephen Thomas³

Abstract

This paper applies an established bid-ask spread decomposition model to spot foreign exchange market in order to assess the impact of 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.

JEL Classification: F31; G12; G15; D4

Keywords: High frequency data, Foreign Exchange, Market microstructure, Bid-Ask Spreads, Order-driven.

¹ Corresponding author. Lecturer in Finance, School of Management, University of Southampton, SO17 1BJ, UK.

Tel: +44 23 8059 2540 Fax: +44 23 8059 3844 F.J.McGroarty@soton.ac.uk

² Professor of Finance, School of Management & Business, University of Wales, Aberystwyth, SY23 3DD. UK.

³ Professor of Financial Markets, School of Management, University of Southampton, SO17 1BJ. UK.

This version: 24th April 2006

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 inter-dealer spot foreign exchange (FX) 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 research done to date using these models focuses on equities.

Allen and Taylor(1992) and Liu and Mole(1998)) both note that technical analysis is more widely accepted and practiced in currency markets than in equity markets. This may mean that shared beliefs are a factor in driving prices and that in turn could lead to greater amounts of certain pricing behaviour than markets where Chartism is less accepted. Furthermore, the lack of formal prohibition of insider trading in the unregulated trans-national FX market, coupled with the known practice in the spot FX market of dealers exploiting their customer order-flow to their own advantage in the

inter-dealer markets, could result in a significant adverse selection component which is linked to future accumulated inventory. Additionally, the phenomenon of central bank intervention has no parallel in the equity market, nor probably in any other financial market. Intervention, at least in its unsterilised form, is a naked attempt to use accumulated inventory imbalances to drive price.

A major difference between the electronic inter-dealer spot FX 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 electronic inter-dealer spot FX market permits market participants two to execute a trade. They can either submit a market order which engages a pre-existing limit order posted by another trader, or they can advertise their own willingness to trade by submitting a limit order. Traders who place either limit or market orders actually want the resulting positions. This is a market-maker-less trading system from which we might expect a very different bid-ask spread decomposition from what we have seen in other markets.

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 electronic inter-dealer spot FX market 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 Q_t ,

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.

$$(1) \quad \Delta P_t = \frac{s}{2}(Q_t - Q_{t-1}) + \lambda \frac{s}{2} Q_{t-1} + e_t$$

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:

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

$(\alpha + \beta)$ equals λ in the previous equation. $(1 - 2\pi)$ indicates the conditional expectation of Q_{t-1} given Q_{t-2} , where π is the probability that a trade is of the opposite sign to the previous one. The second model also requires that $(1 - 2\pi)$ be simultaneously estimated along with the extended regression equation, using (3).

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

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

$$(4) \quad V_t = V_{t-1} + \alpha \frac{s}{2} Q_{t-1} + \varepsilon_t$$

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 . Accumulated market maker inventory (e.g. Huang and Stoll (1997)) determines the mid-quote as (5).

$$(5) \quad M_t = V_t + \beta \frac{s}{2} \sum_{i=1}^{t-1} Q_i$$

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

$$(6) \quad P_t = V_t + \beta \frac{s}{2} \sum_{i=1}^{t-1} Q_i + \frac{s}{2} Q_t + \eta_t$$

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 $\pi \neq \frac{1}{2}$. 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.

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. Market participants on the electronic inter-dealer spot FX market are not obliged to provide two-way quotes. There is no evidence to support the idea that any of these agents behave as market makers to this market. 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. $1-\alpha-\beta$), 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 electronic inter-dealer spot FX 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. In an independent study, McGroarty et al (2005b) examined the distribution of trading volume across the final digits of trade prices. They found price clustering to be important in explaining the observed increase in bid-ask after EMU. 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 :

$$(7) \quad V_t = V_{t-1} + \varepsilon_t$$

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.

$$(8) \quad V_t^* = V_t + \beta \frac{\delta}{2} \sum_{i=1}^{t-1} Q_i$$

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:

$$(9) \quad M_t = V_t^* - \alpha \frac{s}{2} Q_t$$

Previously, in the quote-driven model, Q_t acted as a vote counter, registering aggressive market order trading from informed traders. In an order-driven market trade indicator model, Q_t is the first opportunity to record the information released at M_t 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 M_t and Q_t .

These new fundamental relationships produce the following price equation:

$$(10) \quad \begin{aligned} P_t &= M_t + \frac{s}{2} Q_t + \eta_t \\ &= V_t^* - \alpha \frac{s}{2} Q_t + \frac{s}{2} Q_t + \eta_t \\ &= V_t + \beta \frac{s}{2} \sum_{i=1}^{t-1} Q_i - \alpha \frac{s}{2} Q_t + \frac{s}{2} Q_t + \eta_t \end{aligned}$$

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

$$(11) \quad \begin{aligned} \Delta P_t &= \beta \frac{s}{2} Q_{t-1} - \alpha \frac{s}{2} Q_t + \alpha \frac{s}{2} Q_{t-1} + \frac{s}{2} Q_t - \frac{s}{2} Q_{t-1} + e_t \\ &= (1 - \alpha) \frac{s}{2} Q_t + (\alpha + \beta - 1) \frac{s}{2} Q_{t-1} + e_t \end{aligned}$$

Now, order flow relating to P_{t+1} is a component of Q_t and is revealed by $-\alpha$.

Equation (11) 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 (Q_t and Q_{t-1}). Given that there are quote prices available for the electronic inter-dealer spot FX 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 (11) 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 Q_t . After all, why should order flow linked to P_{t+1} have any different relationship with Q_t than order flow linked to P_t had with Q_{t-1} ? Also, the absence of α from the coefficient of Q_t 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 electronic inter-dealer spot FX market. 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

In 1998, the Bank of International Settlements estimated that the total volume of spot foreign exchange trading was worth almost US\$1.5 trillion per day. After EMU, the total value of FX transactions fell. However, the FX market remains the largest financial market in the world, by many orders of magnitude. BIS (1998) and BIS (2001) both show that spot FX transactions account for a little under half of all trading activity in the FX market. In turn, inter-dealer trading accounts for about two-thirds of total global spot FX volume. Over the past decade, the importance of electronic trading venues in the inter-dealer market has risen sharply. BIS (2001) estimates that between 85% and 95% of inter-bank trading occurred over electronic trading systems in 2000. This compares with only 50% in 1998 (BIS (1998)).

Even these large volumes understate the importance of the electronic inter-dealer market. This is by far the most transparent part of the spot FX market and, as such, it sets mid-price exchange rates across the entire market. Figure 1 helps to illustrate this point. Transactions between FX banks and their customers are bilateral and are not visible to other banks. So, the other banks can not use the buy/sell information of this

trade to update their prices. However, customer transactions give rise to inventory imbalances. The bid-ask spreads on the inter-dealer market are tiny compared with those that banks charge their customers. Banks can (and do) take on inventory from their customers and rapidly offload that inventory on the inter-dealer market at near mid-market rates. (see Lyons (2001) for greater detail on FX market structure.)

There are two electronic venues in the inter-dealer spot FX market, namely EBS and Reuters 2000-2. EBS is the global leader in foreign exchange broking and is dominant in the large currencies involving the USD, EUR and JPY. Reuters 2000-2 dominates the Commonwealth and Scandinavian currencies. Killeen, Lyons and Moore (2003) provide a detailed description of how the EBS market works.

EBS provided the data for the present study, and this dataset that has not previously been available to academic researchers. It contains spot FX quote and trade price data for eight currency pairs from the EBS electronic inter-dealer market. The quotes data comprises the best bid and ask quote prices per second (Greenwich Mean Time (GMT)). Trade data is also time-stamped to the nearest second (GMT). No information about the size of each transaction is provided. Also, there are no identifiers of the parties to each trade. The data consist of two separate sample periods with five exchange rates in each. The first covers the period 01/08/98 to 04/09/98 and consists of the currency pairs USD/DEM, USD/JPY, USD/CHF, DEM/JPY and DEM/CHF. The second covers 01/08/99 to 03/09/99 and contains data on EUR/USD, USD/JPY, USD/CHF, EUR/JPY and EUR/CHF. Each sample contains 20 days of per second observations. In this study, the EUR is taken to be the linear successor to the DEM on the grounds that, pre-EMU, the DEM was a pan-European vehicle currency (see Hartmann (1998)).

The side of each spot FX trade price is provided by EBS. The trade indicator variable, Q_t , 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, ΔP_t , is defined as $P_t - P_{t-1}$, where P_t 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 $\omega = [S \lambda]'$ is the vector of parameters. The orthogonality conditions are therefore expressed as $E[f(x_t, \omega)] = 0$.

The GMM procedure minimises the quadratic function

$$J_T(\omega) = g_T(\omega)' Z_T g_T(\omega)$$

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

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

where

$$\Omega = (D_0' Z_0^{-1} D_0)^{-1}$$

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

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

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 $f(x_t, \omega)$ 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

USDCHF		
Time Period	01/08/98 - 04/09/98	01/08/99 - 03/09/99
No. of Obs.	42,952	72,939
<i>(A) Stage 1 model</i>		
λ	86%	81%
S.E.(λ)	(0.0199)	(0.0086)
(1- λ)	14%	19%
S	0.000160	0.000148
S.E.(S)	(0.000003)	(0.000002)
<i>(B) Stage 2 model</i>		
α	-2%	-41%
S.E.(α)	(0.1087)	(0.0647)
β	87%	121%
S.E.(β)	(0.100516)	(0.062519)
(1- α - β)	14%	20%
S	0.000160	0.000147
S.E.(S)	(0.000003)	(0.000002)
π	0.4028	0.4259
S.E.(π)	(0.0011)	(0.0008)

Table 1(i). The Huang and Stoll(1997) model results for the USD/CHF exchange rate.

USDJPY		
Time Period	01/08/98 - 04/09/98	01/08/99 - 03/09/99
No. of Obs.	399,124	225,825
<i>(A) Stage 1 model</i>		
λ	72%	64%
S.E.(λ)	(0.0069)	(0.0048)
(1- λ)	28%	36%
S	0.006751	0.009588
S.E.(S)	(0.00005)	(0.000054)
<i>(B) Stage 2 model</i>		
α	68%	-142%
S.E.(α)	(0.0587)	(0.0716)
β	5%	206%
S.E.(β)	(0.060567)	(0.069797)
(1- α - β)	27%	36%
S	0.006714	0.009490
S.E.(S)	(0.00005)	(0.000053)
π	0.5573	0.4655
S.E.(π)	(0.0003)	(0.0005)

Table 1(ii). Huang and Stoll(1997) model results for the USD/JPY exchange rate.

EURUSD		
Time Period	01/08/98 - 04/09/98	01/08/99 - 03/09/99
No. of Obs.	484,005	310,300
<i>(A) Stage 1 model</i>		
λ	56%	45%
S.E.(λ)	(0.0053)	(0.0036)
(1- λ)	44%	55%
S	0.000060	0.000067
S.E.(S)	(0)	(0)
<i>(B) Stage 2 model</i>		
α	100%	-215%
S.E.(α)	(0.064)	(0.0744)
β	-44%	259%
S.E.(β)	(0.065773)	(0.073154)
(1- α - β)	44%	56%
S	0.000060	0.000066
S.E.(S)	(0)	(0)
π	0.5404	0.4736
S.E.(π)	(0.0003)	(0.0004)

Table 1(iii). Huang and Stoll(1997) model results for the EUR/USD exchange rate.

EURCHF		
Time Period	01/08/98 - 04/09/98	01/08/99 - 03/09/99
No. of Obs.	73,898	29,654
<i>(A) Stage 1 model</i>		
λ	74%	67%
S.E.(λ)	(0.0135)	(0.0123)
(1- λ)	26%	33%
S	0.000038	0.000065
S.E.(S)	(0.000001)	(0.000001)
<i>(B) Stage 2 model</i>		
α	-33%	-6%
S.E.(α)	(0.1211)	(0.1316)
β	107%	73%
S.E.(β)	(0.116317)	(0.128533)
(1- α - β)	26%	33%
S	0.000038	0.000065
S.E.(S)	(0.000001)	(0.000001)
π	0.4416	0.4524
S.E.(π)	(0.0008)	(0.0012)

Table 1(iv). Huang and Stoll(1997) model results for the EUR/CHF exchange rate.

EURJPY		
Time Period	01/08/98 - 04/09/98	01/08/99 - 03/09/99
No. of Obs.	128,064	42,743
<i>(A) Stage 1 model</i>		
λ	91%	79%
S.E.(λ)	(0.0096)	(0.0113)
(1- λ)	9%	21%
S	0.006683	0.020216
S.E.(S)	(0.000073)	(0.000319)
<i>(B) Stage 2 model</i>		
α	5%	8%
S.E.(α)	(0.1498)	(0.0455)
β	86%	71%
S.E.(β)	(0.147768)	(0.043994)
(1- α - β)	9%	21%
S	0.006686	0.020267
S.E.(S)	(0.000074)	(0.000323)
π	0.4659	0.3745
S.E.(π)	(0.0006)	(0.0012)

Table 1(v). Huang and Stoll(1997) model results for the EUR/JPY exchange rate.

Table 1. The results from the original Huang and Stoll(1997) model for the USD/JPY, USD/CHF, EUR/USD, EUR/JPY and EUR/CHF exchange rates. Note the EUR in 1999 refers to the euro, but in 1998 it refers to the deutschmark. In order to compare the 1998 and 1999 EUR values, a conversion rate must be introduced – the appropriate rate is the fixed EUR/DEM conversion exchange rate of 1.95583.

α =adverse selection component

β =inventory component

(1- α - β)=price clustering component

λ = α + β

S=bid-ask spread

π =probability of reversal

In the stage 1 model, λ represents the combined adverse selection and inventory management bid-ask spread components. Our analysis reveals very high λ values for the inter-dealer spot FX market. In other words, under the Huang and Stoll(1997) / Glosten and Harris(1988) paradigm, the order processing plays only a small part in the spot FX market. However, the size of the order processing component in FX bid-ask spreads appears to have risen considerably since monetary convergence. Spot FX bid-ask spreads also appear to have appreciated notably over the same period. At first, this may seem inconsistent, until you factor in that spot FX volume has fallen drastically in this period also. The post-euro fall in λ pervades all 5 FX rates studied, while the increased bid-ask spread is evident in 4 of the 5. USD/CHF is the only

exchange rate bid-ask spread which does not rise. Instead, it shows a fall of over 7%. On the other hand, this is the only one of the 5 currency pairs to experience any increase in volume in 1999.

At stage 2, the model blows apart. In many cases, the stage 2 model produced negative values for α , while many of the β values were well in excess 100%. 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 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. Furthermore, the π values for these raw (i.e. not aggregated) trades are mostly well 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 the extended form of the original model was eroded by the finding that many of the t-statistics were below the 95% critical value level.

5(b) Modified Model Results

Table 2 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.

USDJPY		
Time Period	01/08/98 - 04/09/98	01/08/99 - 03/09/99
No. of Obs.	399,124	225,825
<i>(A) Summary Statistics</i>		
Av. Spread	0.009915	0.010257
Av. Daily Volume	399,124	225,825
Av. Volatility (Rtn)	0.0405%	0.0323%
<i>(B) % Breakdown of Bid-Ask Spread (with Standard Errors)</i>		
α	29%	7%
S.E.(α)	(0.0046)	(0.0045)
β	43%	61%
S.E.(β)	(0.0052)	(0.0056)
(1- α - β)	28%	32%
<i>(C) The Components of the Average Quoted Spread</i>		
α	0.002900	0.000732
β	0.004233	0.006277
(1- α - β)	0.002782	0.003247
<i>(D) % Change in the Components of the Average Quoted Spread</i>		
α		-75%
β		48%
(1- α - β)		17%

Table 2(i): The components of the USD/JPY bid-ask spread.

USDCHF		
Time Period	01/08/98 - 04/09/98	01/08/99 - 03/09/99
No. of Obs.	42,952	72,939
<i>(A) Summary Statistics</i>		
Av. Spread	0.000231	0.000177
Av. Daily Volume	42,952	72,939
Av. Volatility (Rtn)	0.0362%	0.0301%
<i>(B) % Breakdown of Bid-Ask Spread (with Standard Errors)</i>		
α	29%	17%
S.E.(α)	(0.0133)	(0.0084)
β	56%	70%
S.E.(β)	(0.0149)	(0.01)
(1- α - β)	15%	13%
<i>(C) The Components of the Average Quoted Spread</i>		
α	0.000068	0.000031
β	0.000130	0.000123
(1- α - β)	0.000034	0.000023
<i>(D) % Change in the Components of the Average Quoted Spread</i>		
α		-54%
β		-5%
(1- α - β)		-32%

Table 2(ii): The components of the USD/CHF bid-ask spread.

EURUSD		
Time Period	01/08/98 - 04/09/98	01/08/99 - 03/09/99
No. of Obs.	484,005	310,300
<i>(A) Summary Statistics</i>		
Av. Spread	0.000082	0.000073
Av. Daily Volume	484,005	310,300
Av. Volatility (Rtn)	0.0267%	0.0244%
<i>(B) % Breakdown of Bid-Ask Spread (with Standard Errors)</i>		
α	25%	9%
S.E.(α)	(0.0039)	(0.0036)
β	38%	42%
S.E.(β)	(0.0044)	(0.0039)
(1- α - β)	37%	49%
<i>(C) The Components of the Average Quoted Spread</i>		
α	0.000020	0.000007
β	0.000031	0.000031
(1- α - β)	0.000030	0.000036
<i>(D) % Change in the Components of the Average Quoted Spread</i>		
α		-40%
β		81%
(1- α - β)		118%

Table 2(iii): The components of the EUR/USD bid-ask spread.

EURJPY		
Time Period	01/08/98 - 04/09/98	01/08/99 - 03/09/99
No. of Obs.	128,064	42,743
<i>(A) Summary Statistics</i>		
Av. Spread	0.010843	0.024639
Av. Daily Volume	128,064	42,743
Av. Volatility (Rtn)	0.0393%	0.0399%
<i>(B) % Breakdown of Bid-Ask Spread (with Standard Errors)</i>		
α	36%	18%
S.E.(α)	(0.0069)	(0.012)
β	50%	65%
S.E.(β)	(0.007)	(0.0117)
(1- α - β)	13%	16%
<i>(C) The Components of the Average Quoted Spread</i>		
α	0.003950	0.004549
β	0.005460	0.016035
(1- α - β)	0.001433	0.004055
<i>(D) % Change in the Components of the Average Quoted Spread</i>		
α		52%
β		287%
(1- α - β)		273%

Table 2(iv): The components of the EUR/JPY bid-ask spread.

EURCHF		
Time Period	01/08/98 - 04/09/98	01/08/99 - 03/09/99
No. of Obs.	73,898	29,654
<i>(A) Summary Statistics</i>		
Av. Spread	0.000071	0.0001
Av. Daily Volume	73,898	29,654
Av. Volatility (Rtn)	0.0173%	0.0066%
<i>(B) % Breakdown of Bid-Ask Spread (with Standard Errors)</i>		
α	45%	33%
S.E.(α)	(0.0088)	(0.0098)
β	37%	45%
S.E.(β)	(0.008)	(0.0113)
(1- α - β)	18%	21%
<i>(C) The Components of the Average Quoted Spread</i>		
α	0.000032	0.0000
β	0.000027	0.0000
(1- α - β)	0.000013	0.0000
<i>(D) % Change in the Components of the Average Quoted Spread</i>		
α		2%
β		68%
(1- α - β)		65%

Table 2(v): The components of the EUR/CHF bid-ask spread.

Table 2: The components of the bid-ask spread for the USD/JPY, USD/CHF, EUR/USD, EUR/JPY and EUR/CHF spot exchange rates, computed using the Modified Model. The currency code EUR refers to the euro and to its predecessor, the deutschemerk. The EUR rates comparison in part D has 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

Part B of Table 2 reveals the percentage components of the bid-ask spread / price innovation for electronic inter-dealer spot FX rates. Part C of Table 2 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. In particular, not the part D of table 2(iii) shows that by far the largest change in the components of the EUR(DEM)/USD following EMU was a 118% increase in the price clustering component. (The EUR/DEM conversion exchange rate is applied to all cases where EUR denominated amounts are compared to DEM denominated amounts.)

Compared with the original model results for spot FX, where β often accounted for more than 100% of the bid-ask spread, the modified model's β component accounts for an average of around 45% of the bid-ask spread in 1998 and 57% in 1999. In every spot FX case, the 1999 β value is larger than that in 1998. Furthermore, in all but one case, the inventory component is bigger than either the information component or the price clustering component. This fits in with the conclusions of McGroarty et al (2005) who found that private information could not account for observed excess volatility in the spot foreign exchange market.

The 1999 results show a sharp decline in α from 33% in 1999 to 17% in 1998. This suggests that "informed" FX limit-order traders are less well able to predict and profit from future price moves since currency convergence than they were before. It seems unlikely that there would be a marked difference in either the macroeconomic fundamentals or the ability to interpret fundamentals between the two sample periods. This suggests that the ability of informed traders to aggregate and interpret information and order flow linked future accumulated inventory in the lower-volume post-EMU period is the most likely source for the stark decline in the information component of the bid-ask spread, and correspondingly why the importance of inventory has risen after EMU.

6. Conclusions

In every case, the asymmetric information component comprises less than 50% of price change and of the bid-ask spread. In 9 out of 10 cases, inventory is a more important factor than asymmetric information. In 3 out of 10 instances, price clustering proves to be a more significant factor than asymmetric information, while in another 3 instances, their magnitudes are broadly similar. In all cases studied here, there is a smaller asymmetric information component after EMU than there was before. This is counterbalanced by a larger post-EMU inventory component in every instance.

The modified trade indicator model proved more appropriate for the electronic inter-dealer spot FX 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 electronic inter-dealer FX 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, as is usually supposed. However, a fuller explanation for these observations requires further research.

References

- Allen, H., and M. Taylor, 1992, "The use of technical analysis in the foreign exchange market", *Journal of International Money and Finance*, 11: 304-314
- Angel, J. J., 1994, "Limit versus market orders", Mimeo, School of Business Administration, Georgetown University.
- BIS (Bank of International Settlements), 1998, Central bank survey of foreign exchange and derivative market activity in April 1998.
- BIS (Bank of International Settlements), 2001, Central bank survey of foreign exchange and derivative market activity in April 2001.
- Bloomfield, R., M. O'Hara and G. Saar, 2005, "The 'make or take' decision in an electronic market: evidence on the evolution of liquidity", *Journal of Financial Economics*, 75, 165-200.
- Choi, J. Y., D. Salandro, and K. Shastri, 1988, "On the Estimation of Bid-Ask Spreads: Theory and Evidence," *Journal of Financial and Quantitative Analysis*, 23, 219–230.
- Cohen, K. J., S. F. Maier, R. A. Schwartz and D. K. Whitcomb, 1981, "Transaction costs, order placement strategy, and existence of the bid-ask spread", *Journal of Political Economy* 89, 287-305.
- Easley, D. and M. O'Hara, 1987, "Price, trade size and information in securities markets", *Journal of Financial Economics*, 19, 69-90.
- Foucault, T., O. Kadan, and E. Kandel, 2001, "Limit order book as a market for liquidity", Mimeo, HEC School of Management.
- George, T. J., G. Kaul, and M. Nimalendran, 1991, "Estimation of the Bid-Ask Spreads and its Components: A New Approach," *Review of Financial Studies*, 4, 623–656.
- Glosten, L., 1994, "Is the electronic open limit order book inevitable?", *Journal of Finance*, 49, 1127-61.
- Glosten, L.R. and L.E. Harris, 1988, "Estimating the components of the bid-ask spread", *Journal of Financial Economics*, 21, 123-142.
- Glosten, L.R. and P.R. Milgrom, 1985, "Bid, ask and transaction prices in a specialist market with heterogeneously informed traders", *Journal of Financial Economics*, 14, 71-100.

Goettler, R., Parlour, C. and Rajan, U., 2005, “Information Acquisition in a Limit Order Market”, presented at the Norges Bank/BI conference on The Microstructure of Equity and Currency Markets, Oslo

Hansen, L., 1982, “Large sample properties of generalised method of moment estimators”, *Econometrica*, 50, 1029-1084.

Harris, L., 1994, “Minimum price variations, discrete bid-ask spreads and quotation sizes”, *Review of Financial Studies*, 7, 149-178.

Harris, L., 1998, “Optimal dynamic order submission strategies in some stylised trading problems”, *Financial Markets, Institutions and Instruments*, 7, 1-75.

Hartmann, P., 1998, “Currency Competition and Foreign Exchange Markets”, Cambridge University Press.

Huang, R., and H.R. Stoll, 1997, “The components of the bid-ask spread: a general approach”, *Review of Financial Studies*, 10, 995-1034.

Killeen, W., R. Lyons and M. Moore, 2003, “Fixed versus floating exchange rates: Lessons from order flow” *Journal of International Money and Finance*, forthcoming.

Kyle, A.S., 1985, “Continuous auctions and insider trading”, *Econometrica*, 53, 1315–1335.

Liu, Y., and D. Mole, 1998, “The use of fundamental and technical analyses by foreign exchange dealers”, *Journal of Finance*, 54: 1705-1765

Lyons, R.K., 2001, “The microstructure approach to exchange rates”, MIT Press.

Madhavan, A., M. Richardson and M. Roomans, 1997, “Why do security prices change? A transaction-level analysis of NYSE stocks” *Review of Financial Studies*, 10: 1035-1064.

McGroarty, F.J.A., 2003, “Determinants of prices and spreads in global currency and money markets”, PhD thesis, University of Southampton, UK.

McGroarty, F., Thomas, S. and O. ap Gwilym, 2005a, “Private information, excessive volatility and intraday empirical regularities in the spot foreign exchange market”, Discussion Papers in Centre for Risk Research, CRR-05-01. Southampton: University of Southampton.

McGroarty, F., Thomas, S. and O. ap Gwilym, 2005b, “Microstructure Effects, Bid-ask Spreads and Volatility in the Spot Foreign Exchange Market Pre and Post-EMU”, *Global Finance Journal*, forthcoming.

Osler, C.L., 2003, “Currency orders and exchange rate dynamics: an explanation for the predictive success of technical analysis”, *Journal of Finance*, 58, 1791-1820.

- Osler, C.L., 2005, "Stop-loss orders and price cascades in currency markets", *Journal of International Money and Finance*, 24, 219-241.
- Parlour, C., 1998. "Price dynamics in limit order markets", *Review of Financial Studies*, 11, 789-816.
- Rock, K., 1990. "The specialist's order book and price anomalies", Mimeo, Graduate School of Business, Harvard University.
- Roll, R., 1984, "A simple implicit measure of the effective bid-ask spread in an efficient market", *Journal of Finance*, 39, 1127-1139.
- Seppi, D. J., 1997. "Liquidity provision with limit orders and a strategic specialist", *Review of Financial Studies*, 10, 103-150.