Price Discovery on Foreign Exchange Markets with Differentially Informed Traders

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Abstract

This paper uses Reuters exchange rate data to investigate the contributions to the price discovery process by individual banks in the foreign exchange market. We propose multivariate time series models as well as models in tick time to study the dynamic relations between the quotes of individual banks. We investigate the hypothesis that German banks are price leaders in the deutschmark/dollar market. Our empirical results suggest an important but not exclusive role for German banks in the price discovery process. There is also a group of banks, German and non-German, that lags behind the market and does not contribute to the price discovery process. We do not find evidence for stronger price leadership of Deutsche Bank on days with suspected Bundesbank interventions in the foreign exchange market.

Keywords: exchange rates, moment estimators, high frequency data, microstructure.

JEL codes: F31, C32

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1 Introduction

It has often been denied that asymmetric information could be important in the foreign exchange market. Because all participants have access to the same public information, the existence of private information seems unlikely. However, Lyons (1999) discusses several channels through which private information could play an important role in the foreign exchange market. Because trading is structured as a decentralized market where traders advertise their quotes on trading screens and strike deals over the phone, the information on order flow and transaction prices remains largely private. Goodhart (1988) and Lyons (1997) argue that this market structure has important implications for the price discovery process on foreign exchange markets. The unavailability of the other traders' order flow induces differential information into the market: traders learn about the fundamental value of the foreign currencies from their own customers' orders only. In the words of Goodhart (1988), also stated in Peiers (1997), "A further source of informational advantage of traders is their access to, and trained interpretation of, the information contained in the order flow". Ito, Lyons and Melvin (1997) provide empirical evidence supporting this view by looking at the volatility of before and after trading restrictions in the Tokyo lunch hour were lifted. Melvin and Covrig (1998) extend this analysis and find that Japanese banks have some form of price leadership in periods with potentially large differences in information about order flow. Lyons (1997) explains the information based trading in the foreign exchange market by the phenomenon of "hot potato trading". Dealers want to pass on inventory imbalances, and thereby have informational effects on the price.

Unfortunately, due to the lack of individual trading data, most of the empirical research does not analyze specific individual behaviour. Only a small number of papers utilize individual trade information. In the foreign exchange microstructure literature, the work of Lyons (1995) is the most prominent example. This lack of emphasis on individual behaviour is unfortunate since potentially much can be learned from individual trade patterns. A study of the behaviour of individual banks may also shed light on the as yet unresolved issue why the quotes are so noisy. We try to see if this is related to strategic interactions between market makers.

This paper therefore investigates the role of individual dealers in the price discovery process on foreign exchange markets. The central hypothesis in our paper is that large banks have an information advantage when trading in the foreign exchange market. As large banks will have a much larger customer base, their dealers will have a better view of demand and supply of a currency. We investigate whether the superior information on order flow has have a systematic influence on the quotes originating from these banks. A related question is what one can learn about the underlying value from the quotes of large banks. This question is again motivated by the particular structure of the foreign exchange market. There are two indirect channels from which traders can learn about their competitor's orders: via the inter-dealer market and from their quotes.

A particular hypothesis we investigate is the "price leadership" hypothesis put forward by Goodhart (1988). Peiers (1997) recently investigated this hypothesis by studying the strategic interactions on the US dollar/Deutsche Mark market for periods around suspected interventions in the foreign exchange market (related to periods of tension in the EMS). The specific hypothesis tested in her paper was the price leadership of Deutsche Bank in such periods. We contrast the price discovery process around (suspected) interventions with the process on "ordinary" days.

As Peiers (1997) we address these issues using the Olsen HFDF93 dataset. This data set contains a continuous and complete record of buy and sell quotes from the Reuters trading screens. The records do not only give the price information but also reveal the identity of the quote issuer. Although these quotes are indicative and customer oriented, and are therefore probably less informative than firm quote or transaction data, the availability of the trader's identity is a substantial advantage over most micro data sets. An important difference with firm quote data is that the bid/ask spread in the HFDF93 is much wider, but according to Goodhart, Ito and Payne (1996) the midquotes seem to give a good indication of the actual market price.

The methodology of this paper is related to the work of Hasbrouck (1995), who analyzes the price discovery process on related financial markets. Hasbrouck's model is a Vector Autoregression (VAR) for thevector of prices (the bank's quotes in our setup). The VAR allows formeasurement of lead and lag relations between the quote revisions ofindividual banks, such as to identify price leaders in the market. The VAR also takes account of the property that quote revisions are not perfectly correlated in the short run, but follow the same common (stochastic) trend in the long run. In the jargon of multivariate time series analysis, the quotes of different banks are cointegrated. The contributions to the price discovery process by individual market makers are measured by the "information share" of each individual trader, defined as the fraction of the total information in the market that can be attributed to a particular bank.

Although our methodology is similar in spirit to Hasbrouck's, we do not use the VAR model. The VAR has two drawbacks for our purposes. The first is the difficulty the VAR has to capture the time series profile of quote revisions, in particular the pronounced negative first order autocorrelation.[1] The VAR can only capture this pattern with very long lags, which tends to make parameter estimates unstable. The second drawback is the awkward definition of the information share. In the VAR there is always a part of the information, caused by the correlation between innovations, that cannot be attributed to individual banks. As a result, information shares in the VAR are not uniquely defined.

Instead, we propose a price discovery model that has three appealing properties: (1) direct imposition of cointegration between the price quotes of different banks; (2) a parsimonious lag structure; (3) a unique and intuitive definition of the information share. The structure of the model is a multivariate unobserved components time series model. The quotes are composed of two components, one common underlying long run component, called the *efficient price*, and an idiosyncratic component specific for each bank. To identify these components we assume that the efficient price follows a random walk, and that the idiosyncratic components are transitory. This makes the quotes of individual banks cointegrated by construction. The random-walk-plus-noise structure is also well suited to describe the empirically observed strong negative first order serial correlation in the quote revsions. The information shares are based on the covariance between the quote revisions of a bank with the innovation in the efficient price. The stronger this covariance, the higher the information share.

A final methodological point is the treatment of the irregular spacing of the quote data. We use two sampling models: tick time and calendar time. In tick time, each new quote is treated as one observation. The nature of the Olsen data is such that there is only one bank issuing a quote at a time. The other sampling assumption is calendar time, in which we sample quotes on fixed time intervals. Given the irregular quote pattern of banks there will be many intervals without quote updates. The usual procedure of dealing with these is to impute a zero return for such intervals. De Jong, Mahieu and Schotman (1998) demonstrate that this imputation procedure leads to a

[1] This autocorrelation is documented e.g. by Dacorogna et al. (1994) .

serious bias in the serial covariance estimates, which may bias the lead-lag patterns in the time series model and may also lead to an overstatement of the accuracy of the results. Therefore, we treat such events as missing observations and use estimation techniques specifically designed to deal with missing observations.

The remainder of the paper is organised as follows. Section 2 provides some key descriptive statistics of the data. Section 3 describes our price discovery model. Sections 4 and 5 report the empirical results for two different sampling assumptions, tick time and calendar time. Section 6 concludes.

2 Data

The data for this paper are taken from the HFDF93 dataset collected by Olsen and Associates. This dataset contains all quotes on the Reuters screens in the period October 1, 1992 trough September 30, 1993. A unique feature of this dataset is that it contains the identity of the bank issuing the quotes. In this section we describe the most important aspects of the data.

2.1 Activity patterns

Following Peiers (1997) we identify the large banks with a potential information advantage by their quote activity. Table 1 shows the number of quotes from the eleven most active banks in the dollar/dmark market, where activity is measured by the number of quotes issued by a bank.[2] We see that the market is dominated by European banks. All of the most active banks in on the Reuters screen are European, except for Chemical Bank. The market share of Deutsche Bank is highest: when it is active, it accounts for almost 9% of all quotes. The eleven banks together make up half of all quotes during European business hours. Although the foreign exchange market is active around the clock, individual banks do not trade 24 hours a day and there are very few quotes outside the European business day hours (4-16 GMT).[3] This relatively low activity outside European hours is partly due to the limited use of Reuters screens in Tokyo and the US (see Goodhart (1991)). Sapp (1998) reports a higher share in trading activity by US banks in the North American hours, but

[2] Many of them are also large in market capitalization.
[3] In the summer 4am GMT corresponds to 7am in continental Western Europe.

Reuters has relatively few quote updates in that time segment. This may partly explain why we find that European banks are the most active.

Table 2 shows the market share (defined as the fraction of quotes issued by that bank) of the major players per hour. Most banks adjust their quotes over the full span of the trading day (4-16GMT), although the hours at the margins of this interval are somewhat less active. A noticable exception to this rule is Credit Suisse, which is very active in the early hours of the day but hardly active later in the day. The opposite holds for Lloyds Bank, which does not put any quotes on the screens in the early hours (London is still closed), but is the most active participant towards the end of the day (when Frankfurt has already closed). This is basically the case for all days in the sample.

We now turn to the sequencing of quotes, which plays an important role in our empirical models. Table 3 shows the Markov transition matrix for the identity of the banks issuing quotes.[4] The table reveals that most of the conditional quote probabilities are close to the marginal probability, with the exception of Credit Suisse, which has a very high probability of issuing two subsequent quotes, and Lloyds bank which almost always issues quotes directly after another bank.

Table 4 shows the average duration between two quotes, conditional on the identity of the issuers. The table reveals no particular pattern, the durations seem to be independent of the identity of quote issures. On average, the duration between two quotes is around 9 seconds.

2.2 Analysis of quote revisions

Figure 4 shows the distribution of quoted bid-ask spreads. A very remarkable feature is the concentration on round numbers, in particular 5 or 10 pips. It is worth to emphasise here that quotes are only indicative in this market. Apparently, banks do frequently adjust the location of the quotes, but the spread between bid and ask is not used as a signalling device. Huang and Masulis (1998) show that the spread is not very variable over the trading day either. Comparing the Olsen quotes with data from the electronic Dealer 2000 trading system, Goodhart, Ito and Payne (1996) conclude that the mid-quote is a fairly good indication of the prices that the bank charges, but that the quoted spread is not a good measure of the actual spread or

[4] Each element $\pi_{k\ell}$ denotes the probability that a quote is issued by bank ℓ, conditional on the previous quote being from bank k.

transaction costs. Evans (1998) also provides evidence in this direction. Therefore, in the remainder of this paper we will not use bid and ask quote data or data on spreads. Instead, we work with the quoted bid-ask midpoint throughout.

Figures 1–3 shows the midquote pattern of the most active banks on May 25, 1993. This is a typical day without special characteristics such as interventions, but with a significant depreciation of the dmark versus the dollar around 14 hours GMT. This day was selected because in many ways it is a typical day as far as the quote patterns are concerned. The figures also graph a smoothed version of the quotes by the remaining banks, to give an indication of market-wide price movements. We see that most banks follow the movements of the market quite closely. On the other hand, the variability of the quotes around the market quote seems to differ among banks.

Table 5 shows the distribution of absolute mid-quote changes for the most active banks. One of the striking results is that most changes are very small, and a non-negligible fraction of the midquote changes is zero. The most extreme case is Lloyds Bank: 38% of their new mid-quote are identical to the prevailing midquote, and another 28% only move either bid or ask by a single tick. For the other banks the situation is less dramatic, but still the (abolute) quote changes are quite small compared with the bid-ask spread. As for the average absolute price revision, we see some substantial differences, partly related to the number of zero quote updates and the activity of the bank. Table 6 shows the average absolute quote revision conditional on the identity of the bank that issued the prevailing quote. There is not much of a pattern here, except for Lloyds bank. When Lloyds updates its own quote the absolute revision is quite large, but otherwise its quotes tend to be very close to the prevailing quote.

Table 7 reports the variance and autocorrelations of percentage quote revisions, conditional on the identity of the bank issuing the last quote. There are some pronounced differences in the conditional variances. For example, the quote revisions by UBS are more volatile than average, whereas BHF, Rabobank and Den Norske Bank have less volatile quote updates. As for the autocorrelations, most striking is the large negative first order autocorrelation. The second order covariance is significantly positive, but higher order autocorrelations are virtually zero.[5]

[5] DeJong, Mahieu and Schotman (1998) find a similar pattern for the covariance structure in calendar time.

The strong negative first order autocorrelation was already documented by Dacorogna et al. (1994) and is typical for first differences of data that are measured with some "noise". This term shouldn't be taken too literally, but we argue that this correlation pattern points at the presence of a substantial transitory component in the quotes. This component could be the result of price discreteness or microstructure effects. The strenght of the autocorrelation depends on the relative magnitude of the variance of the "signal" (i.e. the variance of the true return) and the variance of the "noise" (the measurement error). In a pure signal plus noise model, the first order autocorrelation converges to -0.50 if the time between quotes shrinks to zero. In our estimates we see that for most banks, and on average, the autocorrelation is slightly above this value. Credit Suisse and Lloyds Bank are rather different from the rest and are characterized by a very negative first order correlation and a strong positive second order correlation. This could be the result of the very distinct activity pattern of these banks. Because of these unusual trading patterns and peculiar autocorrelation functions we will omit these two banks from the estimation of the price discovery models in subsequent sections.

So far, we analysed the tick-by-tick quote patterns. A potential drawback of sampling in tick time is the possibility on such a high frequancy of erratic patterns in bank identity or quote levels. Therefore, we also take a look at returns over fixed calendar time intervals. We sample the quotes of each bank on 30 second intervals, thus creating a time series of quotes for each bank. It is important to note that some banks don't update their quote for long stretches of time so that their quotes are often out of line with the market. Because the quotes are indicative only, and carry no obligation to trade at these prices, we feel that such stale quotes are not very reliable indicators of the bank's information. We therefore define only quote updates as observations. If there is more than one quote update in a particular interval, the last quote is treated as the price observation for that interval. If there is no new quote, we treat this period as a missing observation. This approach differs from the usual procedure to substitute a zero return for intervals with no new quote. De Jong, Mahieu and Schotman (1998) show that substituting zero returns for missing observations leads to a serious bias in the estimates of the serial covariances. Instead, we use an estimator proposed by DeJong and Nijman (1997) that delivers consistent estimates of serial covariances of returns (quote revisions) in the presence of missing observations.

Table 8 reports the variance and autocorrelations of quote revisions on a 30 second interval. The table also reports the fraction of 30 second intervals with a quote revision by each bank. For most banks, this fraction is between 7% and 25%. Again, we see major differences in the variance and the first order serial correlation. Typically, the first order serial correlation is negative and stronger so for the banks with a higher variance. Again, this points at the presence of a substantial transitory ("noise") component in the quotes. The second order autocovariance is typically very small.

Finally, we take a look at the cross correlations between the quote revisions. In principle, we could correlate the returns of each pair of banks, but it turned out that due to the relatively large number of missing observations for some banks, and the distinct trading patterns, that this didn't give very stable estimates. Instead, we calculate only the covariances of the returns of each bank with the "market", which is defined as all the other banks. Since the market is the aggregate of all banks but one, the time series of market quotes has far fewer missing observations: around 93% of the 30 second intervals has a quote update. Figure 5 graphs the cross covariances of the major banks with the market. For some of the banks the market is clearly leading (Credit Suisse, BHF, Rabobank). The peak in the cross correlation function is at negative lags, indicating that these banks lag behind the market. The cross covariances for positive lags (laeds of the banks) are all virtually zero. For most other banks the contemporaneous cross correlation is sizeable. Three banks (UBS, Dresdner Bank, Societé Generale) also have significant lead correlations with the market. Notice that these lead and lag covariances are not an artifact of thin trading. Our estimation methododology is especially designed to estimate the lead-lag covariances of the "true" returns, even if there are intervals without a quote revision.

2.3 Summary

In this subsection we summarize the main features of the data. There are substantial differences in the activity of banks, both in number of quotes and in the time of day when the banks are most active. Second, there is no clear pattern in the sequence of bank identities. The quote changes are small (in absolute value), but noisy. The variance of quote revisions differs substantially among banks, but for all banks there is a very pronounced first order serial correlation. There are significant covariances between the quote changes of the banks. Individual banks lag behind the market at most one minute, so convergence to the overall price level is relatively quick.

Although these results alone are already quite interesting, we cannot say much about the relative contribution of each bank to the price discovery process yet. In the next section we therefore propose a multivariate time series model for price discovery, that allows for an assesment of the individual bank's information. The model is specifically designed for the type of quote data we have. In particular, it recognizes that in the long run the quotes should reflect the same underlying value, but also takes account of transitory effects and differences in variance among banks.

3 Model

In this section we present our model for the price discovery process in markets with multiple dealers (banks). The main idea of the model is that price quotes of all banks are derived from one common, but unobserved efficient price. We assume that the quotes equal the efficient price times an idiosyncratic component that can be either noise or reflect the strategic behavior of a bank. This component will be specific to the bank that sets the quote. To fix some notation, let P^* be the efficient price, P the vector of quoted bid-ask midpoints, and U the vector of idiosyncratic components, where the i^{th} elements of P and U refer to bank i. We consider $n-1$ individual banks and a rest category that we will call the "market". Letting $p = \ln P$, $p^* = \ln P^*$, and $u = \ln U$, we have that the logarithm of the vector of quotes equals

$$p = \iota p^* + u \tag{1}$$

The aim of this section is to develop a multivariate time series model for this quote vector. The main assumption of the model is that the efficient price p^* is a random walk with serially uncorrelated increments. The noise term u is assumed to be transitory and takes account of all temporary deviations of the quotes from the efficient price. Notice that the quotes of all banks share the same random walk component. Therefore, by construction, the quote seriesare cointegrated. Economically this is a very intuitiverestriction, since we expect the quotes of each bank to revert to the-same efficient price in the long run. The random walk assumption for the efficient price excludes fundamental exchange rate predictability, but for intraday data this is a good approximation and it is standard in the price discovery literature (see e.g. Hasbrouck, 1995).

We now state the assumptions of our model more formally. Suppose a specific sampling scheme for the data is given, and data are (potentially) recorded at times $t = 1, .., T$. Denote the change of the efficient price over the interval $(t-1, t)$ by

$$r_t = p_t^* - p_{t-1}^* \tag{2}$$

The maintained assumption of the price discovery model is that the unconditional serial covariances of r_t and u_t (the vector with elements u_{it}) are stable in the given sampling interval. We make the following assumptions

$$\begin{aligned} E[r_t^2] &= \sigma^2 && (3) \\ E[r_t u_t] &= \psi && (4) \\ E[r_t u_{t-k}] &= 0, \quad k \neq 0 && (5) \\ E[u_t u'_{t-k}] &= \Omega_k, \quad -K \leq k \leq K && (6) \end{aligned}$$

These assumptions state that the fundamental news r_t is serially uncorrelated. The fundamental news r_t and the idiosyncratic component u_t are uncorrelated at all leads and lags, but may be correlated contemporaneously. The autocovariance structure of u_t is in principle unrestricted. The model therefore has a specific unobserved components (UC) structure, namely a random walk plus noise (see Harvey, 1989, for an introduction to structural time series models). There is only contemporaneous correlation between the news and the noise; introducing serial correlation in r_t or cross correlation between r_t and u_t at leads and lags will lead to an underidentified model.

Because of the unobserved components structure, the efficient price and the noise terms, cannot be observed directly. However, the properties of the model are completely described by the serial covariances of the observed quotes. Since the quote level is nonstationary, the analysis will be based on moments of the first differences. In principle, a matrix Y_t of pairwise differences of quotes by all banks can be defined

$$Y_{ij,t} = p_{it} - p_{j,t-1} = r_t + u_{it} - u_{j,t-1} \tag{7}$$

A complete description of the serial auto- and cross-covariances of all elements of Y_t would notationally be very cumbersome. In our empirical work we use two sampling schemes, calendar time and tick time, for which the algebra can be kept relatively simple. For comparison with the usual VAR model for price discovery, we start the discussion for the calendar time assumption.

3.1 The model in calendar time

For the first model we assume that the process evolves in calendar time. Suppose a time series of quotes for each bank is collected at deterministic points in time. Typically, these point are equally spaced in calendar time but that is not necessary. In this sampling scheme, all the relevant information is given by the vector of quote updates with respect to the bank's own previous quote[6]

$$y_t = p_t - p_{t-1} = r_t \iota + u_t - u_{t-1} \tag{8}$$

For an arbitrary lag structure the data moments are

$$\begin{aligned} C_0 = E[y_t y_t'] &= \sigma^2 \iota\iota' + \iota\psi' + \psi\iota' - \Omega_{-1} + 2\Omega_0 - \Omega_1 && (9) \\ C_1 = E[y_t y_{t-1}'] &= -\iota\psi' - \Omega_0 + 2\Omega_1 - \Omega_2 && (10) \\ C_k = E[y_t y_{t-k}'] &= -\Omega_{k-1} + 2\Omega_k - \Omega_{k+1}, \qquad k \geq 2 && (11) \end{aligned}$$

and $C_{-k} = C_k'$ for $k > 1$.

First, consider the simplest case where the noise term u_t is serially uncorrelated. In that case the non-zero moments are

$$\begin{aligned} c_{0,ij} &= \sigma^2 + 2\omega_{ij} + \psi_i + \psi_j && (12) \\ c_{1,ij} &= -\omega_{ij} - \psi_i && (13) \end{aligned}$$

for all i, j, where ω_{ij} are the elements of Ω_0. The variance of the quote revisions is determined by the fundamental variance, the variance of the noise term and the covariance between noise and news. Because of the common news component, the contemporaneous cross covariance between quote revisions of different banks also depends on the fundamental variance and on the covariance between the idiosyncratic terms. The first order covariances are a function of two sets of parameters: the variance of the noise term and the covariance between the noise term and the news term. Among other things, these parameters determine the first order autocorrelation,

$$\rho_{1,ii} = \frac{-(\omega_{ii} + \psi_i)}{\sigma^2 + 2(\omega_{ii} + \psi_i)} \tag{14}$$

The lowest value this correlation can take is -0.5. We therefore expect $\omega_{ii} + \psi_i$ to be large relative to σ^2, given the empircially observed serial correlations close

[6] Strictly spoken this is only true if there are no missing observations in the time series of individual bank's quote updates.

to -0.5. The lead and lag covariances between the quote revisions of individual banks are determined by ψ and the off-diagonal elements of Ω_0. There is an inherent identification problem here since the first order covariance is also determined by the covariance between news and noise. In particular, ω_{ij} always appears in combination with ψ_i. Partial identification is obtained because Ω_0 is symmetric. The moments that include ψ can be written as

$$c_{1,ij} = -\omega_{ij} - \psi_i, \qquad j \leq i \tag{15}$$

$$c_{1,ij} - c_{-1,ij} = \psi_j - \psi_i, \qquad j > i \tag{16}$$

These equations identify all elements of Ω_0, but only the difference between ψ_i and ψ_j. To fully identify the system, we have to impose one restriction on the vector ψ. The next section suggests an economically meaningful restriction.[7] With a more general lag structure, the identification of ψ and Ω_0 is basically identical, because the higher order moments ($k > 1$) are all determined by the autocorrelations Ω_k of the noise term u_t.

The first equation of the moment equations can be rearranged to obtain the result that for all i, j, the sum of all the lead and lag moments is equal to the fundamental variance

$$c_{0,ij} + c_{1,ij} + c_{-1,ij} = \sigma^2 \tag{17}$$

$$c_{1,ij} = -\omega_{ij} - \psi_i \tag{18}$$

This property of the model is a direct result of the cointegration of all the quote series, and also holds in a model with a more general lag structure. For example, in a model with L lags

$$\sum_{\ell=-L}^{L} c_{\ell,ij} = \sigma^2 \tag{19}$$

From this discussion it transpires that the calendar time model contains several overidentifying restrictions:

- The cointegration restrictions on $\sum c_{\ell,ij}$: $n(n+1)/2$ moments and one parameter.
- Overidentifying restrictions on ψ from $c_{1,ij}$ for $i < j$: $n(n-1)/2$ moments and $n-1$ parameters.

[7] It isn't obvious that ψ can be identified. For example, in a full UC system with n random walk components, hence no cointegration, r_t is a vector of n elements and $\mathsf{E}[r_t e_t]$ cannot be identified. But in our model, it turns out that the cointegration restrictions allow for identification of some elements of $\psi = \mathsf{E}[r_t e_t]$.

These restrictions are a general property of the model and independent of the lag length.

At this point a comparison of the UC model with the usual VAR model (introduced for these purposes in the market microstructure literature by Hasbrouck, 1995) is warranted. The VAR model for p_t can be written as

$$\Delta p_t = \Pi p_{t-1} + A(L)\Delta p_{t-1} + e_t \tag{20}$$

where Π is subject to a number of cointegrating restrictions. In our setting, where the quotes of all banks are based on the same fundamental exchange rate, there are $n-1$ cointegrating relations. An equivalent but more insightful representation is the "common trends" specification

$$y_t = \Delta p_t = \iota\theta' e_t + C(L)\Delta e_t \tag{21}$$

This specification highlights that the quote changes have one common permanent component, which is a linear combination of the innovations,

$$r_t = \theta' e_t \tag{22}$$

All the other effects are transitory. Hasbrouck (1995) proposes to use the fraction of the variance of $\theta' e_t$ explained by bank i as the information share of that bank. This definition has the drawback that it is not unique if the error terms of the VAR are mutually correlated. One solution to this problem is to impose a particular ordering in the banks, but essentially such an ordering is arbitrary. Indeed, Sapp (1998) shows that the estimated information shares can vary substantially among the different orderings of banks.

The differences between the VAR and the UC model are now clear. In the VAR model the innovation vector e_t is a mixture of news and noise. On the contrary, in the UC model there is an explicit separation between news and noise. The separate noise component for each bank also allows for differences in the variance of the noise term without affecting the variance of the news term or the covariance between news and noise, and hence the information share. In a VAR this is not possible, because e_t is both noise and news. Empirically this is a great advantage because the noise term is able to capture the very pronounced first order autocorrelation of the quote data. In a VAR such a strong first order serial correlation can only be captured by very long lags, which makes the estimates often unstable and makes it difficult to extract the long run component of the price vector. The UC model also avoids estimating lot of parameters in the matrix Π. For example, in a system with n banks, there are $n-1$ cointegrating restrictions (with known cointegrating vectors) and therefore $n(n-1)$ free parameters in Π.

3.2 The model in tick time

The alternative sampling assumption is tick time, where the sampling scheme coincides with the quote updates. The timing of these is random. A typical feature of the Olsen dataset is that each quote is at least two seconds apart from the previous one; there are no simultaneous quote updates. This implies that for every observation there is only one element of the quote revision matrix Y_t observed. Denote the (scalar) observed quote revision (with respect to the previous quote revsion of any bank) by

$$y_t = r_t + J_t' u_t - J_{t-1}' u_{t-1} \tag{23}$$

where J_t is the vector with the bank's identity. We first show that the parameters of the tick time price discovery model can be estimated by a regression analysis that exploits the variance and covariances of consecutive prices differences.

For example, with serially uncorrelated idiosyncratic terms the moments of the model, conditional on the sequence of bank identities, are given by

$$\mathsf{E}[y_t^2|J_t, J_{t-1}] = \sigma^2 + (J_t + J_{t-1})'\omega^2 + 2J_t'\psi \tag{24}$$

$$\mathsf{E}[y_t y_{t-1}|J_t, J_{t-1}, J_{t-2}] = -J_{t-1}'\omega^2 - J_{t-1}'\psi \tag{25}$$

where ω^2 is the vector with diagonal elements of Ω_0. Some of the model parameters do not appear in these equations. Notably, the off-diagonal elements of Ω_0 are absent. Moreover, due to the sampling in tick time, the bank identity vector J_t contains only one non-zero element. Hence, $\iota' J_t = 1$ for all t and therefore in the first equation one of the elements of J_t and J_{t-1} is redundant. As a result, not all elements of ψ are identified. This is similar to the underidentification result in the calendar time model. These results also hold in a model with a more general lag structure, because, just like in the calendar time model, the higher order moments $\mathsf{E}[y_t y_{t-k}|J_t, .., J_{t-k}]$ for $k > 1$ are only determined by the higher order covariance matrices of the noise term, Ω_k.

Comparing sampling in tick time with the sampling in calendar time, we see that there are fewer overidentifying restrictions. The reason for this is very simple: in tick time we never simultaneously observe quote revisions by two or more banks, we only have (by construction) sequential quote revisions. As a result, only the diagonal elements of the contemporaneous covariance matrix of the vector of quote revisions can be identified, so that there are $n-1$ overidentifying restrictions on σ^2 due to cointegration. Moreover, only the diagonal elements of Ω_0 can be identified, which removes all the overidentifying restrictions for ψ.

3.3 Information shares

We base information shares on what we can learn about the efficient price from a quote revision by bank i. For example, consider the fundamental price revision as a function of the observed quote change of bank i. In a linear setup, the revision is given by the regression equation

$$\mathsf{E}[r_t|y_t, J_t = e_i] = \beta_i y_t \tag{26}$$

where

$$\beta_i = \frac{\text{Cov}(r_t,\, y_t|J_t = e_i)}{\text{Var}(y_t|J_t = e_i)} \tag{27}$$

On average, in the whole sample of quotes, the price revision or information value that can be attributed to the quotes of bank i is therefore

$$I_i = \beta_i \text{Var}(y_t|J_t = e_i) q_i = \text{Cov}(r_t,\, y_t|J_t = e_i) q_i \tag{28}$$

where q_i is the fraction of the intervals where bank i issued a new quote. So, we find that the information value depends on the covariance of the quotes of bank i with the news, and on the quote intensity of this bank. Working out this covariance in the unobserved components model,

$$\text{Cov}(r_t,\, y_t|J_t = e_i) = \sigma^2 + \psi_i \tag{29}$$

we find an explicit formula for the information value of bank i

$$I_i = \left(\sigma^2 + \psi_i\right) q_i \tag{30}$$

This definition of information values has some appealing properties. First (ceteris paribus) a bank that issues more quotes is more informative, i.e. it has a larger contribution to the price discovery process. Also, a bank with a relatively high value of ψ_i, i.e. a high contemporaneous covariance between its idiosyncratic term and the fundamental news, will have a high information value. A drawback of this definition is that information value is not guaranteed to be positive.

The information *share* of bank i is then found by dividing its information value by the sum of all information values

$$IS_i = \frac{\text{Cov}(r_t, y_t | J_t = e_i) q_i}{\sum_{j=1}^{n} \text{Cov}(r_t, y_t | J_t = e_j) q_j} \tag{31}$$

This is equivalent to

$$IS_i = \frac{\text{Cov}(r_t, y_t | J_t = e_i) \pi_i}{\sum_{j=1}^{n} \text{Cov}(r_t, y_t | J_t = e_j) \pi_j} \tag{32}$$

with $\pi_i = q_i / \sum_{j=1}^{n} q_j$, which is the unconditional probability of an arbitrary quote in the sample being originated by bank i: $\pi_i = P(J_t = e_i)$.[8] Now consider the denominator of the information share. This is basically the unconditional covariance between the efficient price innovation and an arbitrary quote from the sample

$$\sum_{j=1}^{n} \text{Cov}(r_t, y_t | J_t = e_j) \pi_j = \text{Cov}(r_t, y_t) \tag{33}$$

For logical consistency of the model, we want this unconditional covariance to equal the variance of the fundamental news, σ^2. This assumption basically says that the covariance between an arbitrary quote from the sample and the news term is not affected by the covariance between the fundamental news and the idiosyncratic terms. In the UC model, this normalization implies information shares of the form

$$IS_i = \frac{(\sigma^2 + \psi_i)\, \pi_i}{\sigma^2} \tag{34}$$

Of course, we want the information shares to add up to one, which imposes a linear restriction on ψ

$$\sum_{j=1}^{n} \psi_j \pi_j = \pi' \psi = 0 \tag{35}$$

This is the additional identifying restriction for ψ in the UC model.

[8] Notice that the information shares are based on the fraction q_i of intervals with a new quote for bank i. In tick time, this is equal to the fraction of quotes issued by bank i. In calendar time, we could take the fraction of intervals with non-missing observations. This choice has the advantage that for long observation intervals, q_i will be close to one for all banks, and if there are no significant lead and lag covariances ($\psi = 0$) the information shares will be split equally among all banks ($IS_i = 1/n$). This basically states that in that special case each quote is as informative as another.

4 Price discovery in tick time

In this section, we analyse the price dicovery process using the model in tick time. The regression equations described in section 3 can be generalized to an arbitrary lag structure, but from section 2 we know that the serial covariances of the tick by tick quote changes are significant only up to second order. Therefore, we include only one lag in the autocovariance structure of the noise term in the the price discovery model. The model to be estimated therefore becomes

$$
\begin{aligned}
\mathsf{E}[r_t^2] &= \sigma^2 && (36)\\
\mathsf{E}[r_t u_t] &= \psi && (37)\\
\mathsf{E}[u_t u_t'] &= \Omega && (38)\\
\mathsf{E}[u_t u_{t-1}'] &= \, , && (39)
\end{aligned}
$$

with moment conditions (conditional on J_t, J_{t-1} and J_{t-2})

$$
\begin{aligned}
\mathsf{E}[y_t^2] &= \sigma^2 + (J_t + J_{t-1})'\omega^2 + 2J_t'\psi - 2J_t' \, , \, J_{t-1} && (40)\\
\mathsf{E}[y_t y_{t-1}] &= -J_{t-1}'\omega^2 - J_{t-1}'\psi + J_{t-1}' \, , \, J_{t-2} + J_t' \, , \, J_{t-1} && (41)\\
\mathsf{E}[y_t y_{t-2}] &= -J_{t-1}' \, , \, J_{t-2} && (42)
\end{aligned}
$$

Notice that , is fully identified by the second order covariances.

The moment conditions suggest a SUR regression model to estimate the parameter vector $\theta = (\sigma^2, \omega^2, \psi, \mathrm{vec}(\, , \,))'$. Define the matrix of explanatory variables

$$
X_t = \begin{pmatrix} 1 & 0 & 0 \\ J_t + J_{t-1} & -J_{t-1} & 0 \\ 2J_t & -J_{t-1} & 0 \\ -2\mathrm{vec}(J_t J_{t-1}') & \mathrm{vec}(J_{t-1}J_{t-2}') + \mathrm{vec}(J_t J_{t-1}') & -\mathrm{vec}(J_{t-1}J_{t-2}') \end{pmatrix} \qquad (43)
$$

Let $z_t = (y_t^2, y_t y_{t-1}, y_t y_{t-2})'$, and let η_t be a (3×1) error vector. Consider the system of regression equations

$$
z_t = X_t'\theta + \eta_t \qquad (44)
$$

Because the term y_t is common to y_t^2, $y_t y_{t-1}$ and $y_t y_{t-2}$ the elements of the error term η_t are likely to be mutually correlated. For the GLS estimator we assume that the covariance matrix of the errors is

$$
\mathsf{E}[\eta_t \eta_t'] = \Sigma \qquad (45)
$$

In practice, we obtain initial estimates using OLS on the system and from there we apply two rounds of feasible GLS estimation.[9] Because of the underidentification of the model, ψ is estimated subject to the constraint $\pi'\psi = 0$.[10]

4.1 Empirical results for the full sample

Table 9 shows the two round SUR estimates of the tick time price discovery model over the full sample. For legibility, the returns have been multiplied by 10^4 before estimating the model, so the unit of the return is one basis point. The fundamental news innovation variance is estimated at 0.50, which (with an average duration between quotes of 9 seconds) corresponds to a standard deviations of returns over one trading day (4-16PM) of 0.5%. The estimates of the noise variance are much larger than the fundamental variance; for most banks the signal to noise ratio is around 6. Absent any other correlations, this signal to noise ratio would imply first order autocorrelations of around -0.43, which is close to the sample autocorrelations. For Societé Generale and ABN-AMRO the noise is smaller than for other banks, but still much larger than the fundamental news variance.

We now turn to the covariance between the news and noise term and the information shares, ψ_i, which forms the basis of our information share definition. There appears to be a dichotomy in the banks analysed. One group of banks has positive estimates for ψ_i and positive information shares. The banks that belong to this group are Deutsche Bank, Societé Generale, Dresdner Bank, ABN-AMRO and, perhaps, UBS. Notice that these are large banks and two of these are the major German players in this market. The "rest" category of banks is relatively important as well, the information share of this category is higher than its activity share. The remaining banks have a negative estimate for ψ_i and very small or even negative implied information shares. As a formal test, a significantly positive ψ_i implies an information share that is significantly larger than the activity share of this bank. This holds for all banks in the first group, and for the "rest" category. The second group has significantly negative estimates of ψ_i, and hence information shares below the activity share.

[9] Standard errors are calculated from the usual SUR variance-covariance matrix $\text{Var}(\hat{\theta}) = (X'(\hat{\Sigma}^{-1} \otimes I_n)X)^{-1}$ where X is the matrix that stacks $X_1', .., X_n'$.

[10] We replace the term $J_t'\psi$ in the model by $\bar{J}_t'\bar{\psi}$, where $\bar{J}_t = A'J_t$ and A is a $n \times (n-1)$ matrix with property $\pi'A = 0$. The moment equations of the SUR system are adjusted accordingly. The coefficients ψ are then found as $\psi = A\bar{\psi}$ and automatically satisfy $\pi'\psi = 0$.

As for the interaction between the noise terms, there isn't much of a pattern and we cannot document clear strategic interactions. Perhaps, estimating the model with so many free parameters is too much even with the large number of data we have. To get some more reliable results we estimate the model with the restriction that the columns of , are equal, hence , $= (\gamma \quad \cdots \quad \gamma)$. This is equivalent to the restriction $\mathsf{E}[u_{ki}u_{\ell,i-1}] = \gamma_k$ for all ℓ. Economically, this restriction means that the reaction of bank k's quotes to the previous quote is independent of the identity of the bank that issued the previous quote. This may be a natural restriction in this case because, due to the short time span between quote revisions, the identity of the previous quote's issuer may be unimportant. With this restriction we obtain the following model

$$\mathsf{E}[y_t^2] = \sigma^2 + (J_t + J_{t-1})'\omega^2 + 2J_t'\psi - 2J_t'\gamma \tag{46}$$

$$\mathsf{E}[y_t y_{t-1}] = -J_{t-1}'\omega^2 - J_{t-1}'\psi + (J_t + J_{t-1})'\gamma \tag{47}$$

$$\mathsf{E}[y_t y_{t-2}] = -J_{t-1}'\gamma \tag{48}$$

Table 10 shows the results of estimating this restricted tick time model over the full sample. The estimates for the fundamental news and noise variances shares are fairly robust against this restriction. The dichotomy among the banks' information shares is preserved. But now we do observe a clear pattern in the interactions between the noise terms: the estimates of γ_i for the second group of banks, i.e. the group with low information shares, is typically negative. A potential interpretation of this result is given by the following model, where there is a lagged response of noise to fundamental news, and no response of noise to lagged noise:

$$\mathsf{E}[r_t^2] = \sigma^2 \tag{49}$$

$$\mathsf{E}[u_t r_t] = \psi \tag{50}$$

$$\mathsf{E}[u_t r_{t-1}] = \phi \tag{51}$$

$$\mathsf{E}[u_t u_t'] = \Omega \tag{52}$$

This model is observationally equivalent to the restricted tick time model, with ϕ equal to $-\gamma$.[11] The negative value of γ_i can therefore be interpreted as a lagged

[11] The assumptions imply the following moment conditions

$$\begin{aligned} \mathsf{E}[y_t^2] &= \sigma^2 + (J_t + J_{t-1})'\omega^2 + 2J_t'\psi \\ \mathsf{E}[y_t y_{t-1}] &= -J_{t-1}'\omega^2 - J_{t-1}'\psi + J_t'\phi \\ \mathsf{E}[y_t y_{t-2}] &= J_{t-1}'\phi \end{aligned}$$

which are equivalent to the moment conditions of the restricted tick time model: ψ in this model is equivalent to $\psi - \gamma$ in the previous model, and ϕ is equivalent to $-\gamma$.

response to fundamental news by the quotes of these banks.

To summarize the results of this part, we draw the following conclusions. The quotes of the large German banks are informative, and these players appear to be price leaders. Price leadership is not exclusive for German banks, however. There are also non-German banks that provide relatively informative quotes and are price leaders. On the other hand, there is a second group of banks that lag behind the market and give quotes that are not informative.

4.2 Empirical results for intervention days

The sample period contains a number of days where the Deutsche Bundesbank intervened in the foreign exchange market. Peiers (1997) reports the suspected days and times of these interventions. The period around interventions is particularly interesting for the investigation of information effects in the foreign exchange markets because information differentials may be more pronounced in such periods. Peiers (1997) argues that Deutsche Bank is often used by the Bundesbank as their agent for interventions. This would give DB an informational advantage over other banks because they know an important part of the order flow, which is not observed by other participants. Indeed, Peiers (1997) concludes that DB is a price leader in the Dmark-dollar market around interventions. This informational advantage could also hold for other German banks that are closer to rumours about interventions than non-German banks.[12]

In this part we will reconsider the evidence in Peiers using our price discovery model. We feel that our tick time model is more suitable for the question than the calendar time VAR model used by Peiers. The tick time model avoids the interpolation of quotes over one-minute intervals that Peiers employs to deal with the irregular spacing of quotes. Instead, we look at the tick-by-tick price patterns. Another contribution of our analysis is the inclusion of all banks in the model.[13]

Table 11 reports the estimates of the tick time price disovery model for the sample period of one hour before to one hour after the intervention times as reported in Table I of Peiers (1997). In total, there are 10859 quote updates in this sample, which amounts to one quote per 9 seconds, which is very similar to the quote frequency in the full sample. Looking at the parameter estimates, we see that the fundamental variance

[12] Melvin and Covrig (1998) find price leadership of Japanese banks in the yen/dollar market in periods with suspected strong information differentials.

[13] Peiers considers only the six largest banks from Table 1).

more than doubles in the intervention periods. The estimates of the noise variance are not systematically bigger than the full sample estimates, however. Also, there are few changes in the estimates of the information shares. An exception is Dresdner Bank, which has a significantly negative estimated ψ_i and a very low information share. In contrast, in the full sample Dresdner Bank was one of the more informative players. We repeated this analysis for a smaller window of 25 minutes (both ways) around intervention time and found similar results.[14]

We conclude that there is more fundamental volatility during the intervention periods, but there are no clear differences in price leadership and information patterns. In particular, there seems to be little evidence for unusual price leadership of Deutsche Bank and no evidence for a special role of other German banks.

5 Price discovery in calendar time

The tick time assumption made in the previous section has some potential drawbacks. Because of the very short interval between quote updates, the sequencing of the quotes, and hence the bank identities, may contain some inaccuracies. Moreover, longer run price patterns may be obscured by the large "noise" component in the quotes. It would be interesting to see whether the same information shares and price leadership patterns are found when we use a different sampling assumption. In this section we therefore study the longer run interactions between banks in calendar time.

The calendar time analysis proceeds in three steps. First, we create a time series of quotes for each bank on 30 second intervals. This interval is short enough to show lead-lag relationships between the quote updates of individual banks, but it is longer than the average interval between two "ticks" (9 seconds), so that we smooth out some potential erratic short term patterns.[15] Next, we estimate the serial covariances of these time series. Because of the relative short interval, there are many missing observations for the quote revision series of individual banks. We therefore use the DeJong and Nijman (1997) procedure to obtain consistent estimates of the serial covariances. Finally, we estimate the price discovery model using these moments and test whether we find the same dynamics and information shares as in the tick time model.

[14] Details are available upon request from the authors of this paper.

[15] See also DeJong, Mahieu and Schotman (1998) for a motivation of this interval length.

To see how the parameters of the calendar time price discovery model are identified from the data moments (serial covariances), recall the system of moment equations (9)–(11)

$$C_0 = \mathsf{E}[y_t y_t'] = \sigma^2 \iota\iota' + \iota\psi' + \psi\iota' - \Omega_{-1} + 2\Omega_0 - \Omega_1 \tag{53}$$

$$C_1 = \mathsf{E}[y_t y_{t-1}'] = -\iota\psi' - \Omega_0 + 2\Omega_1 - \Omega_2 \tag{54}$$

$$C_k = \mathsf{E}[y_t y_{t-k}'] = -\Omega_{k-1} + 2\Omega_k - \Omega_{k+1}, \qquad k \geq 2 \tag{55}$$

An equivalent but more convenient system to solve is

$$S_0 \equiv \sum_{\ell=-\infty}^{\infty} C_\ell = \sigma^2 \iota\iota' \tag{56}$$

$$S_1 \equiv \sum_{\ell=1}^{\infty} C_\ell = -\iota\psi' - \Omega_0 + \Omega_1 \tag{57}$$

$$S_k \equiv \sum_{\ell=k}^{\infty} C_\ell = -\Omega_{k-1} + \Omega_k, \quad k > 1 \tag{58}$$

Summing the higher order moments once again we obtain

$$S_0 \equiv \sum_{\ell=-\infty}^{\infty} C_\ell = \sigma^2 \iota\iota' \tag{59}$$

$$D_1 \equiv \sum_{\ell=1}^{\infty} S_\ell = -\iota\psi' - \Omega_0 \tag{60}$$

$$D_k \equiv \sum_{\ell=k}^{\infty} S_\ell = -\Omega_{k-1}, \quad k > 1 \tag{61}$$

In practice, the infinite summations have to be truncated at some point. For reasons of stability, we decided to do the summation over a relatively long horizon, up to $L = 10$. It turned out that the summed moments S_k for $k > 1$ were almost zero. Hence, we can assume that $\Omega_k = 0$ for$k > 0$. The only relevant moment equations are therefore

$$S \equiv \sum_{\ell=-L}^{L} C_\ell = \sigma^2 \iota\iota' \tag{62}$$

$$D \equiv \sum_{\ell=1}^{L} C_\ell = -\iota\psi' - \Omega \tag{63}$$

where for notational convenience the subscript is omitted from D_1 and Ω_0.

Due to the relatively large fraction of missing observations and the distinct trading pattern of the banks it was not feasible to estimate the full covariance matrices C_k for a system of 10 banks. Instead, we estimated the serial covariances between the quote revisions of each bank and the "market", defined as the collection of all other banks. Therefore, we include only the autocovariances and the cross covariances between a bank versus the market. In that case the moment equations are (for $i = 1, .., n$)

$$\begin{aligned} s_{ii} &= \sigma^2 && (64) \\ s_{i0} &= \sigma^2 && (65) \\ s_{00} &= \sigma^2 && (66) \\ d_{ii} &= -\psi_i - \omega_{ii} && (67) \\ d_{i0} &= -\psi_i - \omega_{i0} && (68) \\ d_{0i} &= -\psi_0 - \omega_{0i} && (69) \\ d_{00} &= -\psi_0 - \omega_{00} && (70) \end{aligned}$$

where the individual banks are indexed with an i, and the market has index 0.[16] From these equations it follows that the fundamental variance σ^2 is overidentified, and a particular weighting of the moments identifying the variance has to be made. As before, ψ is underidentified and an identifying restriction is necessary. In this setup is natural to assume that the information shares of all banks together plus the market add up to one, which implies the restriction

$$\pi_0 \psi_0 + \sum_{i=1}^{n} \pi_i \psi_i = 0 \tag{71}$$

from which a unique solution for the vector ψ can be found. How to define the activity share π_i is not obvious in this case, but a possible choice is

$$\pi_i = \frac{q_i}{q_0 + \sum_{i=1}^{n} q_i} \tag{72}$$

where n is the number of banks. With this assumption, the elements of ψ, the diagonal elements of Ω and the covariance between the market noise and the bank noise ($\omega_{0i} = \omega_{i0}$) are exactly identified. In particular, the parameters ψ_i and ψ_0 are determined from the equality

$$\psi_i - \psi_0 = d_{0i} - d_{i0} = \sum_{\ell=1}^{L} \text{Cov}(\Delta p_{0t}, \Delta p_{i,t-\ell}) - \text{Cov}(\Delta p_{it}, \Delta p_{0,t-\ell})$$

[16] Strictly speaking, for each bank i there is a different definition of the market. Empirically, the moments of the various definitions of the market turned out to be virtually the same. Therefore, we use only one index for the market series.

i.e. by the difference between the lead and lag covariances of the bank and the market quote changes.

Before we go to estimates of the model parameters we first report the basic input. Table 12 reports the summed serial covariances of the data. The table reveals an inconsistency between the data and the model. In the model, the sum of all lead and lag covariances should be equal to the fundamental variance. However, the sum of the autocovariances for the bank, cross covariances and autocovariances of the market are all quite different. The summed lead covariances from market to bank (d_{0i}) are typically positive, whereas the summed lead covariances from bank to market (d_{i0}) are close to zero.

Table 13 reports the estimates of the price discovery model based on these moments. We let σ^2 be determined only by the summed autocovariances of the market. The reason for this is that the market series has the lowest fraction of missing observations. The variance of the fundamental news component is 1.81, which is about 3.6 times the estimate in the tick time model. This is what could be expected because on average there are around 3.4 quote updates in each 30 second interval. Just like in the tick time model we find that the variance of the noise component is large relative to the fundamental variance. As for the information shares, the lead of the market to the individual banks gives negative estimates of ψ_i and information shares that are lower than the activity share for the individual banks. Among banks we find the same pattern as in tick time, with Deutsche Bank and Societé Generale having the highest information share, and a group of uninformative banks. The market has the highest information share, also relative to its activity share.

6 Conclusion

In this paper we investigated the role of individual banks in the price discovery process on the foreign exchange market. Large banks are the main participants in this market and each bank has some private information concerning the order flow. We investigate whether this information structure leads to differences in the contribution to price discovery and to specific dynamic interaction between banks. In particular, we investigate the hypothesis of price leadership by German banks in the deutschmark/dollar market.

The empirical results indicate that there are clear differences in the contribution to price discovery among banks. There is one group of banks with a relatively high information share. We find an important, but not exclusive, role for large German banks in this group. For example, Deutsche bank is an important market leader, but there are other banks (also non-German) with comparable information shares. In contrast to this informative group of banks there is another group with very low information shares. The quote revisions of these banks typically lag behind the market quote revision.

To check the robustness of these results to the sampling assumption, we estimated the price discovery model both on a tick-by-tick basis and on fixed 30 second intervals. The findings of the tick time analysis are confirmed by the calendar time analysis, although we find slightly smaller information shares for the major dealers and somewhat higher share for the remaining banks.

The final topic we investigated is the price leadership pattern on days with suspected Bundesbank intervention in the foreign exchange market. In contrast to Peiers (1997) we do not find a special role for German banks in the hours around intervention times, and we do not find an unusual price leadership of Deutsche Bank in these periods either.

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Table 1: Most Active Banks

	Acronym	Total quotes	quotes within trading hours
Deutsche Bank	DB	121,055	101,355
Chemical Bank	CHEM	67,554	54,372
BHF Bank	BHF	70,227	56,586
Rabobank	RABO	57,274	53,672
Societé Generale	SG	72,891	67,014
Der Norske Bank	NORS	38,958	38,902
Credit Suisse	CSUI	76,180	73,900
Dresdner Bank	DRES	39,875	32,891
Lloyds Bank	LLOY	48,082	40,912
Union Bank of Switzerland	UBS	38,600	30,285
ABNAMRO Bank	ABNA	35,971	25,595

Notes: Entries show the total number of quotes by a bank in the HFDF93 data. Trading hours are defined as the twelve hour period 4-16 GMT.

Table 2: Market Shares

	4	5	6	7	8	9	10	11	12	13	14	15	All
DB	6	7	9	10	9	9	11	12	10	8	8	6	9
CHEM	3	2	3	4	4	5	5	6	6	5	5	8	5
BHF	6	6	7	5	5	5	6	7	5	4	4	1	5
RABO	1	1	2	4	6	7	8	8	6	5	4	2	5
SGEN	1	1	1	5	7	7	8	7	7	7	7	8	6
NORS	0	0	1	3	5	5	5	5	5	4	3	1	3
CSUI	27	33	18	3	1	1	2	2	2	2	2	3	6
DRES	2	2	2	3	4	3	3	3	3	3	3	2	3
LLOY	0	0	1	3	3	4	4	5	4	4	5	9	4
UBS	3	3	4	4	2	2	2	2	2	2	3	2	3
ABNA	3	3	2	2	2	2	2	2	2	2	2	2	2
rest	48	43	49	54	51	49	45	42	48	53	53	57	49
nobs	39	83	96	109	112	107	100	95	101	108	107	80	1138

Notes: Entries show the number of quotes by each bank by hour of the day as a percentage of the total number of quotes during that hour. Times refer to GMT. The last column gives the overall market share of each bank during the twelve hour period 4-16 GMT. The last line gives the number of quotes in each hour (in thousands).

Table 3: Markov transition matrix for bank identity

	db	chem	bhf	rabo	sgen	nors	csui	dres	lloy	ubs	abna	rest
DB	8.11	5.50	6.12	5.82	6.18	3.68	4.78	2.88	3.96	2.59	2.32	48.07
CHEM	10.54	5.84	5.67	5.89	6.20	3.49	3.90	2.75	3.71	2.32	2.09	47.61
BHF	11.40	5.86	3.30	6.08	5.81	3.35	6.29	2.89	2.04	2.54	2.39	48.05
RABO	11.23	6.00	6.99	4.61	6.42	4.00	2.40	2.94	3.10	2.29	2.21	47.80
SGEN	9.14	4.94	4.64	4.99	11.80	4.53	1.95	2.82	3.89	2.42	2.18	46.70
NORS	10.01	4.97	5.22	5.85	7.44	3.89	1.85	3.46	3.13	2.88	2.28	49.01
CSUI	6.61	2.70	4.89	1.77	1.68	1.00	33.18	1.76	1.16	3.19	2.15	39.92
DRES	8.95	4.51	4.75	4.79	5.74	4.12	3.97	4.20	4.53	3.03	2.31	49.10
LLOY	8.62	6.29	4.70	5.88	6.59	3.54	2.09	3.23	0.07	2.31	2.10	54.57
UBS	8.97	4.39	4.48	4.01	5.24	3.68	7.81	3.16	3.85	3.51	2.09	48.82
ABNA	9.07	4.49	5.10	4.37	5.85	3.63	5.27	2.94	3.52	2.75	3.47	49.56
rest	8.62	4.50	4.76	4.52	5.50	3.40	5.27	2.90	4.23	2.65	2.22	51.44
overall	8.90	4.78	4.97	4.72	5.89	3.42	6.49	2.89	3.59	2.66	2.25	49.44

Notes: Entries show the percentage of quotes by bank k (row) followed by a quote of bank ℓ (column). The last row is the marginal percentage of quotes issued by bank ℓ.

Table 4: Conditional durations

	db	chem	bhf	rabo	sgen	nors	dres	lloy	csui	ubs	abna	rest
DB	11	11	13	11	9	9	10	9	13	10	10	10
CHEM	10	16	11	10	9	9	9	10	15	10	16	12
BHF	11	11	14	12	10	10	9	9	13	10	18	10
RABO	10	10	10	10	9	9	9	9	12	9	10	9
SGEN	10	10	11	10	8	8	8	9	12	8	8	9
NORS	9	9	10	9	8	9	8	8	9	8	8	8
DRES	10	9	12	9	11	8	9	8	13	9	10	9
LLOY	7	8	8	8	7	7	7	13	8	7	7	8
CSUI	9	9	9	9	9	8	8	9	7	8	13	10
UBS	12	11	11	9	9	8	9	9	18	11	22	11
ABNA	10	33	11	10	8	8	11	8	16	9	18	13
rest	10	13	11	9	9	8	10	10	16	10	29	11

Notes: Entries show the duration in seconds between quotes by bank k (row) predeced by a quote of bank ℓ (column).

Table 5: Marginal Distribution of Quote Revisions

	0	$\frac{1}{2}$	1	$1\frac{1}{2}$	2	$2\frac{1}{2}$	3	$3\frac{1}{2}$	4	$4\frac{1}{2}$	5	$5\frac{1}{2}$	6	$6\frac{1}{2}$	Avg
DB	10	11	9	8	11	11	7	5	3	4	6	3	1	1	2.95
CHEM	8	14	12	10	9	9	6	6	3	4	3	3	1	2	2.80
BHF	14	19	8	11	7	11	5	5	3	4	4	2	1	1	2.34
RABO	14	19	9	9	8	8	6	4	3	3	5	2	1	1	2.43
SGEN	9	11	14	6	14	12	8	4	3	4	4	3	1	1	2.62
NORS	10	11	15	9	11	10	7	6	4	4	3	3	1	2	2.53
DRES	13	10	6	7	8	13	6	4	2	4	10	3	1	1	3.11
LLOY	38	28	2	4	3	6	3	3	1	2	3	1	1	1	1.48
CSUI	14	13	12	5	13	5	9	2	4	2	8	1	2	1	2.64
UBS	14	9	3	6	8	13	7	4	2	3	14	2	1	1	3.33
ABNA	15	9	11	6	11	12	8	4	3	4	6	2	1	1	2.63
rest	11	10	10	7	10	11	7	4	3	4	7	3	1	1	2.95
Overall	12	12	10	7	10	10	7	4	3	4	7	2	1	1	

Notes: Entries show the percentage of absolute quote changes by banks that fall in a particular category. Column "0" gives the percentage of zero change in the midquote. The other categories are at fixed interval lengths of 0.5×10^{-4}, i.e the column "0.5" contains the quote revisions $0 < |P_i - P_{i-1}| \leq \times 0.5 \times 10^{-4}$, without taking logarithms. The average absolute quote revision is in units of 10^{-4}.

Table 6: Conditional absolute quote revisions

	db	chem	bhf	rabo	sgen	nors	dres	lloy	csui	ubs	abna	rest
DB	2.76	2.62	2.50	2.71	2.59	2.80	3.17	4.09	2.90	3.32	2.68	3.06
CHEM	2.64	2.31	2.03	2.22	2.45	2.49	3.14	3.90	3.19	3.33	2.87	2.95
BHF	2.38	2.09	1.68	1.54	2.25	2.14	2.70	2.86	2.24	2.79	2.37	2.48
RABO	2.29	2.04	1.80	3.40	2.21	2.24	2.69	2.74	2.19	2.70	2.30	2.51
SGEN	2.80	2.74	2.71	2.74	2.51	2.36	2.79	3.58	2.67	2.94	1.93	2.53
NORS	2.77	2.65	2.49	2.64	1.97	2.23	2.78	3.41	2.69	2.65	2.07	2.49
DRES	3.37	3.26	2.93	3.03	2.71	2.95	3.57	3.65	3.03	2.93	2.64	3.09
LLOY	1.18	1.99	2.15	1.82	1.63	1.97	1.18	10.68	1.51	1.17	1.52	1.40
CSUI	2.38	2.69	1.96	2.34	2.32	2.63	2.46	3.33	3.13	2.49	2.00	2.40
UBS	3.44	3.51	3.34	3.16	2.78	3.01	3.21	3.77	3.71	4.23	3.03	3.27
ABNA	2.79	3.20	2.80	2.90	2.20	2.51	2.61	3.48	1.98	2.87	2.70	2.58
rest	3.13	3.11	2.80	2.96	2.43	2.70	3.04	3.81	3.10	3.28	2.59	2.90
Overall	2.95	2.80	2.34	2.43	2.62	2.53	3.11	1.48	2.64	3.33	2.63	2.95

Notes: Entries show the average absolute quote revision by bank k (row) preceded by a quote of bank ℓ (column) in units of 10^{-4}. The last row gives the weighted average of the rows.

Table 7: Variance and autocorrelations of quote revisions in tick time

	Var	ρ_1	ρ_2
DB	6.33	-0.38	-0.03
CHEM	5.93	-0.47	-0.05
BHF	4.37	-0.61	-0.10
RABO	4.97	-0.54	-0.01
SGEN	5.16	-0.48	0.01
NORS	4.74	-0.62	-0.04
DRES	6.92	-0.40	-0.01
LLOY	3.23	-0.79	0.40
CSUI	5.39	-0.75	0.31
UBS	8.10	-0.39	0.02
ABNA	5.24	-0.42	0.05
rest	6.37	-0.42	0.02
Overall	5.91	-0.46	0.03

Notes: Entries show the conditional variance and autocorrelations of quote revisions $\Delta \ln P$ by bank k, irrespective of which bank issued the earlier quotes.

Table 8: Variance and autocorrelations of quote revisions in calendar time

	Var	ρ_1	ρ_2	obs
DB	8.33	-0.40	0.02	0.25
CHEM	6.48	-0.41	0.08	0.14
BHF	3.40	-0.04	-0.17	0.15
RABO	6.30	-0.36	0.05	0.14
SGEN	5.58	-0.25	0.02	0.16
NORS	5.18	-0.22	0.04	0.10
CSUI	6.55	-0.28	0.02	0.13
DRES	9.13	-0.29	-0.04	0.09
LLOY	20.76	-0.56	0.12	0.11
UBS	10.21	-0.29	-0.04	0.08
ABNA	6.61	-0.33	-0.04	0.07

Notes: Entries show the conditional variance and autocorrelations of quote revisions $\Delta \ln P$ in calendar time. Moments have been computed over 30 seconds intervals using the estimator of DeJong and Nijman (1998). "obs" is the fraction of 30 second intervals with a quote revision by that bank.

Table 9: Price discovery model in tick time

σ^2	0.50	(0.02)					
	ω^2		ψ		π	IS	nobs
DB	2.94	(0.06)	0.10	(0.04)	0.09	0.11	100,920
CHEM	3.35	(0.08)	-0.73	(0.05)	0.05	-0.02	53,948
BHF	2.65	(0.08)	-1.00	(0.05)	0.05	-0.05	56,322
RABO	3.20	(0.08)	-0.94	(0.05)	0.05	-0.04	53,505
SGEN	1.15	(0.08)	0.30	(0.05)	0.06	0.10	66,827
NORS	2.35	(0.10)	-0.91	(0.06)	0.03	-0.03	38,835
DRES	2.41	(0.11)	0.34	(0.06)	0.03	0.05	32,738
UBS	3.31	(0.11)	0.10	(0.07)	0.03	0.03	30,085
ABNA	0.67	(0.12)	0.93	(0.07)	0.02	0.06	25,267
rest	2.10	(0.02)	0.14	(0.01)	0.59	0.78	672,893

Notes: This table reports GLS estimates of the price discovery model in tick time. Parameters: σ^2 is the variance of the fundamental news; ω_i is the variance of the idiosyncratic component; ψ_i is the covariance between news and the idiosyncratic component; π is the activity share and IS the information share of bank i. "nobs" is the number of observations per bank in the estimation. The matrix , in the panel below is the covariance between current and lagged idiosyncratic terms. Standard errors in parentheses.

					,					
DB	0.53	0.32	-0.07	0.01	-0.03	-0.29	-0.18	-0.27	0.13	-0.00
	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.09)	(0.10)	(0.11)	(0.03)
CHEM	0.79	1.25	0.28	0.33	0.04	-0.18	0.09	-0.13	-0.56	-0.11
	(0.07)	(0.09)	(0.09)	(0.09)	(0.09)	(0.12)	(0.13)	(0.14)	(0.15)	(0.04)
BHF	0.65	0.28	0.64	0.02	-0.23	-0.47	-0.07	-0.23	0.01	-0.16
	(0.07)	(0.09)	(0.12)	(0.09)	(0.09)	(0.12)	(0.13)	(0.13)	(0.14)	(0.03)
RABO	0.62	0.60	0.41	-1.61	-0.11	-0.38	-0.05	0.21	0.07	-0.01
	(0.07)	(0.09)	(0.08)	(0.10)	(0.09)	(0.11)	(0.13)	(0.14)	(0.15)	(0.04)
SGEN	-0.05	-0.43	-0.45	-0.61	0.04	-0.13	0.05	0.06	0.34	0.07
	(0.07)	(0.09)	(0.09)	(0.09)	(0.06)	(0.09)	(0.12)	(0.13)	(0.13)	(0.03)
NORS	0.12	0.04	-0.01	-0.10	0.07	0.20	0.23	-0.08	0.35	0.01
	(0.08)	(0.12)	(0.11)	(0.11)	(0.10)	(0.13)	(0.14)	(0.15)	(0.17)	(0.04)
DRES	-0.24	-0.70	-0.87	-0.44	-0.01	-0.52	-0.05	-0.30	0.52	-0.04
	(0.10)	(0.13)	(0.13)	(0.13)	(0.12)	(0.14)	(0.14)	(0.16)	(0.18)	(0.05)
UBS	0.23	-0.99	-0.45	-0.40	0.08	-0.05	0.20	-0.23	-0.27	-0.17
	(0.10)	(0.14)	(0.14)	(0.14)	(0.13)	(0.15)	(0.16)	(0.16)	(0.20)	(0.05)
ABNA	-0.16	-1.04	-0.95	-0.76	0.25	-0.44	0.28	-0.76	0.30	-0.15
	(0.11)	(0.15)	(0.14)	(0.15)	(0.13)	(0.17)	(0.18)	(0.19)	(0.17)	(0.05)
rest	-0.24	-0.55	-0.46	-0.41	0.09	-0.27	-0.12	-0.38	0.26	-0.23
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.01)

Table 10: Price discovery model in tick time with restricted ,

σ^2	0.50	(0.02)							
	ω^2		ψ		γ		π	IS	nobs
DB	2.70	(0.04)	0.12	(0.03)	0.03	(0.02)	0.09	0.11	100,920
CHEM	2.96	(0.06)	-0.36	(0.04)	-0.23	(0.03)	0.05	0.01	53,948
BHF	2.53	(0.06)	-0.71	(0.04)	-0.29	(0.03)	0.05	-0.02	56,322
RABO	2.97	(0.06)	-0.54	(0.04)	-0.36	(0.03)	0.05	-0.00	53,505
SGEN	1.07	(0.05)	0.23	(0.03)	0.04	(0.02)	0.06	0.09	66,827
NORS	2.12	(0.07)	-0.60	(0.04)	-0.26	(0.03)	0.03	-0.01	38,835
DRES	2.57	(0.08)	0.25	(0.05)	-0.07	(0.03)	0.03	0.04	32,738
UBS	3.48	(0.08)	0.24	(0.05)	-0.30	(0.04)	0.03	0.04	30,085
ABNA	0.99	(0.09)	0.50	(0.06)	0.19	(0.04)	0.02	0.05	25,267
rest	2.42	(0.02)	0.06	(0.01)	-0.16	(0.01)	0.59	0.68	672,893
total									1,131,338

Notes: This table reports GLS estimates of the price discovery model in tick time with the restriction that $\gamma_{k\ell} = \gamma_k$. Parameters: σ^2 is the variance of the fundamental news; ω_i is the variance of the idiosyncratic component; ψ_i is the covariance between news and the idiosyncratic component; γ_i is the covariance between the idiosyncratic term of bank i and the previous idiosyncratic term; π is the activity share and IS the information share of bank i. "nobs" is the number of observations per bank in the estimation. Standard errors in parentheses.

Table 11: Price discovery model in tick time with restricted , : Intervention days

σ^2	1.11	(0.20)							
	ω^2		ψ		γ		π	IS	nobs
DB	3.30	(0.59)	0.50	(0.35)	-0.16	(0.26)	0.09	0.13	1,004
CHEM	3.82	(0.73)	-0.67	(0.44)	-0.96	(0.32)	0.06	0.02	664
BHF	1.51	(0.84)	-0.54	(0.51)	-1.05	(0.36)	0.05	0.02	495
RABO	2.81	(0.79)	-0.86	(0.49)	-1.24	(0.34)	0.05	0.01	556
SGEN	0.69	(0.75)	0.92	(0.46)	0.22	(0.33)	0.06	0.10	618
NORS	0.41	(0.86)	-0.01	(0.53)	-0.92	(0.37)	0.04	0.04	474
DRES	8.78	(0.82)	-3.65	(0.50)	1.27	(0.36)	0.05	-0.11	517
UBS	2.62	(1.17)	0.35	(0.73)	-0.39	(0.50)	0.02	0.03	256
ABNA	-0.19	(1.04)	1.64	(0.65)	0.50	(0.45)	0.03	0.07	325
rest	2.88	(0.25)	0.23	(0.10)	-0.21	(0.12)	0.55	0.66	5,950
total									10,859

Notes: This table reports GLS estimates of the price discovery model in tick time with the restriction that $\gamma_{k\ell} = \gamma_k$. Sample period is the period between one hour before and one hour after the suspected intervention times reported in Table I of Peiers (1997). Parameters: σ^2 is the variance of the fundamental news; ω_i is the variance of the idiosyncratic component; ψ_i is the covariance between news and the idiosyncratic component; γ_i is the covariance between the idiosyncratic term of bank i and the previous idiosyncratic term; π is the activity share and IS the information share of bank i. "nobs" is the number of observations per bank in the estimation. Standard errors in parentheses.

Table 12: Calendar time moments

	s_{ii}	s_{0i}	s_{00}	d_{0i}	d_{i0}
DB	2.55	2.59	1.81	0.14	1.32
CHEM	3.13	3.00	1.81	0.12	2.15
BHF	2.72	2.46	1.79	0.16	1.90
RABO	2.82	2.71	1.81	0.18	2.13
SGEN	2.93	3.20	1.80	0.63	0.72
NORS	2.91	3.30	1.81	0.19	1.66
DRES	2.39	2.83	1.81	0.27	0.58
UBS	2.50	3.05	1.81	0.17	0.67
ABNA	2.18	2.31	1.80	0.16	0.51

Notes: The first three columns report the sum over all leads and lags (up to $L = 10$) of the auto- and cross-covariances of bank and market. The final two columns report the sum over all cross-covariances from lag 1 to 10.

Table 13: Price discovery model in calendar time

σ^2	1.81				
	ψ_i	ω_{ii}	ω_{i0}	π	IS
DB	-0.53	3.42	-0.80	0.12	0.08
CHEM	-1.38	3.05	-0.77	0.07	0.02
BHF	-1.09	1.43	-0.81	0.07	0.03
RABO	-1.30	3.04	-0.83	0.07	0.02
SGEN	0.55	0.77	-1.28	0.08	0.10
NORS	-0.82	1.95	-0.84	0.05	0.03
DRES	0.34	3.03	-0.92	0.04	0.05
UBS	0.16	3.70	-0.82	0.04	0.04
ABNA	0.30	1.91	-0.81	0.03	0.04
market	0.65	2.72		0.44	0.60

Notes: This table reports the estimates of the price discovery model in calendar time. The individual banks are labelled $1,..,n$ and the market, defined as all quotes except those of bank i, is labelled 0. The parameters are: σ^2 is the variance of the fundamental news; ψ_i is the covariance between news and the idiosyncratic component of bank i; ω_{ii} is the variance of the idiosyncratic component of bank i; ω_{0i} is the covariance between the idiosyncratic term of bank i and the idiosyncratic term of the market; π is the activity share and IS the information share of bank i

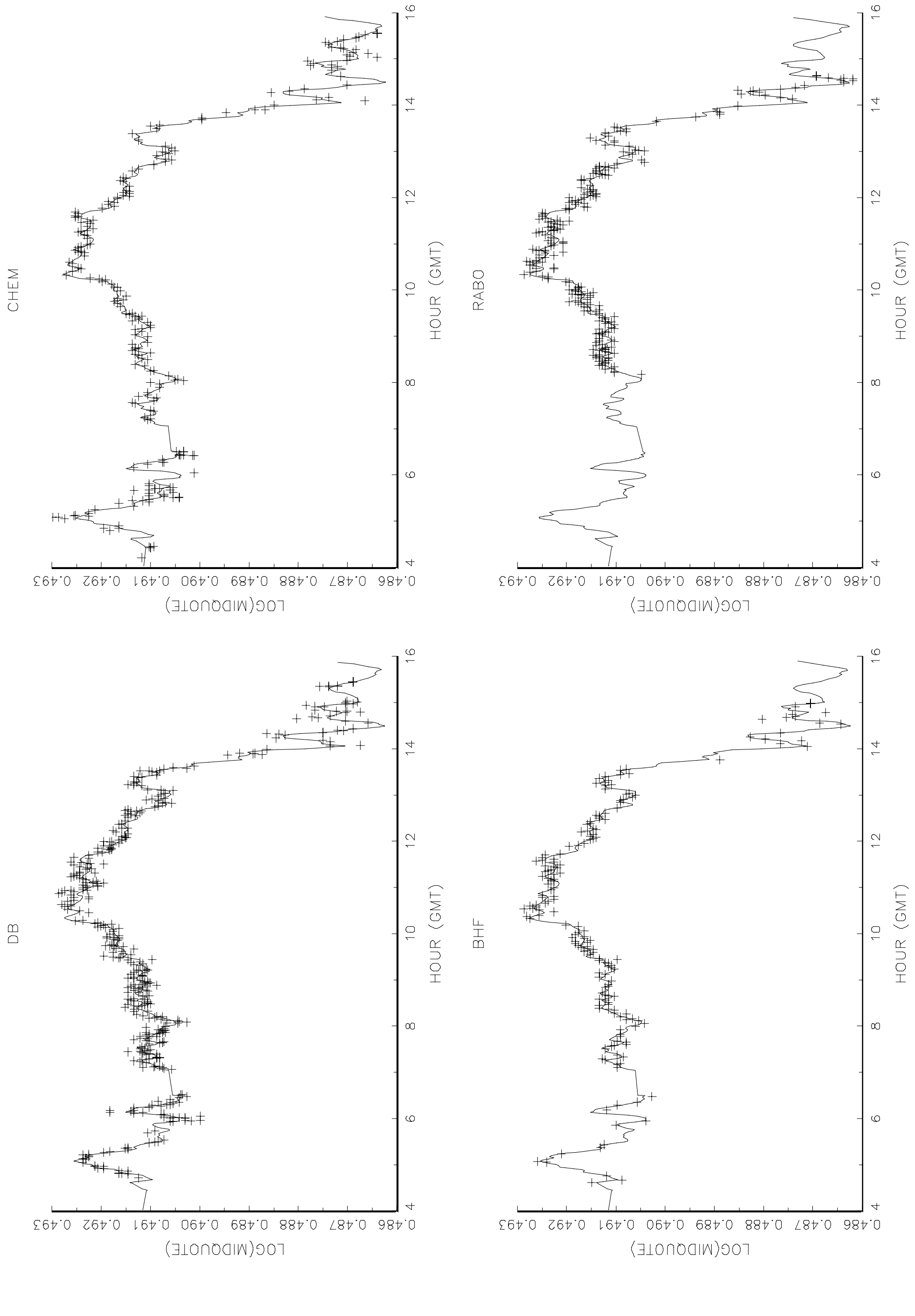

Figure 1: Quotes on May 25, 1993

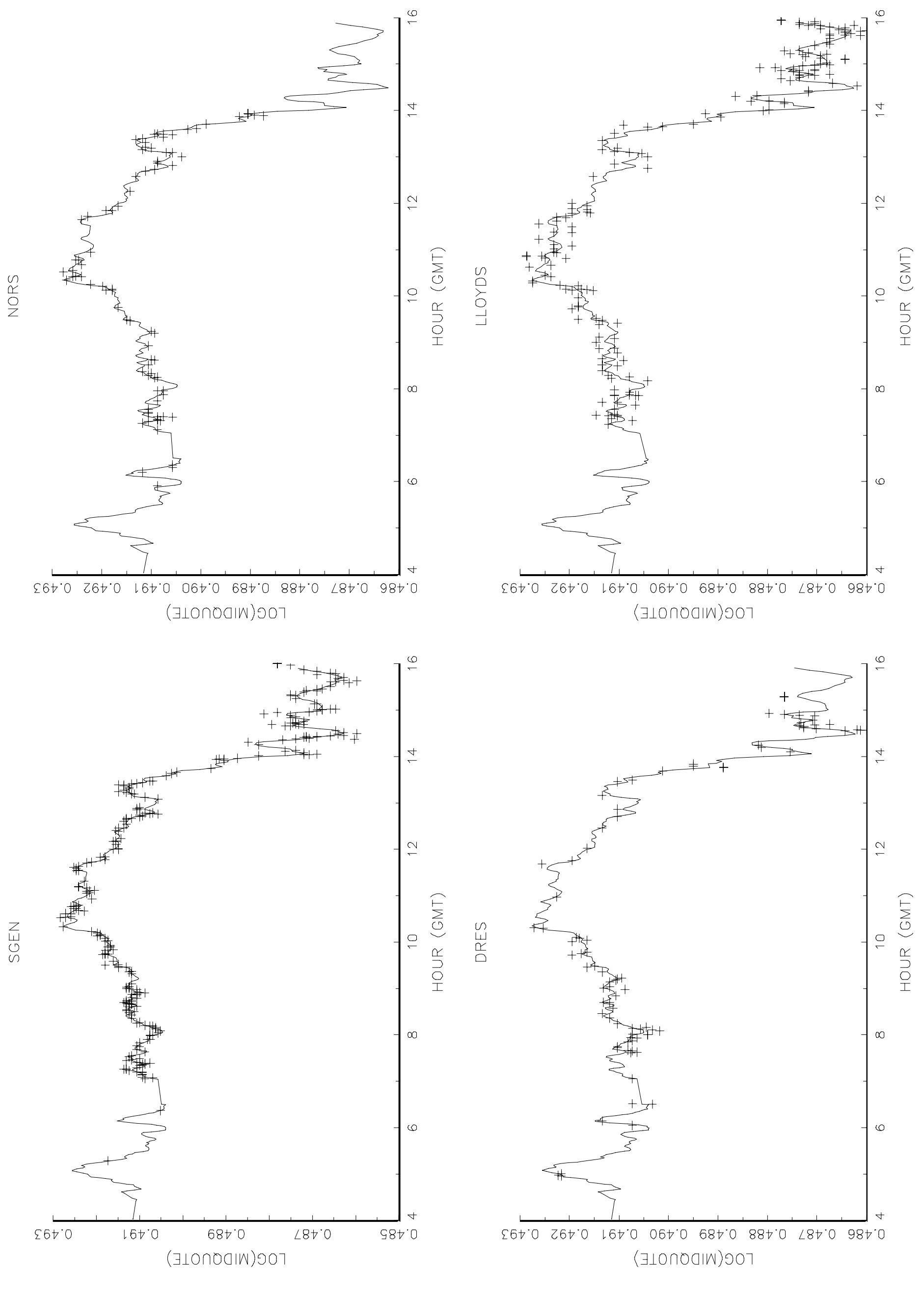

Figure 2: Quotes on May 25, 1993

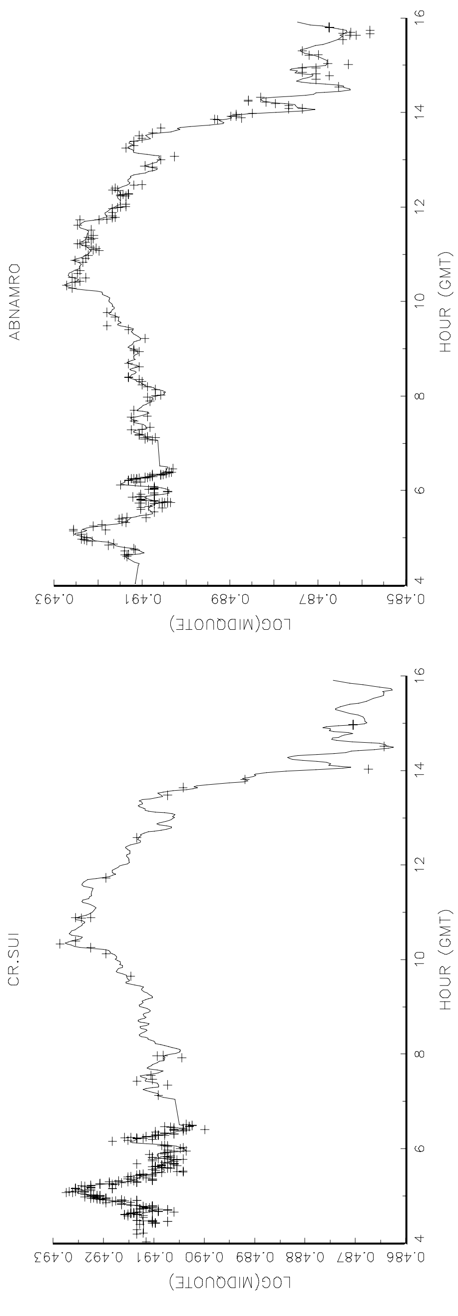

Figure 3: Quotes on May 25, 1993

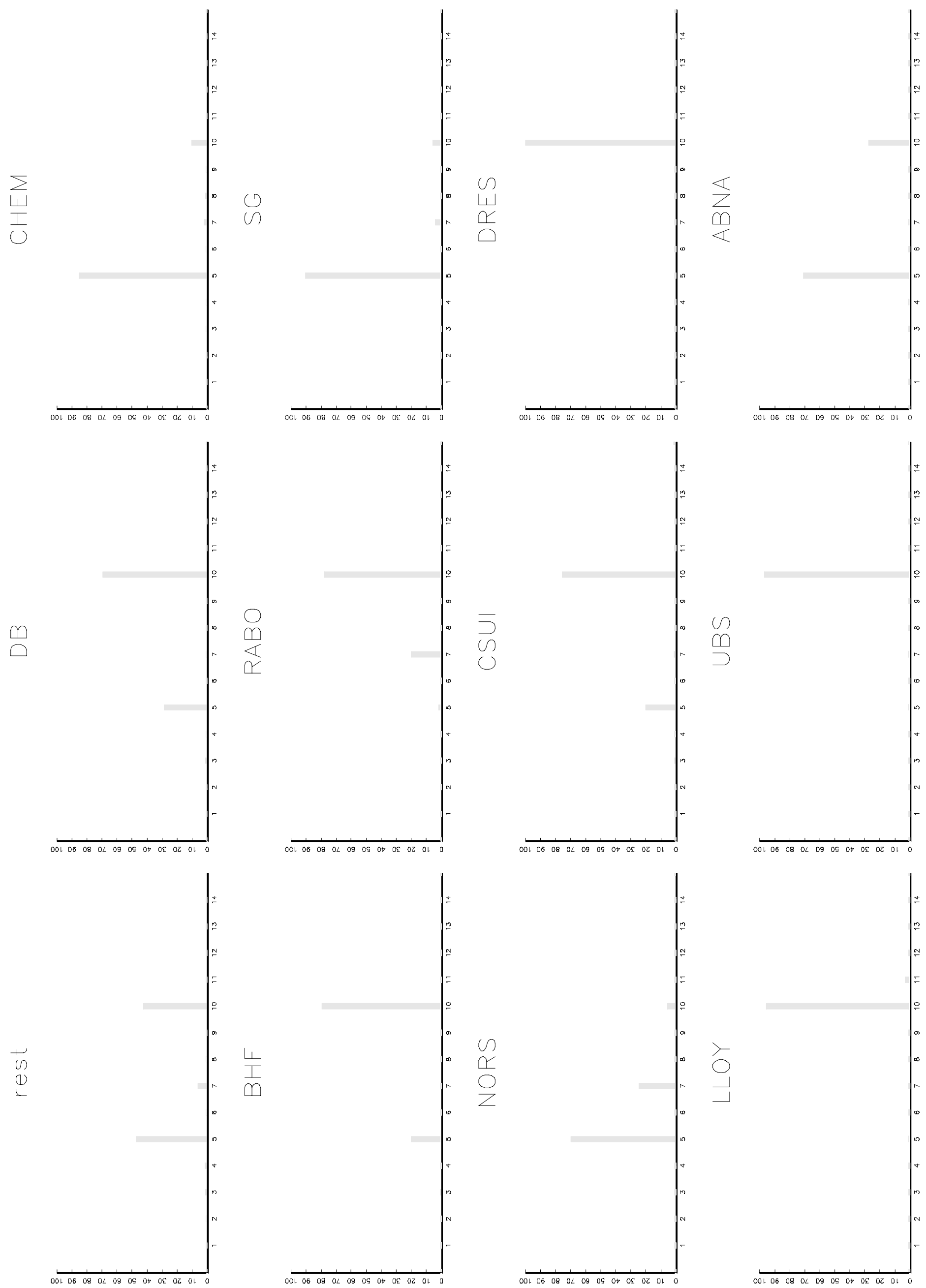

Figure 4: Histogram of quoted bid-ask spreads

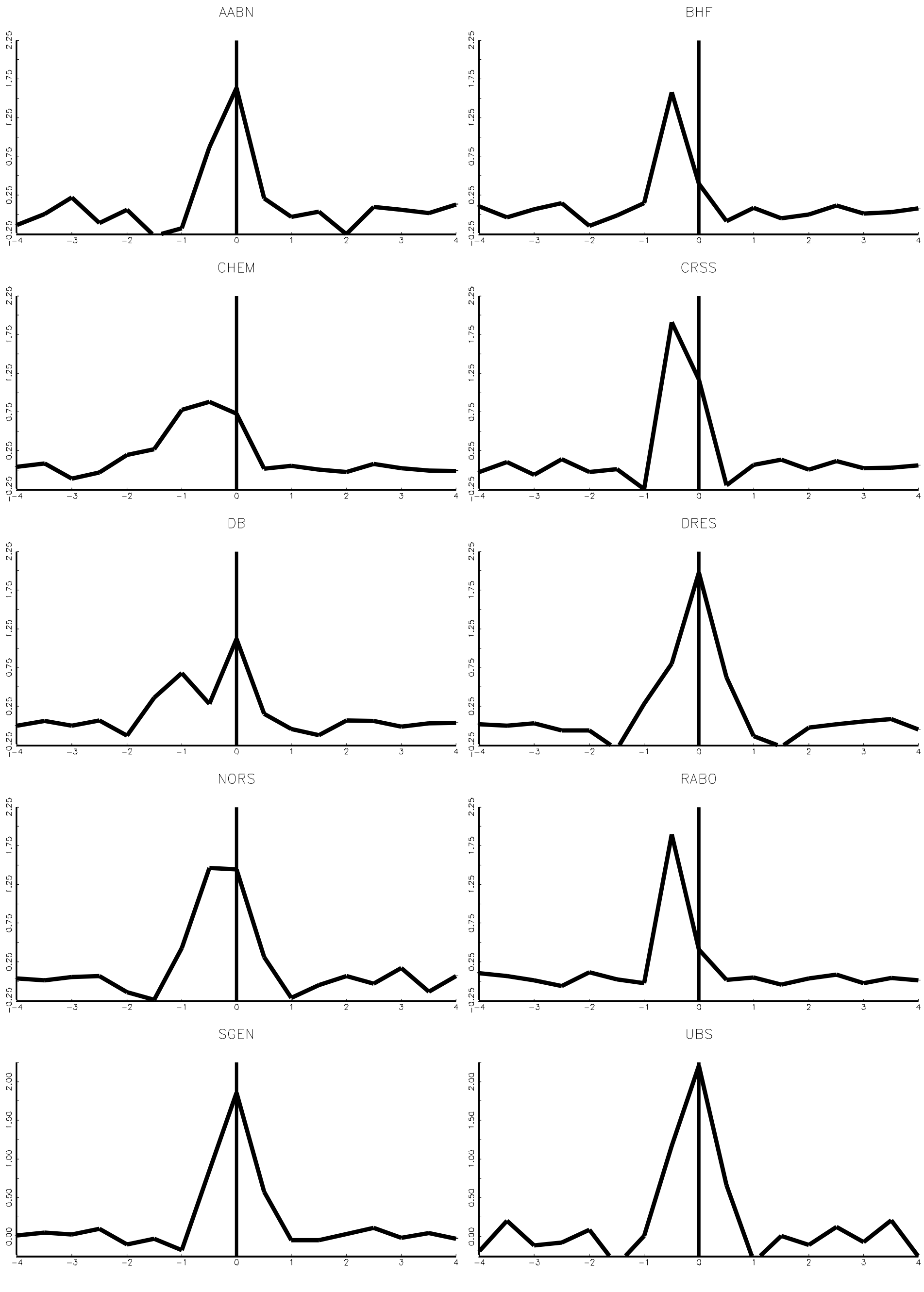

Figure 5: Cross covariance functions