

The response of individual FX dealers' quoting activity to macroeconomic news announcements*

Walid Ben Omrane¹

Andréas Heinen²

September 2003

Abstract

This paper analyses the effect of nine categories of news announcements on the quoting activity of individual FX dealers on the Euro/Dollar exchange rate from May to October 2001. We use the Double Autoregressive Conditional Poisson model (DACP), which is designed for time series of count data, which can be both under- or overdispersed. We find that dealers' quoting activity reacts differently to the same announcements, some increasing their activity, whilst others decrease it in response to the same news. We attribute this to the heterogeneous interpretation of the news content by individual traders. This means that studies of quoting activity at the aggregate level can miss the point. Finally, we identify the news announcements that impact quoting activity as non-common knowledge news.

Keywords: Foreign Exchange, Market Microstructure, Time Series, Count Data.

JEL Classification codes: F31, G15, C35.

*The authors would like to thank Luc Bauwens for helpful discussions and suggestions. The usual disclaimers apply.

¹Department of Business Administration, Finance Unit, Catholic University of Louvain, Place des Doyens 1, 1348 Louvain-la-Neuve, Belgium, e-mail: benomrane@fin.ucl.ac.be.

²Center of Operations Research and Econometrics, Catholic University of Louvain, 34 Voie du Roman Pays, 1348 Louvain-la-Neuve, Belgium, e-mail: heinen@core.ucl.ac.be

1 Introduction

In recent years, there has been a lot of work dedicated to the study of the effect of macroeconomic news announcements on foreign exchange markets. Interest has focused on the effect of news announcements on the exchange rate (Andersen, Bollerslev, Diebold, and Vega (2002) is a recent example), its volatility (Andersen and Bollerslev (1998), DeGennaro and Shrieves (1997) to name just a few), as well as on market activity. The effect of news announcements on the latter has been studied, amongst others, by DeGennaro and Shrieves (1997), Melvin and Yin (2000), Bauwens, Ben Omrane, and Giot (2003). A positive effect on activity has been found for certain categories of news announcements, whereas other types of news do not seem to impact activity. In a recent paper, Evans (2002) distinguishes two types of information, which affect exchange rates: common knowledge (CK) news, which is known simultaneously and interpreted in the same way by all market participants and non-common knowledge (NCK) news, which is not known by everybody or is known by everybody, but gives rise to differing interpretations.

In this paper we analyse the effect of news announcements on quoting activity from a disaggregated point of view. This is new, as the existing literature has only considered the impact of news announcements on aggregate activity. By looking at a sample of major dealers on the Euro/Dollar exchange rate, we offer *prima facie* evidence of the fact that banks' quoting activity reacts differently to the same news announcements, and that there is heterogeneity of reaction, which can explain the mixed aggregate results. This supports the view, that even in the face of public news announcements, banks react differently, maybe because of their divergent interpretations of the implications of the news for the exchange rate. In particular, for certain types of announcements, some banks increase their activity, whilst others decrease it, which can lead to an ambiguous effect at the aggregate level. This implies that aggregate studies tend to underestimate the importance of public news announcements for market activity. This has potentially important implications for empirical studies like the one of Evans (2002), which is based on the identifying assumption that CK news affects exchange rates instantaneously, but does not affect trading patterns, while NCK news has an effect on both. We show that news announcements can have an effect on individual banks, but no effect on aggregate quoting activity, and this could lead to erroneously classifying shocks as CK, on the grounds that they have no effect on market activity, whereas they simply appear

not to have an effect, due to aggregation. Our results also allow us to classify the different types of news announcements into CK and NCK news, according to the taxonomy of Evans (2002). It seems that scheduled news are NCK news, as they have a strong impact on quoting activity. Unscheduled news seem to belong to the category of CK news, as they do not have a very important impact of quoting activity. The paper is structured as follows. In section 2 we present the literature, in section 3 the data, in section 4 the models and results and the last section concludes.

2 Literature Review

We now turn to a review of some of the literature on news announcements and some activity measures. DeGennaro and Shrieves (1997) use three categories of news announcements (scheduled, and unscheduled macroeconomic news announcements as well as interest rate reports) and six different periods around the event and analyse their impact on quoting activity. They find a significant effect of all three categories of news, but at different times relative to the announcement. Melvin and Yin (2000) work with a sample of USD/Japanese Yen and USD/DEM data for December 1993 to April 1995 in hourly data. They take as news variable the number of news events that happen within an hour and do not make any distinctions between different categories of news. They find a significant impact of news on quoting activity, working with deseasonalised variables, and conclude that quoting activity is not self-generating.

Evans and Lyons (2003) identify two channels for the transmission of macro news to exchange rates: a direct effect and an indirect effect via order flow. The news variable is the number of news announcements that occur within the period. Identification of the various effects is done by the imposition of orthogonality conditions on the various innovation terms in the model and estimation is carried out using the generalized method of moments (GMM). Changes in midquotes are regressed on order flow with two error terms, one with a constant variance, which represents information directly impounded into prices, another one whose variance depends of the number of information events and represents the common knowledge effect of macro news on the exchange rate. The order flow itself is also the sum of two shocks, one of whose variance depends on news. This shock is interpreted as the indirect effect of news on exchange rates via induced order flow. In order to justify that macroeconomic news affects

order flow, they mention differences in interpretation of the news or differences in opinion as regards the impact of the news on the exchange rate.

A relatively new literature has been concerned with the analysis of individual banks. In this strand of the literature papers deal mainly with the identification of price leaders in the market around central bank interventions, but also in normal trading. Peiers (1997) analyses the midquotes of several banks on the Dollar/DM exchange rate around central bank intervention of the European central bank using a vector autoregression (VAR) and Granger causality to identify the price leading bank. The sample of banks includes Deutsche Bank, Société Générale, Chemical Bank, Rabobank, Den Norske and BHF Bank. Deutsche Bank is the first to react, 60 minutes prior to the announcement, followed by other banks, 25 minutes before the announcement. Wang (2001) and Sapp (2002) instead use cointegration analysis. They focus on a small subset of banks and analyse their midquotes as a cointegrated VAR. The midquotes of all the banks are integrated of order one ($I(1)$) and they cannot deviate in the long run, which means that they are cointegrated. The number of cointegrating relationships is equal to the number of banks minus one, which means that there is only one stochastic trend driving the system, which can therefore be interpreted as the fundamental market price. Wang (2001) analyses price leadership amongst three leading New York-based dealers on the USD/DEM market: J.P. Morgan, Chemical Bank and Citibank. Sapp (2002) works on the same market and estimates a cointegrated VAR system and deduces measures of information shares, for all the trading period as well as around central bank interventions. This is used to help identify the banks whose information share is largest around central bank interventions.

We follow the literature in taking the number of quotes of banks as a proxy for the number of transactions, which is tantamount to assuming that a fixed proportion of posted quotes correspond to actual trades. This assumption has been made, amongst others, by Goodhart and Figliuoli (1991) and Bollerslev and Domowitz (1993), who prefer to use quote arrival as a proxy for market activity, than transaction volume, because quotes signal a willingness to trade. DeGennaro and Shrieves (1997) use the same assumption, as they consider the seasonal and stochastic parts of quoting activity to be a proxy for the expected and surprise components of market activity. Furthermore, their results are suggestive of the fact, that the surprise part of market activity reflects informed trading. Melvin and Yin (2000) have made the same assumption.

So far there has been, to the best of our knowledge, no work on the response of individual banks' quoting activity to news. Bauwens, Ben Omrane, and Giot (2003) regress aggregate quoting activity on news and find a significant but short-lived impact of certain types of news announcements. In our analysis we allow for different responses of individual banks to the same news. This can be due to heterogeneous interpretation of the news content, which could be based on private information. In the taxonomy of Evans (2002), different interpretation of the same news is classified as non common knowledge (NCK) information, as opposed to common knowledge (CK) news, which corresponds to news that is available simultaneously to all market participants and is interpreted in the same way. He considers, instead of an equilibrium price, an equilibrium price distribution. He justifies this by the lack of transparency of FX markets, which makes it possible for several transactions to happen simultaneously at different prices. This can also be understood, if one considers that different dealers have different interpretations of the events that influence the exchange rate. His result suggests that CK news is not the predominant source of long term movements in the exchange rate. In the empirical part, based on prices and order flow, CK and NCK shocks are identified by the assumption that CK news lead to an immediate one-for-one change in the mean of the equilibrium price and have no effect on order flow, whereas NCK news has an impact both on prices and order flow, which may take time. Using this definition allows us to classify news announcements according to whether they impact activity or not. If they do not, that means that they can be considered as CK news events, whereas public announcements, that have order flow implications, do so because of heterogeneous interpretation by dealers. Indeed some banks might have different degrees of understanding of the same news, which can lead them to act on their anticipations or to stay away from the market, waiting for better-informed banks to act first.

We distinguish between the reaction to scheduled and unscheduled announcements, the difference being that for the former there is a possibility for banks to speculate and take positions before the announcement. In the case of scheduled news, we interpret a positive coefficient as meaning one of two things. One possibility is that the bank has taken a speculative position before the announcement, the market realisation went against the bank, and the bank is eager to close its position and realise its loss before it gets worse. Alternatively, it could be that the bank did not take any position before the announcement, but wants

to benefit from the volatility of the market after the announcement. On the other hand, if the coefficient is negative, this could mean that the bank has taken a successful speculative position and is waiting for the prices to fully adjust to the news before closing its position and taking full advantage of its speculation. However this could also mean that the bank is risk averse and reduces its quoting, waiting to see other banks' reaction to the news before entering the market again. If the coefficient is not significant and the bank's activity remained unchanged during the announcement, this could mean that the announcement is not relevant for the bank. Another possibility is that all the banks interpret the news in the same way and there is no divergence in beliefs and therefore nothing which could constitute a motive for increased or decreased quoting.

In the case of unscheduled news, there is no possibility for the bank to take a speculative position in anticipation of the announcement. A positive coefficient could therefore mean that the bank wants to take advantage of the agitation around the announcement, whereas a negative one is suggestive of the fact, that the bank is withdrawing from the market and is waiting to see what happens.

3 Data

We work with a tick-by-tick data set bought from Olsen & Associates for the period August 24 to October 26, 2001. The data come from different quoting systems. Until September 10, 2001, the data comes from Reuters, after which Olsen subscribed entirely to Tenfore Systems. This means that the banks which contribute to our data set change in the middle of the sample. We therefore work with two samples of banks during different periods. We selected the most active banks in our sample. Tables 1 and 2 show, that for the first sample, the 7 banks we select cover about 50% of the overall quotes, whereas the 5 banks of the second sample post about 25% of the total number of quotes in the sample. The reason why we focus attention on these banks is that they are the most active dealers in our data and the remaining quotes are posted by a very large number of dealers with a very small contribution. Our first sample of banks contains BG Bank, Copenhagen (BGFX), Berliner Handels- und Frankfurter Bank, Frankfurt (BHFx), Deutsche Bank, Sydney (DEUA), Rabobank, London (RABO), Société Générale, Paris (SGOX) for the period May 14 to September 10, 2001, which corresponds to 9396 5-minute observations. The second sample of banks includes Allied Irish Bank, Dublin

(ALLD), Barclay’s Bank, London (BARL), Dresdner Bank, Frankfurt (DREF), Oolder & de Jong, Amsterdam (OHVA), Oko Bank, Helsinki (OKOH), SHK Bank, Hong Kong (SHKH) and Union Bank of Switzerland, Zurich (UBSZ), for the period August 24 to October 26 2001, for a total of 4968 5-minute quoting intervals.

Descriptive statistics for the first sample are shown in table 1 and in table 2 for the second sample. The mean number of quotes is generally quite small, which justifies the use of discrete distributions like the Poisson. Moreover, most series are overdispersed, with the exception of BHFx, OHVA and RABO, which are underdispersed. This justifies use of the double Poisson, as, unlike other count distributions, it allows for both over- and underdispersion. The histograms of the series in figure 1 reveal that for many banks, there seem to be more zeros than usual, which causes certain of these distributions to be bimodal. The histogram of OKOH has a strange shape, which is due to the fact that in the middle of the sample, there seems to be a regime change. OKOH goes from posting around 42 quotes per 5 minutes to around 8 per 5 minute, which explains the shape of the histogram, since this distribution is a mixture of the distributions in the two regimes.

In this paper we use the same news announcements as in Bauwens, Ben Omrane, and Giot (2003) and we test the impact of nine categories of news. News announcements, shown in table 3 are classified into two groups, scheduled and unscheduled announcements. Four of these categories are new to the FOREX literature (the η_4 , η_6 , η_7 , η_8 coefficients). The first group contains US macroeconomic figures (the η_1 and η_2 coefficients), more specifically employment reports, producer and consumer price indices, gross domestic product and other important figures. This group also includes European macroeconomic figures (η_3), scheduled speeches of senior officials of the government and of public agencies, such as the president of the Federal Reserve, the European Central Bank and the economy and finance ministers (η_4), and US and European interest rate reports (η_5). The second group contains forecasts of key institutes and specialized organizations, such as the IMF, the World Bank, and the IFO institute (an influential service-based research organization in Germany, η_6). This group also contains declarations of OPEC members (η_7), rumors of Central Bank intervention (η_8) and other extraordinary events (natural disasters, wars, terrorist attacks, etc.) are summed up in the η_9 coefficient. To highlight the effect of the possible ‘surprise’ contained in the scheduled US macroeconomic figures, we distinguish so-called positive from negative news

by computing the difference between the expected and realized values. If the realization is larger than the expectation and it is a figure which contributes to the growth of the economy, the news is classified as positive. If the actual figure means instead worse-than-expected inflation or a slowdown of the economy, it is regarded as negative. This methodology is also used in Andersen, Bollerslev, Diebold, and Vega (2002), where they test the effect of non anticipated news announcements on currency returns. They conclude that unanticipated events lead to jumps in the conditional mean of currency returns and that negative news have a greater impact than positive news. As can be seen from table 3, the total number of news announcements in the first sample is 377, the most frequent type of news event is European macroeconomic figures with 105 events, but there are only 3 occurrences of rumors of central bank interventions. In the second sample, there are 251 events, with 53 speeches of government officials and only 3 rumors of central bank intervention.

We compute averages of the activity over 5-minute intervals for all banks and divide them by the mean in order to make them comparable across banks. The results are shown in figure 2. First of all, we note that the seasonality of the banks in the sample is not the same for all, which is not surprising. ALLD, BARL, DREF, SHKH, UBS, BGFX and SGOX all start with a small decrease in the morning until 10 AM GMT, and after that activity starts increasing from around 12 PM GMT, which corresponds to the morning on the East Coast of the US, to a peak around 2 or 3 PM GMT, and then the activity decreases until 5 PM GMT, when European offices start to close. SHKH is somewhat different, as it starts the day with an increase, but then its pattern is similar to the one of the other banks. ALLD and DREF are different from other banks, in that they start closing earlier, which means that their quoting activity decreases sharply shortly before 4 PM GMT, and once again shortly before 5 PM in the case of ALLD. A similar pattern is observed for other banks, but between 6 and 7 PM for most of them, which is why we chose to stop our sample at 5 PM. The remaining banks (BHFX, DEUA, OHVA, OKOH and RABO) do not seem to exhibit any particular seasonality over our sample period. This is confirmed for DEUA, OHVA and OKOH by the Wald test for joint significance of the seasonality variables shown in tables 4 and 5. For BHFX and RABO, the test cannot reject, but the test statistic is smaller than for the other banks. Figure 3, which shows the autocorrelograms of the raw series and of the Pearson residual, confirms this classification. Furthermore we note that DREF has a very strange pattern of

diurnal seasonality, as there are very important spikes on or around the hour, which we are unable to explain.

4 Models and Results

4.1 Modelling quote arrival

In the remainder of the paper we work with the number of quotes of individual banks on the Euro/Dollar exchange market. As the number of quotes is for most banks a relatively small number, usual time series models, based on the normal distribution, are not appropriate. Instead we work with time series models developed specifically for count data. We give a general account of these models, and we refer to Heinen (2003) for more details.

The autoregressive conditional Poisson (ACP) model assumes that the bank's number of quotes in period t , N_t , follows a Poisson distribution, conditionally on past information:

$$N_t | \mathcal{F}_{t-1} \sim P(\mu_t), \quad (4.1)$$

where \mathcal{F}_{t-1} is the information set generated by the past of the series up to and including time $t-1$. The conditional mean is modelled as an autoregressive moving average process of order $(1, 1)$:

$$\mu_t = \omega + \alpha N_{t-1} + \beta \mu_{t-1}. \quad (4.2)$$

We choose to work with a $(1, 1)$ structure for the mean equation, as this is parsimonious and quite flexible. The success of this model is similar to the prevalence of the $(1, 1)$ structure in the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) literature. We can rewrite (4.2) as $\mu_t = \omega + \alpha(N_{t-1} - \mu_{t-1}) + (\alpha + \beta)\mu_{t-1}$, which shows that the sum of the autoregressive coefficients is an indication of the memory in the process, while α measures the impact of past errors on the present mean. The model can be estimated easily using maximum likelihood. This model is somewhat limiting, as it assumes that the counts are conditionally equidispersed, which means that their variance is equal to their mean. In most applications, the data is overdispersed: the variance is larger than the mean. In order to model the dispersion in a more flexible way, we also work with the Double Poisson distribution of

Efron (1986), which is characterised by an additional dispersion parameter ϕ . With the double Poisson, the conditional variance is equal to:

$$V[N_t|\mathcal{F}_{t-1}] = \sigma_t^2 = \frac{\mu_t}{\phi}, \quad (4.3)$$

The distribution will be over- or underdispersed for values of ϕ respectively less or greater than 1. When $\phi = 1$ the distribution reduces to the equidispersed Poisson. The fact that the conditional mean is autocorrelated leads to some overdispersion, whose magnitude depends on the autoregressive coefficients. This is true intuitively by analogy to the mixing of normals: the unconditional distribution of the counts is equal to a mixture of Poisson distributions with a different mean every period. In the case of the double autoregressive conditional Poisson model (DACP), the dispersion *disp*, is:

$$disp = \frac{V[N_t]}{E[N_t]} = \frac{\sigma^2}{\mu} = \frac{1}{\phi} \frac{[1 - (\alpha + \beta)^2 + \alpha^2]}{1 - (\alpha + \beta)^2} \quad (4.4)$$

Whereas the autocorrelation (present as long as α and β are non-zero) leads to overdispersion, the effect of the double Poisson can be to increase or lower this dispersion, leading to either over- or underdispersed models. In most cases, though, the conditional distribution adds to the overdispersion stemming from the autocorrelation to match the overdispersion in the data. The distribution of the double Poisson has the following form¹:

$$f(y, \mu, \phi) = \left(\phi^{\frac{1}{2}} e^{-\phi\mu}\right) \left(\frac{e^{-y} y^y}{y!}\right) \left(\frac{e\mu}{y}\right)^{\phi y} \quad (4.5)$$

In order to evaluate the quality of the models, we use tools developed in density forecast evaluation by Diebold, Gunther, and Tay (1998). The main idea is to use the cumulative distribution of the data under the estimated density and to check whether this is uniformly distributed, as it should be according to the probability integral transformation theorem (PITT) of Fisher (1932). The assumptions of the theorem are that the density is continuous,

¹ $f(y, \mu, \phi)$ is not strictly speaking a density, since the probabilities don't add up to 1, but Efron (1986) shows that the value of the multiplicative constant $c(\mu, \phi)$, which makes it into a real density is very close to 1 and varies little across values of the dependent variable. He also suggests an approximation for this constant: $\frac{1}{c(\mu, \phi)} = 1 + \frac{1-\phi}{12\mu\phi} - 1 + \frac{1}{\mu\phi}$. Furthermore he suggests maximising the approximate likelihood (leaving out the highly nonlinear multiplicative constant) in order to estimate the parameters and using the correction factor when making probability statements using the density.

which is violated in the case of counts. We explain in the Appendix, how we deal with this problem using continuousation.

In order to check that the dynamics of the data is well modelled, we check that the PIT of the data is uncorrelated. Finally, we test the standardised residuals

$$\varepsilon_t = \frac{N_t - \mu_t}{\sigma_t} = \frac{N_t - \mu_t}{\sqrt{\mu_t/\phi}}$$

for any remaining autocorrelation, which indicates a failure of the model to capture the dynamics of the series, and for deviations of their variance from one, which are indications of misspecification of the dispersion.

We are interested in analysing the impact of news announcements on individual banks' quoting activity, allowing for diurnal seasonality. The news variables take the form of dummies $d_{j,t}$, $j = 1, \dots, 9$, for the presence of a certain announcement. The seasonality is modelled using the Fourier Flexible Form (FFF) introduced in the FX literature by Andersen and Bollerslev (1998) at daily, half daily and hourly frequencies. We modify the conditional mean in the following manner to include these exogenous regressors:

$$\mu_t^* = \mu_t \exp \left(\sum_{j=1}^9 \eta_j d_{j,t} + \sum_{p=1,2,12} (\psi_{c,p} \cos \frac{2\pi p Re[t, N]}{N} + \psi_{s,p} \sin \frac{2\pi p Re[t, N]}{N}) \right),$$

where $Re[t, N]$ is the remainder of the integer division of t by N , the number of periods in a trading session. The way we include the regressors separates out the autoregressive part from the effect of seasonality and news, and this functional form guarantees the positivity of the conditional mean.

4.2 Results

The results of estimation are presented in table 4 and 5. There is evidence of diurnal seasonality in the activity of all banks. The three pairs of trigonometric function at the daily, half-daily and hourly frequency are always jointly significant. The effect of news announcements is generally significant for all banks, as can be seen from a Wald test of the joint significance of all announcements. What the analysis using individual banks shows clearly, is that their reaction to the same news announcements is different. There is variation across

banks, both in whether or not they react to a certain category of news and in the way they react to it, by increasing or decreasing their activity.

All banks have relatively high values for the autoregressive parameters, the sum of which varies essentially between .85 and .99. This means that quoting activity is strongly persistent. Again, the use of the double Poisson is justified by the fact that we have estimated both overdispersed distributions (the majority of them) and some underdispersed distributions, like ALLD, OHVA, BHFX, DEUA and RABO. In the case of RABO and BHFX, this is not surprising if one thinks in terms of equation (4.4), as the unconditional distribution is already underdispersed and the very high persistence (.97 for both banks) creates overdispersion. Therefore the conditional distribution has to compensate the overdispersion stemming from the autocorrelation ². For ALLD, the estimated dispersion of the marginal distribution is very modest and the value of ϕ is not significantly different from 1, the equidispersed Poisson case. For BHFX, OHVA and RABO, we estimate an underdispersed parameter, which is not surprising, as they are unconditionally underdispersed as well and the residual is close to being equidispersed. DEUA is strange, as we estimate an underdispersed distribution, but the residual is still strongly overdispersed. Apparently, the model needs more underdispersion in the marginal distribution, in order to compensate for the overdispersion caused by the very high autocorrelation ($\alpha + \beta = .996$). The variance of the standardised residual is within a few percent of one for nearly all other banks, which means that the dispersion is well captured, except for OKOH. Upon closer inspection of its time series, we can see that there seems to be a change of regime in OKOH, which went from heavy quoting to lower levels of activity after October 8, 2001. Inspection of the histograms in figure 1 seems to suggest that a higher than usual proportion of zeros could be the reason for the relatively poor fit of some of the distributions. In terms of the autocorrelations of the standardised errors, shown in figure 3, we can see that in general terms, most of the autocorrelation that is left is below the significance level. Q-statistics are very significantly reduced, compared to the raw data, even though they are still significant. Some significant peaks in the autocorrelogram in figure 3

²A simple use of (4.4) for BHFX, shows that with a ϕ of 1.726, α and β values of respectively .141 and .832, the overdispersion caused by the persistence ($\frac{[1-(\alpha+\beta)^2+\alpha^2]}{1-(\alpha+\beta)^2}$) is equal to 1.37, but with the underdispersed conditional distribution, we finally get an unconditional dispersion of .80, which is close to the observed dispersion of .60 in the data, shown in table 2. The difference is due to the inclusion of regressors.

remain for ALLD and DREF, which seem to be due to the seasonality³.

Another way of testing the specification is to look at the density forecast tools. The probability integral transforms Z (PIT) of the data under the estimated distributions should be uncorrelated and uniformly distributed. Figure 4 shows the quantile plot of Z , which is very close to the 45-degree line for most banks, with notable exception of OHVA and OKOH. This is not surprising as these banks already had overdispersion left in the residual. In terms of the autocorrelogram of Z , shown in 5, there is no significant autocorrelation left, except for ALLD and DREF, which confirms the results from the autocorrelogram of the residuals.

For both samples of banks, it seems that at least one type of scheduled news event has an impact on every bank, except for OHVA. Positive and negative surprises in U.S. and European figures seem to have the most important effect. This is in line with the findings of Andersen, Bollerslev, Diebold, and Vega (2002), that macroeconomic surprises have the most significant impact on the level of the exchange rate. According to Evans (2002), these types of announcements are therefore NCK news, as they impact order flow. Given that they are simultaneously received by all dealers, it has to be the case that they are interpreted differently. A lot of banks react to the first three scheduled news announcements. In particular the larger banks, DREF and SOGX all increase their activity as a response to US and European macroeconomic figures, which means that they might be trying to benefit from the volatility on the market. On the other hand, banks like OKOH, SHKH, BHFx and RABO reduce their quoting in response to U.S. figures, maybe because they speculated successfully or because they want to wait for the big banks to move first, which is the more likely explanation in the present case. Table 6 shows for every announcement the result of a Wald tests of the null hypothesis that the announcement impacts all banks in the same way. The results show that US and European macroeconomic figures affect banks differently in both samples, whereas interest rate reports are only significantly different in sample 2. The remaining announcements have impacts on different banks that are not significantly different. It can be noted however that the latter announcements are much less significant in general. We take this as a sign of heterogeneous interpretation by different banks of this type of announcement. Comparing this to results of the same categories of news on the aggregate activity of the

³In the case of DREF, there seems to be a peak of activity on the hour, as can be seen from its seasonality, as per figure 2.

same banks presented in Bauwens, Ben Omrane, and Giot (2003) on a 24-hour trading day, reveals that aggregate analysis entails a loss of information. In order to make the results fully comparable, we estimate a DACP on aggregate quoting activity, as well as the quoting of the remaining banks of the sample (respectively "Aggregate" and "Rest" in tables 4 and 5) on the same seasonality variables with the same ARMA(1,1) structure and the samples of our two groups of banks (both in terms of the period of the year and the trading hours). We find, for instance in the case of positive U.S. macroeconomic figures, that there are both increases and decreases in quoting activity of individual dealers, which seem to offset each other and explain the lack of significance at the aggregate level. Another example is European and U.S. interest rate reports, which are significant for three banks of sample 2, but not at the aggregate level. However, in the case of negative US and European macroeconomic figures, there are both increases and decreases in activity, but the increases seem to dominate at the aggregate level. This is strong evidence that aggregate analysis of quoting activity can miss the point. In some cases, even though there is no aggregate impact of news on quoting activity, individual banks do respond, but their responses can offset each other, and in other cases, a positive coefficient at the aggregate level can conceal a less unified picture at the level of individual dealers.

It is remarkable that ALLD and BGFY seem to react only to European figures, whereas UBSZ reacts only to negative U.S. figures and interest rate reports, in all cases by increasing their quoting. Speeches by senior government and central bank officials do not impact quoting activity. This means either that these events are not relevant or that they are interpreted in the same way by all market participants, in which case the price will adjust instantly with no additional order flow. The effect of U.S. and European interest reports is also significant and positive for three banks, i.e. BARL, DREF and UBSZ, and not significant for the others, which suggests that these banks lead the market and impose their interpretation of the news, while other banks prefer to abstain from quoting or keep their normal level of activity, as can be seen from the insignificant but consistently negative coefficients on the other banks.

As far as unscheduled news is concerned, SHKH reacts to OPEC member state declarations by reducing its quoting activity, but this effect does not carry through to the aggregate level. The effect of rumors of central bank interventions is not significant for any bank, and also not significant at the aggregate level. Finally, no bank reacts to extraordinary events, but

there is a significant effect at the aggregate level, probably due to the effect of the smaller banks. Finally, nobody reacts to forecasts from economic institutes, which means either that these events are not very relevant or that they are interpreted in the same way by all market participants.

Having analysed the impact of the various announcements on individual banks, we can proceed to classify the news according to Evans (2002). He breaks up news into news which is interpreted differently by market participants and consequently impacts their quoting activity, and news which is interpreted homogeneously and does therefore not influence activity. In terms of scheduled news, it seems that U.S., European figures and interest rate reports have a very significant and different impact on most banks, which makes these variables definite candidates as announcements which are interpreted differently by market participants. However, speeches of senior officials of the government seem to pertain to the category of CK news, given that this variable is not significant for any bank. It could of course also be that this variable simply does not have any informational content, as perceived by FX dealers, but Bauwens, Ben Omrane, and Giot (2003) find that it has an impact on volatility, which is significant at the 1% level. The remaining unscheduled news hardly affect banks' quoting activity and we can thus consider them as CK news, unless markets don't regard them to be very informative at all. Overall we note that the reactions of different banks to the same news announcements is typically heterogeneous.

5 Conclusion

In this paper we show, that FX dealers' quoting activity reacts differently to the same news announcements. We take this as an indication of their heterogeneous interpretation of the news content. This confirms findings of Bénassy-Quéré, Larribeau, and MacDonald (2003) of the heterogeneity of expectations of forecasters and dealers. Moreover, the differences in reaction are more diverse than could be expected a priori, as it is not rare to see that some banks increase their activity, while others decrease it in response to the same announcement. This implies that a non-significant coefficient of a particular announcement at the aggregate level could well mean that certain banks increase their quoting activity, whilst others decrease it. We also find, in the case of interest rate reports, that certain banks increase their quoting activity significantly, even though there is no aggregate effect. This means that aggregate

results have to be interpreted with care. Finally, our result allows us to identify which news items can be considered as non-common knowledge (NCK) in the taxonomy of Evans (2002). Our result suggests that scheduled news announcements are the most important determinants of quoting activity, and consequently we classify them as NCK news, which means that they give rise to differing interpretations. In contrast, unscheduled news seem to belong to the category of common knowledge (CK) news. Unfortunately, we cannot be sure that announcements, which have no impact, are CK or simply irrelevant. One question, that our result raises, is whether dealers who do not seem to react directly to the news do instead wait for other dealers to react to the news and will therefore watch their behaviour. It could therefore be, that some banks react more to other dealers' actions than to the news per se.

6 Appendix: Discrete distributions and PITT

The problem with discrete distributions is that the Probability Integral Transformation Theorem (PITT) of Fisher (1932) does not apply, and the uniformity assumption does not hold, regardless of the quality of the specification of the marginal model. The PITT states that if Y is a continuous variable, with cumulative distribution F , then

$$Z = F(Y)$$

is uniformly distributed on $[0, 1]$.

Denuit and Lambert (2002) use a continuousation argument to overcome these difficulties and apply copulas with discrete marginals. The main idea of continuousation is to create a new random variable Y^* by adding to a discrete variable Y a continuous variable U valued in $[0, 1]$, independent of Y , with a strictly increasing cdf, sharing no parameter with the distribution of Y , such as the Uniform $[0, 1]$ for instance:

$$Y^* = Y + (U - 1) .$$

As can be seen, knowing the value of Y^* , which is the new continuous variable, is equivalent to knowing the value of the underlying count. If $Y^* = 4.38275629$, then we know that $Y = 5$. Hence we do not lose any information by creating this new variable.

Using continuousation, Denuit and Lambert (2002) state a discrete analog of the PITT. If Y is a discrete random variable with domain χ , in \mathbf{N} , such that $f_y = P(Y = y), y \in \chi$, continuoused by U , then

$$Z^* = F^*(Y^*) = F^*(Y + (U - 1)) = F([Y^*]) + f_{[Y^*]+1}U = F(Y - 1) + f_y U$$

is uniformly distributed on $[0, 1]$, and $[Y]$ denotes the integer part of Y .

In this paper, we use the continuoused version of the probability integral transformation in order to test the correct specification of the marginal models. If the marginal models are well-specified, then Z^* , the PIT of the series under the estimated distribution and after continuousation, is uniformly distributed.

References

- ANDERSEN, T., AND T. BOLLERSLEV (1998): “Deutsche mark-dollar volatility: intraday volatility patterns, macroeconomic announcements and longer run dependencies,” *The Journal of Finance*, 1, 219–265.
- ANDERSEN, T., T. BOLLERSLEV, F. DIEBOLD, AND C. VEGA (2002): “Micro effects of macro announcements: real-time price discovery in foreign exchange,” NBER Working paper 8959.
- BAUWENS, L., W. BEN OMRANE, AND P. GIOT (2003): “News Announcements, Market Activity and Volatility in the Euro/Dollar Foreign Exchange Market,” CORE Discussion Paper 2003/29.
- BÉNASSY-QUÉRÉ, A., S. LARRIBEAU, AND R. MACDONALD (2003): “Models of Exchange Rate expectations: How Much Heterogeneity?,” *Journal of International Financial Markets, Institutions and Money*, 13, 113–136.
- BOLLERSLEV, T., AND I. DOMOWITZ (1993): “Trading patterns and prices in the inter-bank foreign exchange market,” *The Journal of Finance*, 4, 1421–1443.
- DEGENNARO, R., AND R. SHRIEVES (1997): “Public information releases, private information arrival and volatility in the foreign exchange market,” *Journal of Empirical Finance*, 4, 295–315.

- DENUIT, M., AND P. LAMBERT (2002): “Constraints on Concordance measures in bivariate discrete data,” Discussion Paper 02-12, Institut de Statistique, Université Catholique de Louvain, Louvain-la-Neuve, Belgium.
- DIEBOLD, F. X., T. A. GUNTHER, AND A. S. TAY (1998): “Evaluating Density Forecasts with Applications to Financial Risk Management,” *International Economic Review*, 39(4), 863–883.
- EFRON, B. (1986): “Double Exponential Families and Their Use in Generalized Linear Regression,” *Journal of the American Statistical Association*, 81(395), 709–721.
- EVANS, M. (2002): “FX Markets and Exchange Rate Dynamics,” *Journal of Finance*, 47(6), 2405–2447.
- EVANS, M., AND R. LYONS (2003): “How is Macro News Transmitted to Exchange Rates?,” NBER Paper 9433.
- FISHER, R. A. (1932): *Statistical Methods for Research Workers*.
- GOODHART, C., AND L. FIGLIUOLI (1991): “Every Minute Counts in Financial Markets,” *Journal of International Money and Finance*, 10, 23–52.
- HEINEN, A. (2003): “Modeling Time Series Count Data: An autoregressive Conditional Poisson Model,” CORE Discussion Paper 2003/62.
- MELVIN, M., AND X. YIN (2000): “Public information arrival, exchange rate volatility and quote frequency,” *The Economic Journal*, 110, 644–661.
- PEIERS, B. (1997): “Informed traders, intervention and price leadership: a deeper view of the microstructure of the foreign exchange market,” *The Journal of Finance*, 4, 1589–1614.
- SAPP, S. (2002): “The incremental volatility information in one million foreign exchange quotations,” *Journal of Financial and Quantitative Analysis*, 37(3), 425–448.
- WANG, J.-X. (2001): “Quote Revision and Information flow among Foreign Exchange Dealers,” *Journal of International Financial Markets*, 11, 115–136.

Table 1: Descriptive statistics of the number of quotes per 5-minute interval of the first sample of banks for the period May 14 to September 10, 2001

	Mean	Std. Dev.	Dispersion	Maximum	Minimum	$Q(10)$
BGFX	7.99	4.57	2.61	28	0	26404
BHFX	9.40	2.37	0.60	17	0	2822.5
DEUA	2.03	2.21	2.42	9	0	53405
RABO	6.86	2.20	0.71	20	0	4608.3
SGOX	15.40	6.71	2.92	46	0	14315
Rest	120.58	56.88	26.83	399	0	57444
Aggreg	162.25	64.03	25.27	472	0	50807

Table 2: Descriptive statistics of the number of quotes per 5-minute interval for the second sample of banks for the period August 24 to October 26 2001

	Mean	Std. Dev.	Dispersion	Maximum	Minimum	$Q(10)$
ALLD	8.07	3.66	1.66	16	0	13854
BARL	11.54	4.15	1.49	22	0	9571.9
DREF	2.27	2.62	3.02	20	0	8217.9
OHVA	14.22	3.73	0.98	21	0	10809
OKOH	31.56	21.86	15.14	82	0	36956
SHKH	3.03	2.15	1.53	16	0	4228.3
UBSZ	10.82	5.59	2.89	44	0	8980.1
Rest	81.66	61.79	46.75	352	0	37913
Aggreg	163.2	78.81	38.06	486	0	34264

Table 3: News categories

Scheduled news announcements				
1 and 2-US macroeconomic figures	Positive	Negative	sample1	sample2
	η_1	η_2	98	54
Employment report	-	+		
ISM index(ex NAPM)	+	-		
Whole sales	+	-		
Gross domestic product (GDP)	+	-		
Producer price index (PPI)	-	+		
Retail sales	+	-		
Housing starts	+	-		
Consumer confidence index	+	-		
Consumer price index (CPI)	-	+		
Construction spending	+	-		
Car sales	+	-		
Business inventories	-	+		
Housing completions	+	-		
Import prices	-	+		
Current account deficit	-	+		
Non-farm productivity	+	-		
Personal income	+	-		
Real earnings	+	-		
House sales	+	-		
3-European macroeconomic figures	η_3		105	51
4-Speeches of senior officials of the government and those of public agencies	η_4		78	53
5-US and European interest rate reports	η_5		36	25
Unscheduled news announcements				
6-Forecasts made by economic institutes	η_6		36	19
7-Declarations of OPEC members	η_7		13	25
8-Rumors of Central Bank interventions	η_8		3	3
9-Extraordinary events	η_9		8	21
Total			377	251

The events are the news headlines released on the Reuters money news-alerts.

For US macroeconomic figures, we separate positive and negative news-alerts by comparing the expected and the announced numbers. If the actual numbers are larger than the expectations for economic variables that contribute to economic growth, the announcements are classified as positive (+). If the actual news release means more inflation or a forthcoming economic slowdown, it is classified as a negative news announcement (-). The expected values are given on Reuters screens a few days before the news announcements.

The employment report includes the unemployment figures.

ISM is the abbreviation for the Institute of Supply Management, ex NAPM, National Association of Purchasing Management. It is a monthly composite index and gives the earliest indication of the health of the manufacturing sector.

The symbol η_j is the coefficient of the dummy variable d_j in the equations reported in Tables 4 and 5.

Table 4: **Estimation results of DACP models for sample 1, May 14 to September 10, 2001.**

The table presents the Maximum Likelihood estimates of the Double Autoregressive Conditional Poisson (DACP) model, with the following mean:

$$\mu_t^* = \mu_t \exp \left(\sum_{j=1}^9 \eta_j d_{j,t} + \sum_{p=1,2,12} (\psi_{c,p} \cos \frac{2\pi p Re[t,N]}{N} + \psi_{s,p} \sin \frac{2\pi p Re[t,N]}{N}) \right), \text{ and}$$

$$\mu_t = \omega + \alpha N_{t-1} + \beta \mu_{t-1}, \text{ for } t = 1, \dots, 9396.$$

where $Re[t, N]$ is the remainder of the integer division of t by N , the number of periods in a trading session. $d_{j,t}$, $j = 1, \dots, 9$. are the dummies for the presence of the news announcement, see table 3 for more detail. The seasonality parameters are not shown, but we show a Wald test $W(\psi's = 0)$ for joint significance of all the seasonality variables. $W(\eta_j = 0)$ is the Wald statistic for the null hypothesis that all nine announcements are jointly non-significant, $Var(\varepsilon_t)$ is the variance of the Pearson residual, and $Q(10)$ is the Ljung-Box statistic of order 10 of the residuals. Parameters that are significant at the 1% and 5% level are indicated by two and one star respectively, and they appear in bold font for better readability.

Parameters	BGFX	BHFX	DEUA	RABO	SGOX	Rest	Agregate
η_1	0.093 (0.129)	-0.063* (0.037)	-0.220** (0.003)	-0.110* (0.020)	0.197** (0.000)	0.044 (0.095)	0.046 (0.066)
η_2	0.087 (0.109)	-0.058 (0.069)	0.169* (0.047)	-0.080 (0.059)	0.186** (0.000)	0.084** (0.001)	0.082** (0.000)
η_3	0.121** (0.003)	-0.027 (0.255)	0.096** (0.007)	0.050 (0.102)	0.135** (0.000)	0.123** (0.000)	0.110** (0.000)
η_4	0.011 (0.855)	-0.003 (0.919)	-0.051 (0.395)	-0.028 (0.433)	0.026 (0.531)	0.014 (0.595)	0.012 (0.642)
η_5	0.114 (0.096)	-0.031 (0.512)	-0.004 (0.958)	-0.022 (0.735)	0.045 (0.374)	-0.001 (0.977)	0.009 (0.762)
η_6	0.135 (0.091)	0.025 (0.633)	0.145 (0.120)	0.057 (0.351)	0.031 (0.677)	0.052 (0.152)	0.055 (0.139)
η_7	-0.193 (0.051)	-0.055 (0.660)	0.031 (0.767)	0.016 (0.865)	0.004 (0.970)	-0.005 (0.940)	-0.020 (0.747)
η_8	-0.391 (0.319)	0.203 (0.734)	0.000 (0.980)	-0.323 (0.108)	-0.237 (0.612)	-0.031 (0.833)	-0.044 (0.768)
η_9	0.169 (0.233)	0.056 (0.534)	-0.090 (0.535)	0.127 (0.239)	0.152 (0.109)	0.045 (0.179)	0.053 (0.157)
ω	0.089** (0.000)	0.253** (0.000)	0.007** (0.000)	0.194** (0.000)	1.326** (0.000)	5.763** (0.000)	7.217** (0.000)
α	0.198** (0.000)	0.141** (0.000)	0.314** (0.000)	0.141** (0.000)	0.288** (0.000)	0.569** (0.000)	0.502** (0.000)
β	0.790** (0.000)	0.832** (0.000)	0.682** (0.000)	0.831** (0.000)	0.623** (0.000)	0.380** (0.000)	0.452** (0.000)
ϕ	0.686** (0.000)	1.726** (0.000)	1.857** (0.000)	1.469** (0.000)	0.501** (0.000)	0.196** (0.000)	0.161** (0.000)
$W(\eta_j = 0)$	25.70** (0.00)	11.56 (0.24)	20.11** (0.01)	19.93* (0.02)	58.28** (0.00)	142.52** (0.00)	116.84** (0.00)
$W(\psi's = 0)$	58.35** (0.00)	34.76** (0.00)	2.53 (0.86)	32.55** (0.00)	82.49** (0.00)	91.25** (0.00)	69.91** (0.00)
$Var(\varepsilon_t)$	0.96	0.95	3.60	0.89	0.96	1.12	1.05
$Q(10)$	115.62** (0.00)	28.89** (0.00)	56.49** (0.00)	68.05** (0.00)	77.39** (0.00)	54.15** (0.00)	84.13** (0.00)
Log likelihood	-23806.84	-21141.99	-9583.01	-20291.97	-28823.29	-45356.05	-42859.43

Table 5: **Estimation results of DACP models for sample 2, August 24 to October 26, 2001.**

The table presents the Maximum Likelihood estimates of the Double Autoregressive Conditional Poisson (DACP) model, with the following mean:

$$\mu_t^* = \mu_t \exp \left(\sum_{j=1}^9 \eta_j d_{j,t} + \sum_{p=1,2,12} (\psi_{c,p} \cos \frac{2\pi p Re[t,N]}{N} + \psi_{s,p} \sin \frac{2\pi p Re[t,N]}{N}) \right), \text{ and}$$

$$\mu_t = \omega + \alpha N_{t-1} + \beta \mu_{t-1}, \text{ for } t = 1, \dots, 4968.$$

where $Re[t, N]$ is the remainder of the integer division of t by N , the number of periods in a trading session. $d_{j,t}$, $j = 1, \dots, 9$. are the dummies for the presence of the news announcement, see table 3 for more detail. The seasonality parameters are not shown, but we show a Wald test $W(\psi' s = 0)$ for joint significance of all the seasonality variables. $W(\eta_j = 0)$ is the Wald statistic for the null hypothesis that all nine announcements are jointly non-significant, $Var(\varepsilon_t)$ is the variance of the Pearson residual, and $Q(10)$ is the Ljung-Box statistic of order 10 of the residuals. Parameters that are significant at the 1% and 5% level are indicated by two and one star respectively, and they appear in bold font for better readability.

Parameters	ALLD	BARL	DREF	OHVA	OKOH	SHKH	UBSZ	Rest	Aggregate
η_1	-0.023 (0.761)	0.047 (0.476)	0.293** (0.000)	0.014 (0.811)	-0.162** (0.001)	-0.303* (0.015)	0.098 (0.147)	0.040 (0.284)	0.008 (0.821)
η_2	0.119 (0.255)	0.190** (0.005)	0.927** (0.000)	0.028 (0.547)	-0.092* (0.033)	-0.021 (0.873)	0.370** (0.000)	0.176** (0.000)	0.143** (0.000)
η_3	0.135** (0.000)	0.073 (0.075)	0.602** (0.000)	0.010 (0.793)	0.072 (0.055)	-0.157 (0.173)	0.028 (0.593)	0.139** (0.000)	0.096** (0.000)
η_4	0.033 (0.507)	0.030 (0.522)	-0.023 (0.784)	-0.039 (0.381)	-0.005 (0.923)	-0.153 (0.103)	0.057 (0.450)	0.024 (0.499)	0.013 (0.635)
η_5	0.087 (0.322)	0.156** (0.008)	0.516** (0.000)	-0.012 (0.869)	0.000 (0.994)	0.184 (0.075)	0.150* (0.050)	0.033 (0.337)	0.051 (0.086)
η_6	0.009 (0.948)	-0.103 (0.210)	-0.212 (0.375)	0.040 (0.679)	0.005 (0.927)	-0.261 (0.158)	-0.058 (0.532)	-0.380 (0.465)	-0.024 (0.513)
η_7	-0.033 (0.714)	-0.039 (0.568)	0.000 (0.999)	-0.039 (0.386)	-0.025 (0.727)	-0.375* (0.045)	-0.007 (0.932)	-0.001 (0.987)	-0.020 (0.699)
η_8	-0.118 (0.966)	0.164 (0.792)	0.531 (0.612)	0.026 (0.941)	-0.067 (0.770)	0.059 (0.953)	0.021 (0.973)	0.304 (0.443)	0.0149 (0.604)
η_9	0.070 (0.511)	0.063 (0.373)	0.160 (0.357)	0.046 (0.451)	0.051 (0.454)	0.035 (0.775)	0.130 (0.228)	0.067 (0.056)	0.070* (0.029)
ω	0.119** (0.000)	0.433** (0.000)	0.273** (0.000)	0.337** (0.000)	0.783** (0.000)	0.202** (0.000)	0.590** (0.000)	1.337** (0.000)	4.405** (0.000)
α	0.347** (0.000)	0.346** (0.000)	0.325** (0.000)	0.433** (0.000)	0.654** (0.000)	0.241** (0.000)	0.281** (0.000)	0.395** (0.000)	0.444** (0.000)
β	0.636** (0.000)	0.614** (0.000)	0.527** (0.000)	0.543** (0.000)	0.321** (0.000)	0.691** (0.000)	0.661** (0.000)	0.587** (0.000)	0.528** (0.000)
ϕ	1.005** (0.000)	0.936** (0.000)	0.604** (0.000)	1.328** (0.000)	0.447** (0.000)	0.815** (0.000)	0.541** (0.000)	0.200** (0.000)	0.169** (0.000)
$W(\eta_j = 0)$	19.28* (0.02)	22.58** (0.00)	272.78** (0.00)	2.87 (0.97)	26.74** (0.00)	20.98** (0.01)	45.05** (0.00)	59.92** (0.00)	73.77** (0.00)
$W(\psi' s = 0)$	63.71** (0.00)	17.80** (0.01)	84.33** (0.00)	3.46 (0.75)	3.60 (0.73)	68.37** (0.00)	38.66** (0.00)	33.53** (0.00)	22.63** (0.00)
$Var(\varepsilon_t)$	1.16	1.00	1.09	1.09	1.63	0.94	0.96	1.18	1.10
$Q(10)$	45.89** (0.00)	69.61** (0.00)	42.56** (0.00)	97.59** (0.00)	100.56** (0.00)	18.47 (0.26)	56.20** (0.00)	42.56** (0.00)	85.78** (0.00)
Log likelihood	-11628.82	-12948.08	-8717.91	-12630.76	-16280.69	-9254.34	-14016.63	-21380.68	-23846.94

Table 6: Wald tests of equality for all banks of the effect of news

Announcement category	Sample 1	Sample 2
Scheduled:		
η_1 - Positive US macro figures	36.71**	49.31**
η_2 - Negative US macro figures	28.96**	228.91**
η_3 - European macro figures	22.91**	70.85**
η_4 - Speeches of senior officials	1.63	6.69
η_5 - Interest rate reports	3.78	29.47**
Unscheduled:		
η_6 - Economic institutes forecasts	2.31	2.07
η_7 - OPEC member declarations	3.41	6.24
η_8 - Central bank intervention rumors	0.87	0.46
η_9 - Extraordinary events	2.53	4.11

This table shows the results of a Wald test for the hypothesis that $\eta_{i,1} = \eta_{i,2} = \dots = \eta_{i,k}$, where the first index refers to the announcement and the second to the bank. This hypothesis is equivalent to testing the $k - 1$ constraints: $\eta_{i,1} = \eta_{i,2}, \dots, \eta_{i,k-1} = \eta_{i,k}$. One and two stars indicate rejection of the null hypothesis at the 5% and 1% respectively. The test statistic takes the following form:

$$W = (R\eta_i)'(R\Sigma_i R')^{-1}(R\eta_i),$$

where for sample 1,

$$R = \begin{pmatrix} 1 & -1 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 1 & -1 \end{pmatrix},$$

$\Sigma_i = \text{diag}(\sigma_{i,1}^2, \dots, \sigma_{i,5}^2)$, $\sigma_{i,k}^2$ refers to the variance of coefficient $\eta_{i,k}$ and $\eta_i = (\eta_{i,1}, \dots, \eta_{i,5})$. Σ_i is diagonal as there is no covariance between the effects of any announcement on two different banks.

Figure 1: Histogram of Banks' Quoting Activity

This figure presents the histogram of banks' quoting activity. ALLD, BARL, DREF, OHVA, OKOH, SHKH and UBSZ are observed from August 24 to October 26, 2001. BGFY, BHFX, DEUA, RABO and SGOX are observed from May 14 to September 10, 2001.

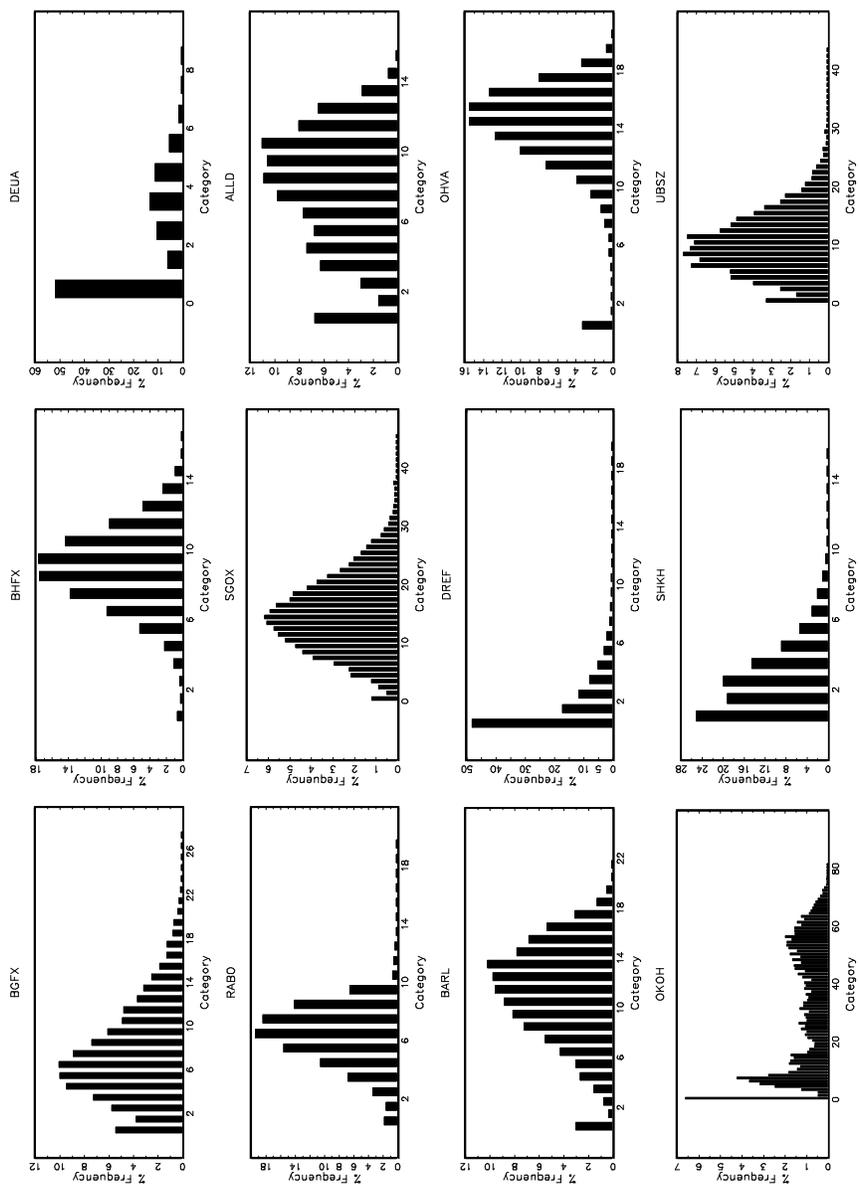


Figure 2: **Time-of-the-day effect**

This figure presents the time-of-day effect of each bank of the two samples. The figure shows the ratio of the 5-minute means over the day relative to the overall mean. ALLD, BARL, DREF, OHVA, OKOH, SHKH and UBSZ are observed from August 24 to October 26, 2001. BGFY, BHFX, DEUA, RABO and SGOX are observed from May 14 to September 10, 2001.

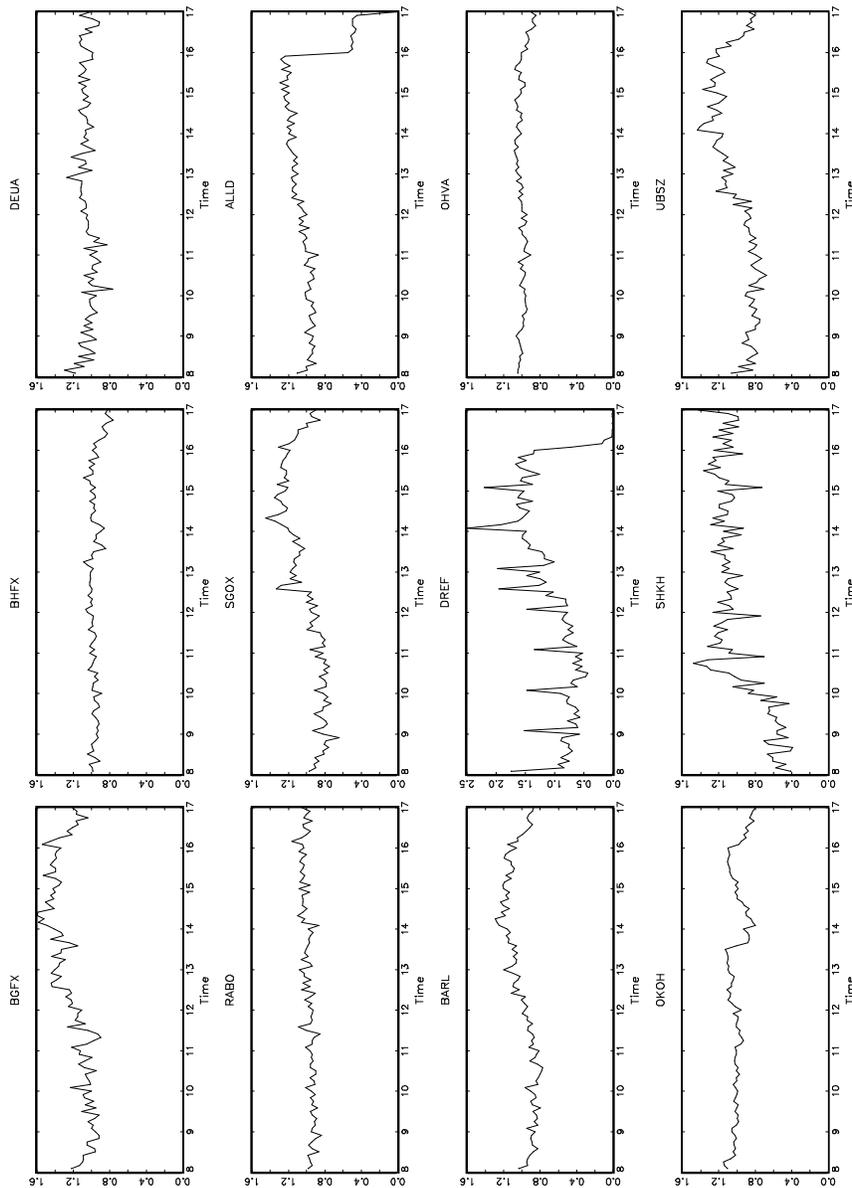


Figure 3: **Correlogram of banks' quoting and standardised residuals from DACP models**

This figure presents the correlogram of banks' activity and of standardised residuals from DACP models. The standardised residuals (Pearson residuals) are defined as $\varepsilon_t = \frac{N_t - \mu_t}{\sigma_t} = \frac{N_t - \mu_t}{\sqrt{\mu_t / \phi}}$. The dashed line represents the autocorrelations of the raw series, and the solid line the autocorrelations of the Pearson residual. The bounds of significance are also plotted.

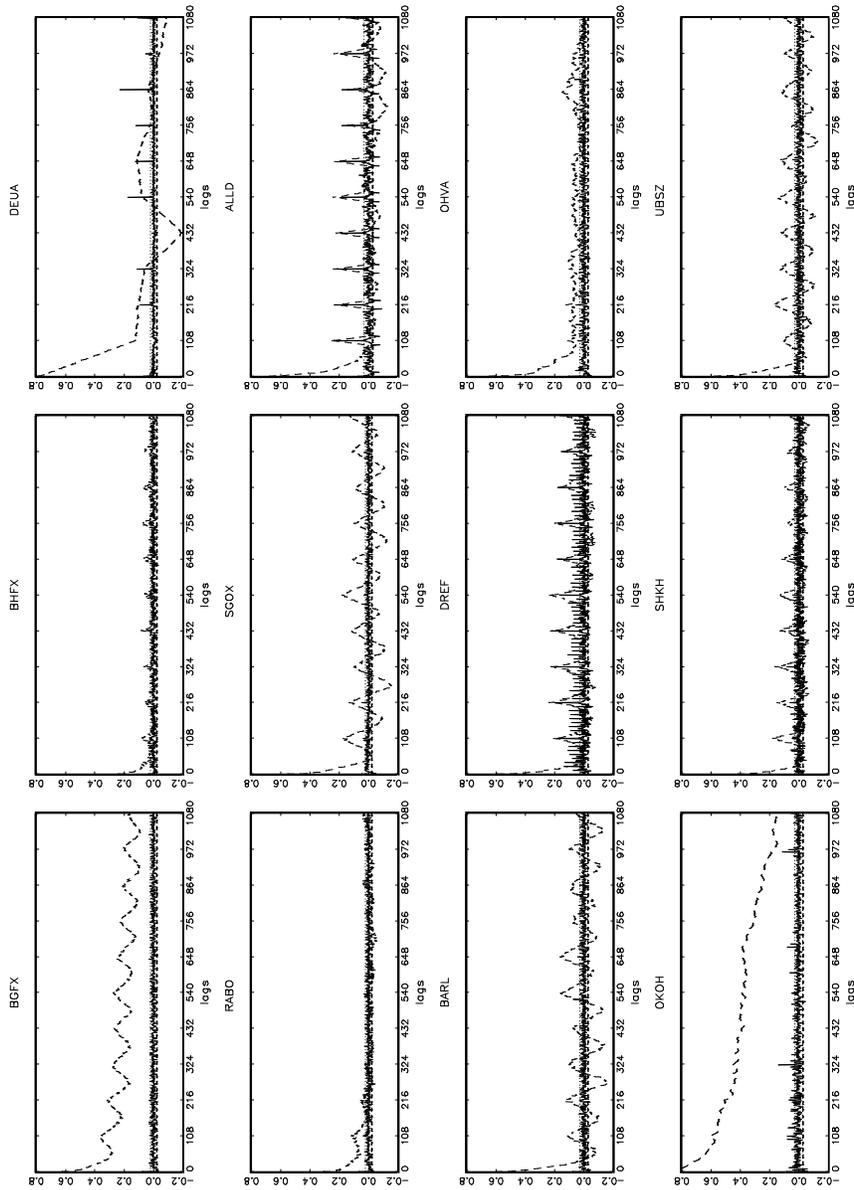


Figure 4: **Quantile plot of the Z statistic of individual banks**

This figure presents the Quantile plot of the Z statistic of individual banks. This statistic is defined as the probability integral transform of the original data under the estimated density, in our case, the double Poisson: $Z_t = F^*(N_t, \mu_t)$, see Appendix 1 for more details.

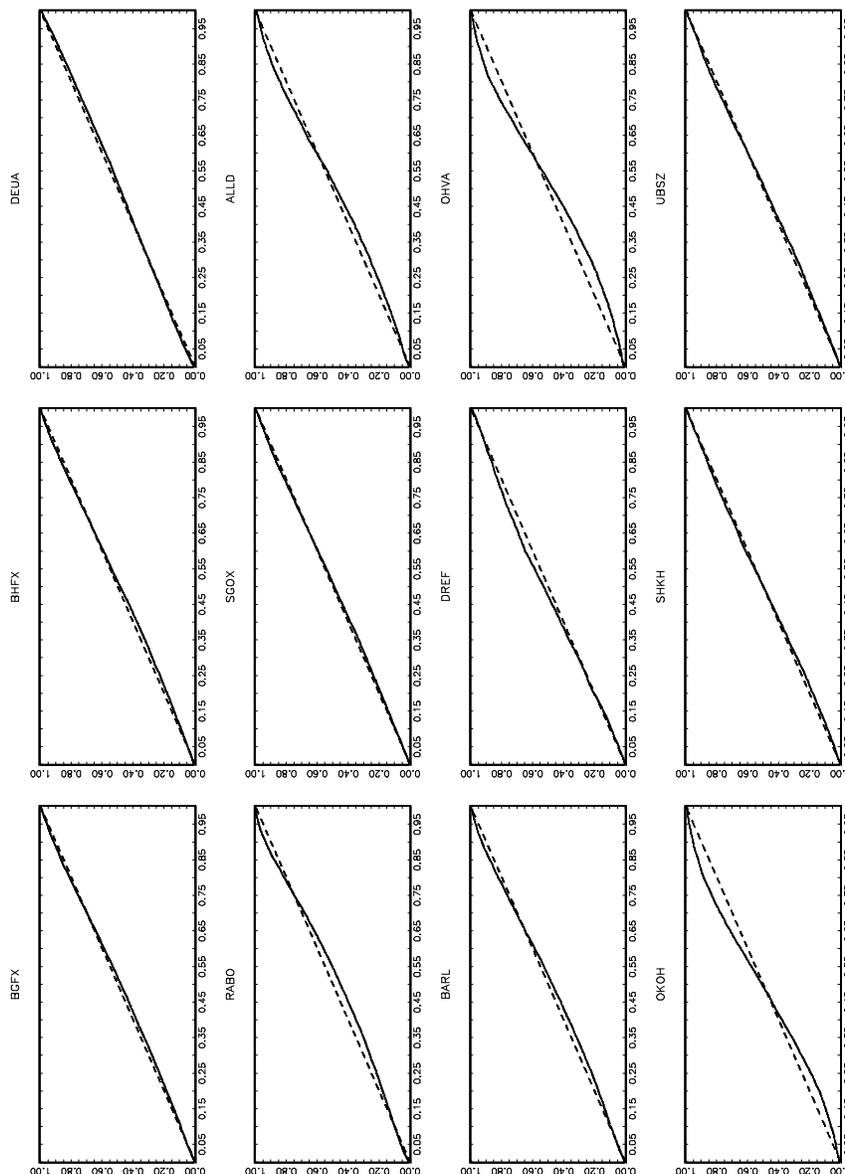


Figure 5: **Z statistic of individual banks**

This figure presents the autocorrelogram of the Z statistic of individual banks. This statistic is defined as the probability integral transform of the original data under the estimated density, in our case, the double Poisson: $Z_t = F^*(N_t, \mu_t)$, see Appendix 1 for more details.

