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EXPLAINING LIQUIDITY DYNAMICS IN THE ORDER DRIVEN FX SPOT MARKET¹

1. INTRODUCTION

The concept of liquidity in the market microstructure literature is generally perceived as "slippery and elusive concept" that is difficult to define (c.f. Kyle, 1985). There is a well-established consensus in the financial market literature that liquidity has at least four major dimensions: depth, tightness, resilience (c.f. Black, 1971; Kyle, 1985) and immediacy (c.f. Sarr, Lybek, 2002). In this paper we focus on the examination of the first three categories mentioned above: we investigate the market depths, the bid-ask spread and some more precise measures of the limit order book (LOB) tightness, as well as the Amihud (2002) illiquidity measure of market resilience.

The aim of this paper is to quantify and describe the intraday dynamics of different liquidity measures of the order-driven interbank EUR/PLN spot market from the perspective of time-varying fraction of informed trading. As the share of trading on private information cannot be observed directly, it has to be approximated and deduced from the quantified intensity of incoming orders. It is widely recognized in the literature that informational motives of currency dealers constitute an important driving force of FX trading. According to King et al. (2013), the amount of information heterogeneity among currency dealers may arise from different exposure to bank clients submitting unbalanced types of market orders (i.e. different amount of buy orders in comparison to sell orders), private research on market fundamentals, or even sharing the views and expectations within an informal social network. Accordingly, we intend to measure the scale of this information discrepancy and relate it to the continually changing liquidity conditions on the EUR/PLN market. The estimates of 'rates' of informed and uninformed trade arrivals are to be obtained from the dynamic sequential trade model proposed by Easley et al. (2008) and adjusted to the intraday setup by Bień-Barkowska (2013). As a result of this, we are able to estimate a time-varying fraction of informed trades from the continually changing differences

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in amounts of buyer- and seller-initiated trades. This time-varying share of informed trading is to be treated at a later stage as an explanatory factor for each individual measure of liquidity provision.

Our study aims to contribute to an extremely scarce literature on liquidity determination in FX markets. To our knowledge, our findings are unique in terms of an in-depth analysis of liquidity dynamics on an intraday level. Some implications about fluctuations in the shape of the order-book can be deduced from the studies of order submissions provided by Lo, Sapp (2008) and Lo, Sapp (2010), however their studies covered Deutsche Mark-US Dollar market and the Canadian Dollar – U.S. Dollar currency pairs, hence the major currencies and not emerging ones. The novelty of our analysis lies in an documentation of a time-of-day as well as day-of-week effects (i.e. intraday and intraweek seasonality) in different measures of liquidity provision. We also evidence long memory effects of liquidity shocks in currency markets and show that the long-range dependence in liquidity can be captured by the Fractionally Integrated Autoregressive Conditional Duration models of Jasiak (1998). Additionally, we also show that the amount of liquidity supplied is closely linked to the share of informed trading in the market. Although significant impact of informed trading on the market tightness was already documented for cross sections of stocks by Brockman, Chung (1998), (1999), (2000) and Easley et al. (2008), in this study we look at liquidity from a different angle paying attention to a time series setup. Accordingly, we will be able to assess how the continually changing informational motives of trading in FX markets impact the behavior of other market participants leading to observed liquidity fluctuations.

In the market microstructure theory, adverse selection costs, the cost of dealer services and the cost of holding inventory constitute three main determinants of market tightness (c.f. Sarno, Taylor, 2002, p. 290). Although the latter two are behind the scope of this paper, the adverse selection costs can be explained in an information-oriented strand of market microstructure literature. Information models date back to the seminal study of Bagehot (1971), where in the market there are two types of traders: liquidity (uninformed) traders and informed traders. The latter can make use of private information at the expense of a market maker. Because market maker does not know with whom he trades, he widens the spread for both trading groups treating it as a premium for an adverse selection risk. Similarly, in the Glosten, Milgrom (1985) model, a market maker can additionally learn the probability of informed trading by knowing the direction (buy or sell) of orders. He cannot distinguish liquidity traders from informed traders and therefore adjusts quoted liquidity conditionally on the sign of incoming orders. The model has been further developed by Easley, O'Hara (1987), who state that not only the stream of incoming orders but also their sizes can have informative value. Thus, the existence of new information can be deduced from the sign and the size of the incoming orders. Accordingly, asymmetric information obliges market makers to update ask and sell prices and scale of market tightness is a weapon against an adverse selection problem. In many later studies bid-ask spread was also

treated as a observable measure of information heterogeneity (c.f. McNish, Wood, 1992; Foster, Viswanathan, 1990; 1993).

The market depth is comprised of limit orders awaiting for an execution in the limit order book (LOB). The amount of quoted depth can be also related to the informational content of trading. De Jong and Rindi state that “(...) the choice between limit and market orders is a strategic element in any trading decision and depends on (...) the asymmetry of the personal evaluations of the risky asset between the agents who submit the orders and those who hit the existing quotes” (c.f. De Jong, Rindi, 2009, p. 134). Although there is a widespread notion that informed traders are much more likely to use market orders than limit orders, Harris (1998) points out that informed traders can also use limit orders. Moreover, liquidity traders can be discretionary, which means that they chose the time of their trading (c.f. Admati, Pfleiderer, 1988). Uninformed traders, being aware of the increased adverse selection costs during periods where informed trading can take place, may prefer to limit the risk that their stale orders will be executed at an unfavorable price. Thus, they may retreat from supplying liquidity to the market, even by canceling the previously submitted orders. Accordingly, market depth should deteriorate as a response to signs of informed trading.

2. EMPIRICAL DATA

The datasets used in this study are comprised of all incoming orders as well as trades executed during the year 2007 in the Reuters Dealing 3000 Spot Matching System with respect to the EUR/PLN currency pair. Trading of the Polish zloty takes place on offshore markets (mainly between London banks) as well as locally in Poland and the datasets used in this analysis take into account both of these trading venues. The EUR/PLN exchange rate is quoted as a quantity of zlotys per one Euro. The transaction currency is euro and the smallest order size is 1 million EUR. During the whole period under study EUR/PLN market featured appreciation trend of the Polish zloty against euro. The Reuters Dealing 3000 Spot Matching System is an electronic brokerage system that operates as an order-driven market and automatically matches incoming buy and sell orders once their prices agree. FX dealers can submit either limit or market orders; limit orders are traditionally perceived as rather passive in nature whereas market orders are liquidity-consuming and more aggressive since they are immediately realized against most competitive limit orders in the LOB. However, only the best bid and ask prices with the corresponding depths at the best ask or at the best depth are observable to other market participants on the trading screens. In our datasets, each transaction is marked with its date, exact time, rate and quantity (in millions) of EUR as well as a buy/sell indicator. Every order includes an exact date and time of submission as well as an execution/cancellation, a firm quote, the size and an indicator for the market side of the quote. The detailed structure of the datasets

makes it possible to rebuild the whole order book at each moment of the market's activity. In order to limit the undesired impact of particularly thin trading periods we have excluded observations registered on weekends and on business days between the hours of 18:00 and 8:00 CET. We also omit days with exceptionally low liquidity due to national holidays. As a result of these deletions our sample covers 250 trading days of trade and order data that was aggregated into 15-minute intervals. We identify the following six liquidity measures:

- ILLIQ measure: the illiquidity measure of Amihud (2002) defined as the absolute mid price change divided by the trading volume between the times $t - 1$ and t , $ILLIQ_t = |\Delta P_t^{mid}| / V_t$ (where $P_t^{mid} = (P_t^{A,best} - P_t^{B,best}) / 2$, $P_t^{A,best}$ denotes the most competitive (lowest) ask price in the LOB, and $P_t^{B,best}$ denotes the most competitive (highest) bid price in the LOB at time t).
- Percentage bid-ask spread: the ratio of the difference between the best ask and the best bid quote prevailing in the LOB at time t and the corresponding mid price, $S_t = (P_t^A - P_t^B / P_t^{mid}) \cdot 10^4$ (in basis points).
- Market depth on the bid side of the market (and respectively, on the ask side of the market): the quantity of all limit buy (sell) orders in the LOB at time t : D_t^b (or D_t^a , respectively) (in millions of EUR).
- Quote slope for the ask side of the market (and respectively, for bid side of the market) measuring entire liquidity in the spirit of Hasbrouck, Seppi (2001). For the ask side of the market the quote slope (QS_t^A) is measured as the difference among the worst (i.e. the highest) and the best (i.e. the lowest) ask price prevailing in the LOB at time t , divided by the entire depth on the ask side of the market; $QS_t^A = (P_t^{A,worst} - P_t^{A,best}) / D_t^A$. Symmetrically, for the bid side of the market, the quote slope (QS_t^B) is defined as the difference between the best (i.e. the highest) and the worst (i.e. the lowest) bid price in the LOB at time t , divided by the entire depth on the bid side of the market; $QS_t^B = (P_t^{B,best} - P_t^{B,worst}) / D_t^B$.
- Liquidity area for the ask side of the market (and respectively, for the bid side of the market). For the ask side of the market, the liquidity area (LIQ_t^A) is defined as the area under the ask supply curve (over the mid price) that corresponds to an immediate buy of exact 5 million EUR: $LIQ_t^A = \sum_{i=1}^5 (P_t^{A,i} - P_t^{mid})$ where $P_t^{A,i}$ indicates the zloty price for an immediate buy of i -th million of euro. Symmetrically, for the bid side of the market, the liquidity area (LIQ_t^B) is defined as

the area under the mid price (and over the bid supply curve) that corresponds to an immediate sell of exact 5 million EUR: $LIQ_t^B = \sum_{i=1}^5 (P_t^{mid} - P_t^{B,i})$, where $P_t^{B,i}$ indicates the zloty price for an immediate sell of i -th million of euro.

For a better exposition of liquidity measures, in Figure 1 we present the snapshot of the LOB a couple of seconds after 8:23 CET on 9 Jan. 2007. The best (most competitive) quote offered on the ask side of the market equals 3.86 and worst (least competitive) quote equals 3.8765. On the other hand, the quote that is first to be hit on the bid side of the market is 3.857 and the least competitive bid offer is 3.848. Clearly, the bid-ask spread which amounts to 0.003 (three tenth parts of the Polish grosz; hence three thousandth parts of the Polish zloty) constitutes an extremely modest and insufficient measure of liquidity supply, similarly to the bid or ask market depths. Indeed, although the entire depth on the bid and on the ask side of the market is the same and equals 29 million EUR, the ask and bid sides of the LOB are obviously not equally tight. The discrepancy between liquidity supply on the ask and on the bid side of the market seems striking if one looks at a sequence of the most competitive ask or sell offers that play the first fiddle in the market game. The ask liquidity area (shaded in light grey) is much larger than the bid liquidity area (shaded in dark grey). Thus, a dealer who decides to immediately buy 5 million EUR bears much higher liquidity costs than a dealer who decides to immediately sell 5 million EUR. This is because only 1 million EUR out of 5 can be traded at the most competitive ask price. Other parts of this buy order have to be executed at less favorable prices (1 million even at 3.87, hence a quote 100 pips higher than the best ask quote). On the contrary, the liquidity provision on the bid side is considerably larger and the dominant part of a 5 million sell order can be executed at the most competitive bid price.

The motivation behind the choice of liquidity measures is the following. The Amihud (2002) measure of illiquidity is closely related to the well-known Kyle's lambda and constitutes a standard proxy for the price impact of trading. Accordingly, the ILLIQ measure captures market resiliency by reflecting a change in a quoted mid price in result of a trade. Other liquidity variables are selected to reflect the shape of a limit order book. The bid-ask spread and the bid (ask) depths are known to be the standard measures of pre-trade liquidity supply. The ask (bid) quote slopes aim to capture the entire liquidity provision on the ask (bid) side of the market. If the nominator of the ask (bid) quote slope rises (i.e. absolute difference between the best and the worst ask (bid) quote increases), so does the steepness of the ask (bid) quote slope. Similarly, the smaller the depth of ask (bid) side of the market, the steeper the quote slope. Hence, the ask (bid) quote slope tends to infinity for the infinitely illiquid market (if the depth tends to zero or the absolute difference between the best and worst price in the LOB is infinitely large). Accordingly, for the infinitely liquid market, the ask (bid) slope will be equal to zero. Although quote slopes capture the tightness of the entire LOB, they have certain drawbacks. First, in the case of only

one limit order prevailing on the ask (or bid) side of the LOB, the quote slope would be equal to zero indicating an infinitely liquid market, which obviously cannot hold true. Second, quote slopes do not take into account the ‘curvature’ of the ask (bid) liquidity supply curves, as they neglect the quotes between the best and worst ask (bid) prices. To overcome this problem, we propose the liquidity areas as potentially more precise measures of the LOB shape. Liquidity areas measure how close the ask (bid) prices (corresponding to the pre-defined most competitive levels of the limit order book) are to the mid price. In the infinitely liquid market, the 5-million-buy or the 5-million-sell would be concluded at the best ask price or at the best sell price. Accordingly, the larger the liquidity areas, the smaller the liquidity supply and the larger are the costs of a 5-million-trade.

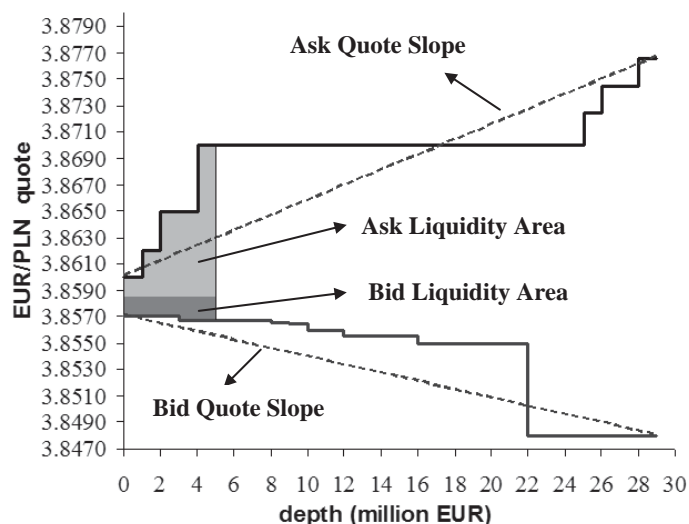


Figure 1. The snapshot of the EUR/PLN LOB on 9th January 2007 (8:23:41.34 CET)

All liquidity variables selected for the study exhibit strong intraday seasonality (diurnality). The diurnality patterns are obtained by computing the expectation of a liquidity variable conditioned on a time-of-day, separately for each day of the week, i.e. from Monday to Friday. Thus, for each day of week we derive a different shape of the intraday seasonality with a nonparametric (kernel) regression of the liquidity variable on a time-of-day indicator. The intraday seasonality factor, which was suggested by Bauwens, Veredas (2004), is given as:

$$S(\tau) = \frac{\sum_{t=1}^T K((\tau - \tau_t)/h) \bar{x}_t}{\sum_{t=1}^T K((\tau - \tau_t)/h)}, \quad (1)$$

where K denotes a quartic kernel function, τ is a time variable rescaled to interval $[0,1]$ (i.e. number of seconds from 8:00 on each day was divided by the cumulative number of seconds from 8:00 to 18:00), \bar{x}_t denotes a liquidity variable, i.e. $\bar{x}_t \in \{ILLIQ_t, S_t, D_t^A, D_t^B, QS_t^A, QS_t^B, LIQ_t^A, LIQ_t^B\}$, h denotes an optimal smoothing parameter selected according to the Silvermann's rule of thumb.

Diurnality patterns augmented for a day-of-week effects are depicted in Figure 2. We see that overall liquidity deteriorates in the mornings and late afternoons when trading is rather scarce. In an overnight period, when the two major headquarters of Polish zloty trading (the London market and the Polish market) are closed, the trading system is lacking liquidity. This result is consistent with many empirical studies on intraday stock trading that report an U-shaped or an inverted J-shaped curve for the intraday seasonality of the bid-ask spread (c.f. Nyholm, 2002; Nyholm, 2003; Ahn et al., 2002; Heflin et al., 2007). We document a distinct U-shaped diurnality pattern not only for the bid-ask spread, but also for the Amihud (2002) illiquidity measure as well as both ask and bid liquidity areas and both ask and bid quote slopes. Moreover, we clearly see that the interbank EUR/PLN market tends to be systematically less liquid on Mondays and Fridays in comparison to other days of the week, which relates to the uncertainty associated with a two-day-long cease in trading on weekends. On Mondays, especially in the morning, there is an increased information heterogeneity in the market because of various news releases during Saturday and Sunday. The uncertainty results in systematically wider bid-ask spread and increased quote-slopes. Similarly, deterioration in quoted liquidity on Fridays (which is especially visible for quote slopes and liquidity areas) can be attributed to increased settlement risk, because FX spot transactions are always settled two working days after they are executed. Our results are consistent with the findings of Brzeszczyński, Melvin (2006), who also document distinct intraday and intraweek seasonality patterns in trading activity for the euro FX market. Intraday seasonality patterns of the market depth are generally much more 'dispersed', but still they seem to be inversely related to these corresponding to bid-ask spread, quote slopes or liquidity areas.

In order to assess the dynamic properties of selected liquidity measures, we divided each liquidity variable by the corresponding diurnality factor $x_t = \bar{x}_t/S(\tau_t)$. This procedure allows us to disentangle between two sources of autocorrelation: intraday seasonality due to systematic and repetitive (on a daily basis) trading activities of currency dealers and the residual persistence in liquidity shocks after elimination of diurnality effects. In the sequel of the paper we use the deseasonalized liquidity variables (i.e. adjusted for both time-of-day as well as day-of-week effects), whose autocorrelation functions are depicted in Figure 3. We can see that nearly all functions exhibit a very slow hyperbolic (and non-exponential) rate of decay. Bid (ask) depths and the bid (ask) quote slopes are the most persistent and indicate long memory effects.

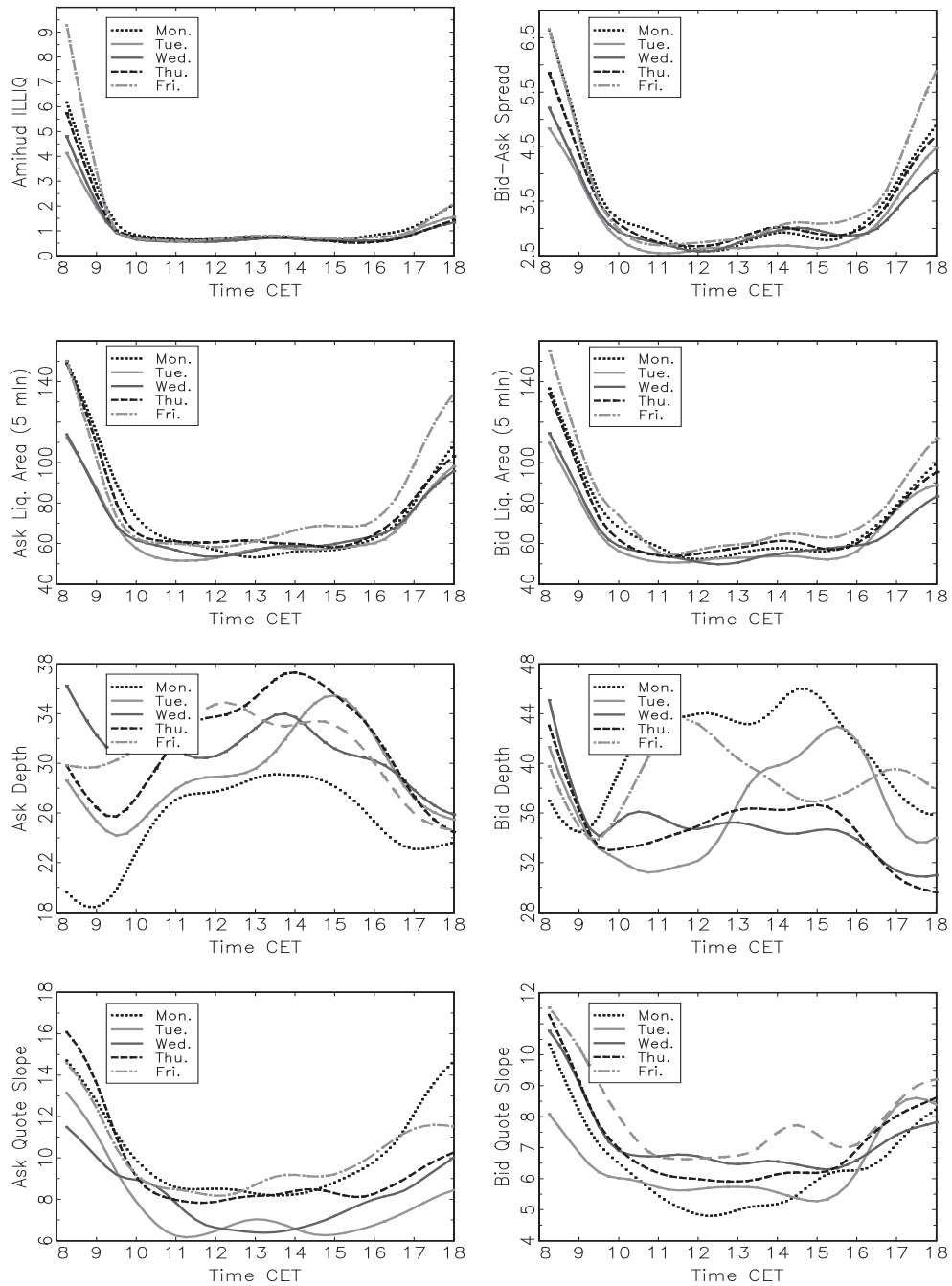


Figure 2. The day-of-week adjusted diurnality patterns for selected liquidity measures

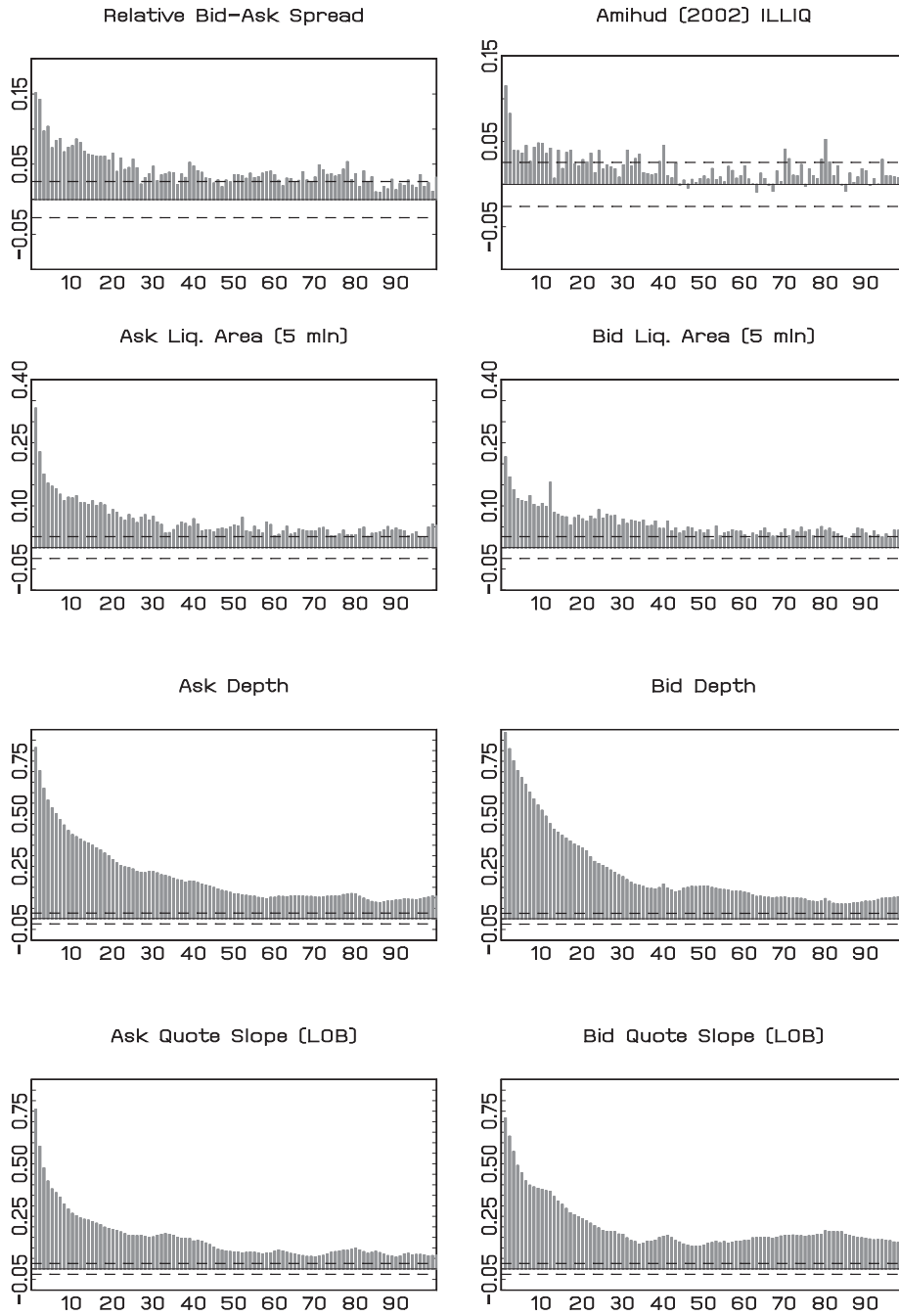


Figure 3. The autocorrelation functions for the deseasonalized liquidity measures

3. ECONOMETRIC METHODS

3.1. FRACTIONALLY INTEGRATED ACD MODELS

We use Autoregressive Conditional Duration (ACD) models introduced by Engle, Russell (1998) to account for dynamic properties of variables under study. Preliminarily, ACD models were proposed to describe trading intensity and applied to autocorrelated time series of financial durations (i.e. times) between selected events (i.e. transactions or price changes). These models were also used to describe transaction volumes by Manganeli (2005) and Doman (2008), Doman (2011) or bid-ask spreads by Nolte (2008). The ACD models can explicitly capture two specific features of financial variables measured at high frequencies. First, they are designed to variables with a positive real domain. Second, they can flexibly describe processes with strong autocorrelation, often with a high degree of persistence. There is a recent upsurge in research on the ACD models, whereas vast surveys on their extensions can be found in Hautsch (2004) or Pacurar (2008). Here we use the logarithmic version of the Fractionally Integrated ACD (FIACD) model proposed by Jasiak (1998) with the Burr distribution for the error term, as suggested by Grammig, Maurer (2000). According to the ACD setup, each adjusted for time-of-day and time-of-week effect liquidity variable x_t ($x_t \in \{ILLIQ_t, S_t, D_t^A, D_t^B, QS_t^A, QS_t^B, LIQ_t^A, LIQ_t^B\}$) can be given as:

$$x_t = \Phi_t \varepsilon_t, \quad (2)$$

where $\Phi_t = E(x_t | F_t)$, F_t denotes an information set up to time point t and ε_t denotes the Burr-distributed error term with a property $E(\varepsilon_t) = 1$. Hence, ε_t : *i.i.d.* Burr(κ, σ^2); κ and σ^2 denote the shape parameters of the Burr distribution², where $0 < \sigma^2 < \kappa$. We decompose the conditional expectation of x_t as:

$$\Phi_t = \exp(\phi_{1,t} + \phi_{2,t}), \quad (3)$$

with the first component, i.e. $\phi_{1,t}$, designed to capture the strong persistence in liquidity with the logarithmic version of the FIACD(p,d,q) model of Jasiak (1998):

$$(1 - \beta_p(L))\phi_{1,t} = \beta_0 + \gamma_\infty(L) \ln(x_{t-1}), \quad (4)$$

where β_0 is a constant, $\beta_p(L)$ denotes a scalar p th order polynomial in lag operator and $\gamma_\infty(L)$ denotes a scalar polynomial in lag operator given as:

² The Burr distribution has three parameters, but the assumption $E(\varepsilon_t) = 1$ makes the third (scale) parameter the function of the shape parameters κ and σ^2 .

$$\gamma_\infty(L) = [1 - \beta_p(L) - [1 - \alpha_q(L) - \beta_p(L)](1 - L)^d]. \quad (5)$$

$\alpha_q(L)$ is a scalar q th order polynomial in lag operator and $(1 - L)^d$ (for $0 < d < 1$) is a fractional lag operator:

$$(1 - L)^d = \sum_{k=0}^{\infty} \varpi_k L^k, \text{ where } \varpi_k = \frac{\Gamma(k - d)}{\Gamma(k + 1)\Gamma(-d)} = \prod_{0 < j \leq k} \frac{j - 1 - d}{j}, \text{ for } k = 0, 1, 2, \dots$$

and $\Gamma(\cdot)$ is the gamma function (c.f. Nolte, 2008).

For $d = 0$, logarithmic FIACD model nests logarithmic ACD(p,q) model of Bauwens, Giot (2000) and its integrated version for $d = 1$. The second component of the conditional expectation, i.e. $\phi_{2,t}$, is designed to capture possible impact of other explanatory variables.

As explanatory variables we choose the proxy for informed trading, i.e. the measure of “probability of informed trading” PIN_t (explained in detail in the next section). In order to recover the independent impact of PIN_t on the top of other popular characteristics of market activity, we decided to enrich the model with three standard control covariates: the volume of all trades from $t - 1$ up to t (TT_t), the observed return on EUR/PLN rate during 15-minute-long interval from $t - 1$ up to t (r_t) and the proxy for volatility (given as a modulus of return $|r_t|$). In order to mitigate the multicollinearity effects, the trade volume and the proxy for volatility were deseasonalized in the same way as the liquidity measures (multiplicative intraday seasonality factor was derived with a kernel regression on a time-of-day variable separately for each day of the week). Henceforth, the component $\phi_{2,t}$ of conditional expectation of liquidity measures is given as:

$$\phi_{2,t} = \gamma_{TT} TT_t + \gamma_{vol} |r_t| + \gamma_{ret} r_t + \gamma_{PIN} PIN_t. \quad (6)$$

In the empirical analysis we will rely on the logarithmic version of the parsimonious FIACD(1,d,1) model, hence the dynamic specification of $\phi_{1,t}$, given as:

$$(1 - \beta_1 L)\phi_{1,t} = \beta_0 + [1 - \beta_1 L - (1 - \alpha_1 L - \beta_1 L)(1 - L)^d] \ln(x_{t-1}). \quad (7)$$

The ACD models can be estimated with the Maximum Likelihood method. However, the “infinity” term (see $(1 - L)^d = \sum_{k=0}^{\infty} \varpi_k L^k$) has to be approximated. Therefore, we proxy infinity with 1000 and initiate first 1000 lags of $\ln(x_t)$ by the unconditional mean of $\ln(x_t)$, as in Nolte (2008). The log likelihood function of the ACD model with the Burr distribution is:

$$\text{Log}L(\Theta) = \sum_{t=1}^T \left[\ln \kappa - \kappa \cdot \ln \xi_t + (\kappa - 1) \cdot \ln x_t - \left(\frac{1}{\sigma^2} + 1 \right) \cdot \ln(1 + \sigma^2 \cdot \xi_t^{-\kappa} \cdot x_t^{\kappa}) \right], \quad (8)$$

$$\text{where } \xi_t = \Phi_t \frac{\sigma^{2 \cdot \left(1 + \frac{1}{\kappa}\right)} \cdot \Gamma\left(\frac{1}{\sigma^2} + 1\right)}{\Gamma\left(1 + \frac{1}{\kappa}\right) \cdot \Gamma\left(\frac{1}{\sigma^2} - \frac{1}{\kappa}\right)} \text{ and } 0 < \sigma^2 < \kappa.$$

Application of the exponential transformation of the expectation (see equation 3) enables adding exogenous explanatory variables to the model (see equation 6). Some of these regressors might have a negative impact on the liquidity measures but this outcome will not interfere with the nonnegativity of the liquidity variable.

3.2. PROBABILITY OF INFORMED TRADING

Sequential trade models introduced by Easley et al. (1996) and developed in Easley et al. (2008) contributed to a huge upsurge in research on how the information possessed by a fraction of market participants may be unveiled to the others through the observed stream of buy and sell orders. According to the market microstructure literature, the reasons for trading can be twofold: (1) exploiting private information, and (2) satisfying liquidity needs or portfolio rebalancing. Therefore, act of trading can take place in order to exploit the information signals (informed trading) or to satisfy liquidity or inventory-related reasons (uninformed trading). Sequential trade models are used to construct a measure known as the ‘probability of informed trading’ (PIN), which reflects the forecasted fraction of all trades that are initiated by access to private information. Easley, Kiefer, O’Hara and Paperman proposed one of the first econometric parameterizations of a sequential trade model, henceforth known as the EKOP model (Easley et al. 1996).

In order to check how the predicted PIN variable influences market liquidity we apply diurnality-adjusted augmentation of the dynamic Easley et al. (2008) model suggested by Bień-Barkowska (2013). In the Easley et al. (2008) approach, buy and sell trades occur according to two independent Poisson processes with the time-varying arrival rates: $\lambda_{B,t}$ and $\lambda_{S,t}$, respectively. It is also assumed that both informed and uninformed traders may initiate trades with a time-varying rates μ_t and ε_t , respectively. Although the detailed presentation of the dynamic EKOP model can be found in Easley et al. (2008), for the sake of legibility of our analysis we sketch its major outline below.

It is assumed that at the beginning of each of the pre-defined time intervals (i.e. 15-minute spells in our setup) new information occurs with a constant probability α , or there is no news with probability $1 - \alpha$. If the information occurs, it can be either “bad” for the transaction currency (EUR) with a constant probability δ or it may be “good” with probability $1 - \delta$. Uninformed traders always conclude their trades with rates: $\lambda_B = \varepsilon_t$ (ask side) and $\lambda_S = \varepsilon_t$ (bid side), respectively. Informed traders switch into trading only after having received the information signal (with an arrival rate μ_t for both sides of the market). Accordingly, during intervals with bad information, the buy transactions are initiated by uninformed traders only and occur with an arrival rate $\lambda_B = \varepsilon_t$ but sell transactions result from both informed and uninformed traders with a rate $\lambda_S = \mu_t + \varepsilon_t$. Symmetrically, during intervals with good news, buys result from informed and uninformed traders ($\lambda_B = \mu_t + \varepsilon_t$), whereas the sells are concluded by uninformed traders only ($\lambda_S = \mu_t$).

In order to estimate the dynamic diurnality-adjusted EKOP model, the following variables have to be defined: (1) trade imbalance, given as the absolute difference between the number of buy³ (B_t) and sell trades (S_t) that are executed between t and $t - 1$, $|B_t - S_t|$, (2) balanced trades, given as the difference between the total number of trades (TT_t) and the trade imbalance, $(TT_t) - |B_t - S_t|$. Additionally, let us by $\psi_{1,t}$ denote the forecasted (at time t) arrival rate of uninformed trades (i.e. $\psi_{1,t} = 2\varepsilon_t$) and by $\psi_{2,t}$ the forecasted (at time t) arrival rate of informed trades (i.e. $\psi_{2,t} = \alpha\mu_t$). According to Bień-Barkowska (2013), both $\psi_{1,t}$ and $\psi_{2,t}$ are subject to a seasonality-adjusted VARMA-type dynamic specification:

$$\psi_{1,t} = \omega_1 + \phi_{11}^* \hat{\psi}_{1,t-1} + \phi_{12}^* \psi_{2,t-1} + \gamma_{11} \xi_{1,t} + \gamma_{12} \xi_{2,t}, \quad (9)$$

$$\psi_{2,t} = \omega_2 + \phi_{21}^* \psi_{1,t-1} + \phi_{22}^* \psi_{2,t-1} + \gamma_{21} \xi_{1,t} + \gamma_{22} \xi_{2,t},$$

where $\xi_{1,t} = TT_t - |B_t - S_t| - 2S(\mathbf{v}, \tau) - \psi_{1,t-1}$ denotes a difference between the deseasonalized number of balanced trades (between $t - 1$ and t) and their predicted quantity at $t - 1$. Similarly, $\xi_{2,t} = |B_t - S_t| - \psi_{2,t-1} - \alpha \cdot S(\mathbf{v}, \tau)$ denotes a difference between the deseasonalized number of unbalanced trades and their predicted quantity at time $t - 1$. Seasonality (diurnality) factors $S(\mathbf{v}, \tau)$ and $S(\mathbf{v}, \tau)$ for balanced or unbalanced trades are given as the Fourier flexible form (c.f. Andersen, Bollerslev, 1997).

³ The main shortcoming of the EKOP model is a possible misclassification bias (c.f. Boehmer et al., 2007). It happens if the transaction datasets do not allow to directly determine which trade is a buy (has been executed with a market buy order or a marketable limit buy order) and which is a sell (has been executed by a market sell or a marketable limit sell order), and thus different classification algorithms must be applied in order to recover a trade direction indicator. In our study, we directly know which side of the market initiated a trade because we have a necessary buy/sell indicator in the dataset; hence we will not obtain biased results due to a misspecification error.

The ratio of arrival rate of informed trades to an arrival rate of all trades (informed and uninformed) results in the (deseasonalized) probability of informed trading (PIN):

$$PIN_t = \frac{\psi_{2,t}}{\psi_{2,t} + \psi_{1,t}}. \quad (10)$$

Thus, the PIN_t variable is a probability of informed trading that is forecasted for time point t on the basis of balanced trades and the trade imbalance up to this time point. In this setup news may arrive at the intra-daily frequency (at the beginning of each of 15-minute-long intervals). Having forty 15-minute intervals per day (as we use observations from 8:00 to 18:00 CET) we allow for 40 possible changes in the information set each day and for clustering in informed/uninformed trading over time.

Estimation of the seasonality-adjusted EKOP model is performed with the maximum likelihood method. The likelihood function uses the mixture of three two-dimensional Poisson distributions that refer to the arrival of ‘bad news’, ‘no news’ or ‘good news’ to the market (c.f. Easley et al., (2008)). The estimation results of the seasonality-augmented EKOP model for exactly the same empirical data as in this study were presented and discussed by Bień-Barkowska (2013). Because the interpretation of these parameter estimates stays beyond the scope of the current analysis, we refrain from presenting them here. However, we applied these published results to obtain the (deseasonalized) PIN_t series, as given by equation (10).

4. DISCUSSION OF EMPIRICAL RESULTS

We report the logarithmic FIACD model estimates⁴ in Table 1. For all liquidity measures, the fractional differencing parameter estimates are statistically different from zero documenting the long memory effects. The smallest value corresponds to the Amihud (2002) illiquidity measure and the second smallest to the percentage bid-ask spread. Thus, these two variables are the least persistent which stays in line with the autocorrelation graphs in Figure 2. The highest degrees of persistence correspond to the quote slopes and the market depths (especially on the bid side of the market) indicating a long-range impact of individual liquidity shocks. Highest persistence of these liquidity measures that take into account the whole shape of the order book and not its first level only (i.e. most competitive quotes) may be explained by leaving many pending and uncompetitive limit orders in the LOB. The further the distance from the best quotes, where the core of the trading process takes place, the less risky

⁴ All models have been pre-programmed and estimated with the application of the ‘maxlik’ library in the Gauss system (using the BHHH optimization algorithm). In order to ensure smooth convergence, explanatory variables were additionally divided by their standard deviations.

it is to let the behind-the-quote order wait in the LOB. Obviously, such least competitive order will be executed only in the case of huge price swings. Thus, once the limit orders are placed “sufficiently” far away from the best quote, they may be left over in the LOB for a quite long time, which results in a long-range autocorrelation of market depths and quote slope measures. In order to conserve space, we do not present the autocorrelation patterns of ACD residuals here. However, the severe autocorrelation has been reduced radically and the ACF coefficients oscillate around zero. Thus, the strong persistence in liquidity shocks have been satisfactory accommodated by the long memory ACD models.

Table 1.

Estimation results of the fractionally integrated ACD Models for selected liquidity measures. Symbols “*”, “**” and “***” indicate estimates significant at 10%, 5% and 1%, respectively.

	ILLIQ Measure	Percentage Spread	Ask Liquidity Area (5 mln)	Bid Liquidity Area (5 mln)
β_0	-0.0717*	-0.0453	-0.2453***	-0.4075***
β_1	0.7030***	0.6370***	0.7482***	0.3313**
α_1	-0.0442***	-0.1141***	-0.0461**	-0.0712***
d	0.0598***	0.2028***	0.2297***	0.2377***
γ_{TT}	-0.0813***	-0.0520***	-0.0580***	-0.0222***
γ_{vol}	0.0983***	0.0677***	0.0772***	0.0122***
γ_{ret}	0.0002	-0.0001	0.0057***	-0.0013
γ_{PIN}	0.3217***	0.1359***	0.0175**	-0.0106 **
κ	0.8905***	2.6797***	3.0998***	3.0893***
σ^2	0.0721***	0.5258***	0.7285***	0.7143***
$LogL$	-8,080.9	-67,114.4	-39,987.8	-39,979.5
	Ask Depth	Bid Depth	Ask Quote Slope	Bid Quote Slope
β_0	0.1115***	0.0253	0.1217***	0.0701*
β_1	0.2891***	0.3637***	0.2671***	0.3176***
α_1	0.3372***	0.1917***	0.2978***	0.2202***
d	0.3674***	0.5293***	0.4709***	0.5525***
γ_{TT}	0.0090	0.0154**	-0.0192***	-0.0100

Table 1.

	Ask Depth	Bid Depth	Ask Quote Slope	Bid Quote Slope
γ_{vol}	-0.0093***	-0.0089**	0.0059	0.0137***
γ_{ret}	-0.0022***	0.0018***	0.0019***	0.0012*
γ_{PIN}	-0.0682***	0.0060	-0.0494	-0.0174
κ	5.7546***	5.6615***	5.1360***	5.1394***
σ^2	0.9814***	0.9756***	1.0854***	1.1220***
$LogL$	-11,278.9	-7,580.7	-23,265.8	-16,440.5

We see that trading volume is generally positively related to the LOB liquidity supply. Accordingly, we confirm that heavy trading coincidences with smaller price impact of individual trades within the next 15 minutes⁵, tight bid-ask spread, larger market depths, flatter quote slopes and smaller liquidity areas. This finding clearly indicates that increased pace of market orders submissions coincide in time with increased pace of the limit order arrival. Accordingly, during heavy trading periods liquidity providers are also very active. In contrast to this, volatility has a significant negative impact on the LOB liquidity. Observed swings in the mid price enlarge the price impact of individual trades, bid-ask spread, liquidity areas and decrease the quoted depth. Previous empirical research on limit order markets have also shown that the bid-ask spread is inversely related to trading volume and positively related to volatility (cf. Brockman, Chung, (1998); (1999); (2000); and Easley et al., (2008)). Thus, in a volatile market it is more costly to place a limit order because there is an increased probability that such order will be executed with a loss if the price swings abruptly in an undesirable direction (i.e. a so called ‘risk of being picked-off’). Volatility is also a common measure of uncertainty, thus its positive impact on the bid-ask spread might be closely related to increased adverse selection risk and the fear of the winner’s curse. Positive EUR/PLN returns and hence the depreciation of the Polish zloty, are associated with the significant deterioration of quoted liquidity on the ask side of the market (where the limit orders to sell euro against zloty are gathered). Accordingly, market trends are continuously reflected by the shape of the LOB, even beneath the best quotes. Obviously, depreciation of the Polish zloty might be much more risky for the pending limit sell orders than it is for the pending limit buy orders. If the trend persists, than the large upward movement of the EUR/PLN rate will cause the abrupt execution of the stale and mis-priced limit sell orders. This is related to the

⁵ Explanatory variables have been appropriately lagged by one period for the ILLIQ measure.

free market option risk of limit orders and a possible loss due to an unfavorable price change. On the other hand, the only risk of stale limit buy orders boils down to a risk of non-execution. This is probably why the ask side of the market reacts in a much more distinct manner to depreciation of the Polish zloty.

Apart from the impact of the control variables we can see that the PIN variable has a significantly positive impact on the Amihud (2002) illiquidity measure, the percentage bid-ask spread and ask liquidity area. Our empirical results agree with Easley et al. (2008) and confirm that the information-based motives of trading do matter for a bid-ask spread determination. We show that on top of the impact of other control variables, if the disproportion between submitted market buy and sell orders suggests that there is new information then the bid-ask spread widens, each buy or sell transaction induces larger changes in prices and the overall instantaneous liquidity of the market deteriorates. Some interesting conclusions can be formulated with respect to the measures of liquidity provision focused on the one side of the LOB only. Accordingly, having controlled for the factors reflected in transaction intensity and price variation we can see the significant impact of the PIN variable on the ask depth and the ask liquidity area. Therefore, a forecasted increase in the proportion of informed traders in the population of market participants significantly impacts the willingness to provide liquidity to the market. What is most important is that the reactions to information-motivated trading on the ask and on the bid market sides are unsymmetrical. The impact of the PIN variable on the ask depth is significantly negative, hence it deteriorates liquidity, but at the same time it is insignificant for the bid depth, or even significantly negative for the bid liquidity area. This is a very interesting result as it may suggest that the market unequally values investments in the emerging market currency versus the investments in Euro when confronted with incoming information. The drawback of the EKOP model is that it cannot differentiate between forecasts of informed trading evoked by good or bad information. Nevertheless, if the probability of informed trading increases (which could be initiated either by good or bad news), the quantity of limit sell orders (orders to sell EUR and to buy PLN) decreases. Accordingly, bank dealers seem to be reluctant to buy Polish zloty via limit orders. This signals that informed trading is taking place irrespective of whether it was caused by the arrival of good or bad information and thus encourages the commercial banks to secure themselves by purchasing more EUR. So, if the fraction of informed traders seems to rise, the uninformed traders are more reluctant to buy zloty and to sell Euro via limit orders than they are to sell zloty and to buy Euro. Our results point toward the conclusion that EUR seems to be perceived as a 'safer' currency when compared to the Polish zloty. The results show that the notion of 'escape to the Euro' occurs once there are premises of informed trading. It should be remembered, however, that posting limit orders is not necessarily limited to uninformed traders. Bloomfield et al. (2005) evidence that informed traders provide even more liquidity than liquidity traders do themselves. As informed traders have superior information they limit the risk of being 'picked-off'. The dominance of informed traders over the process of

limit order submissions has been also demonstrated in the empirical work of Menkoff et al. (2010) and was devoted to studying the trading of the Russian ruble on the Moscow Interbank Currency Exchange.

5. CONCLUSION

This paper's contribution to the literature on the market microstructure of FX markets is twofold. From the econometrics perspective, we derive distinct patterns of the intraday seasonality in liquidity, whereas the diurnality patterns were additionally adjusted for the day-of-week effect. Accordingly, we show how different measures of liquidity fluctuate in systematic way over the distinct days of week. Moreover, we document long-range autocorrelation in different liquidity measures, which does not die out quickly even after adjustment for the time-of-day and day-of-week effects. Accordingly, we suggest to capture the liquidity dynamics by the long memory ACD models of Jasiak (1998). We evidence strong inertness in liquidity provision, especially beyond the best quotes, i.e. first level of the order book. We observe that the degree of persistence, reflected by the estimate of the fractional differencing parameter, rises with 'distance' from the best quotes. Accordingly, the bid-ask spread is the least persistent whereas market depths or the quote slopes that take into account the whole shape of the limit order book exhibit largest inertness. We also show that liquidity fluctuates in line with time-varying market conditions: trading intensity, volatility, previously observed returns as well as the predicted amount of 'probability of informed trading' reflecting the degree of the information heterogeneity. Interestingly, we also evidence that investment in the Polish zloty as an emerging market currency is treated as more risky in comparison to investment in the Euro, because there is a certain asymmetry in providing liquidity on the ask or bid side of the market once the probability of informed trading increases. Our results may be interesting for the academia, as they document that the currency dealers perform the constant monitoring of time-varying trading conditions and our analysis sheds some light on the process of liquidity supply. Secondly, our findings may be interesting for market participants, since we document how the publicly unobservable liquidity supply beyond the best quotes changes in parallel to the observed market characteristics. Thus, although market participants are restricted to observe the first level of the LOB only, we show what kind of 'liquidity terms' could be awaited besides this most competitive order book level.

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OPIS DYNAMIKI MIAR PŁYNNOŚCI NA KIEROWANYM ZLECENIAMI
KASOWYM RYNKU WALUTOWYM

Streszczenie

Przedmiotem artykułu jest badanie dynamiki wybranych miar płynności systemu transakcyjnego Reuters Dealing 3000 Spot Matching, który jest głównym, kierowanym zleceniami, międzybankowym rynkiem kasowej wymiany walutowej dla pary EUR/PLN. W artykule przedstawiono schemat wewnątrz-dziennej i wewnątrztygodniowej sezonowości dla różnych miar płynności rynku obrazujących kształt arkusza zleceń. Do opisu dużej persystencji płynności wykorzystano modele Autoregresyjnego Warunkowego Czasu Trwania (Autoregressive Conditional Duration, ACD) z długą pamięcią. Szczególną uwagę poświęcono oddziaływaniu napływu nowej informacji na wahania płynności. Wykazano statystycznie istotny dodatni wpływ prawdopodobieństwa zawierania transakcji na podstawie prywatnej informacji (PIN) na wielkość zmiany ceny wywołaną pojedynczą transakcją i na wielkość spreadu bid-ask, a także ujemny wpływ na podaż płynności po stronie ask rynku (zlecenia sprzedaży euro). W badaniu uwzględniono również wpływ innych zmiennych kontrolnych, takich jak wolumen transakcji, zmienność i opóźnione stopy zwrotu.

Słowa kluczowe: mikrostruktura rynku, rynek kierowany zleceniami, prawdopodobieństwo zawierania transakcji na podstawie prywatnej informacji, modele ACD

EXPLAINING LIQUIDITY DYNAMICS IN THE ORDER DRIVEN FX SPOT MARKET

Abstract

The paper investigates the dynamics of several intraday liquidity measures for the Reuters Dealing 3000 Spot Matching System that constitutes a major order driven interbank spot market for the EUR/PLN. We derive the time-of-day and the day-of-week effects for different liquidity variables representing the shape of the limit order book. In order to capture the strong persistence exhibited by liquidity, the long memory Autoregressive Conditional Duration (ACD) models are applied. Special attention is paid to the impact of information arrival on liquidity fluctuations. We document the significant positive impact of probability of informed trading (PIN) on the price impact of trading and the bid-ask spread and the negative impact of the PIN on the liquidity supply on the ask side of the market (orders to sell euro), after controlling for the effects of other covariates such as the trading volume, volatility or previously observed returns.

Keywords: market microstructure, order-driven market, probability of informed trading, ACD models

