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Informed and Uninformed Trading in the EUR/PLN Spot Market *

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Discussion Paper

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Abstract

This paper examines an intraday activity of bank trading of the EUR/PLN currency pair via the Reuters Dealing 3000 Spot Matching System in 2007. On the grounds of the *sequential trade model* of Easley, Engle, O'Hara & Wu (2008), we can differentiate between the time-varying patterns for the strategic behavior of informed and uninformed (liquidity) traders. We present evidence for the particular hour-of-day seasonality pattern that characterizes the arrival of uninformed and informed trades. The conditional arrival rates for both trader categories enable the assessment of their interactions and are used to forecast a time-varying probability of informed trading (PIN). The predictions of PIN are used to test the impact of information heterogeneity on the instantaneous liquidity of the market, which is proxied by the bid-ask spread and the market depth.

JEL classification: F31, G15

Keywords: probability of informed trading, dynamic EKOP model, intraday liquidity modeling

1 Introduction

The role of information and the impact of 'news' on the strategic behavior of market participants has been a key-stone in the development of market microstructure models for over thirty years. The precondition of information heterogeneity between market participants dates back to the theoretical information models of Bagehot (1971), Glosten & Milgrom (1985) and Easley & O'Hara (1987). In all these models, market makers learn the fundamental value of an asset via a scenario of orders submitted by traders. Especially during the last two decades, the assumption of information discrepancy among market participants mirrored itself in the widely cited concept of order flow. It is nowadays recognized as one of the most crucial variables for the market microstructure models of FX trading. The concept of order flow seems to build a bridge between the pure theoretical framework of microstructural information models and the practical puzzles as well as enquiries concerning a short-term description of the exchange rate dynamics, e.g. Evans & Lyons (2002a); Evans & Lyons (2002b). The precondition of information asymmetries, which is crucial for functioning of FX markets, have been evidenced and discussed in Evans & Lyons (2007), Bjonnes, Osler & Rime (2008), Rime, Sarno & Sojli (2010), Menkoff, Osler & Schmeling (2010), among others.

Orders which arrive to the market can give an insight into the trading intentions of market participants - their expectations and preferences. Pieces of information that are asymmetrically dispersed among market participants can be therefore finally reflected in currency prices. Order flow, defined as the difference between the number (or volume) of buyer-initiated and seller-initiated transactions can, therefore, be perceived as a measure of 'backed-by-money expectations' (see Lyons (1995)). Recent research studies have provided a clear evidence of a significant impact that order flow has on the FX rate changes for major currency pairs, such as the USD/EUR, GBP/EUR and JPY/USD (e.g. Payne (2003); Breedon & Vitale (2010); Rime et al. (2010)) as well as for some emerging market currency pairs. In the study of Scalia (2008) for the CZK/EUR market, a significant impact of order flow on FX returns rises with the news of central bank interventions; whereas the study of Frömmel, Kiss & Pintér (2010) about HUF/EUR interbank trading proves that order flow can work as an important transmission channel between macroeconomic announcements or central bank communication and currency prices.

The application of order flow and its unique power for the explanation, or even prediction of the FX rate movements, has been paralleled by the development of market microstructure literature on stock markets. Introduction of the sequential trade models has contributed to numerous research studies on unveiling information possessed by some

market participants through the composition or timing of submitted orders, e.g. Easley, Kiefer, O'Hara & Paperman (1996); Easley et al. (2008). The theoretical framework of these sequential trade models stems from the theory of microstructural information models. In short, under such a modeling framework, one assumes that the reasons for trading can be twofold: (1) access to private information (2) satisfying liquidity needs or portfolio rebalancing. Therefore, as this trading process further unfolds, the act of trading can take place in order to exploit the information signals (informed trading) or to satisfy liquidity reasons (uninformed trading). Hence, the sequential trade models describe the trading process as a game between three economic agents: risk-neutral market maker (providing liquidity to the market) as well as informed and uninformed traders. Market makers act in an environment full of uncertainty with respect to a set of information possessed by their transaction counterparties. Moreover, sequential trade models are often 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 an access to private information. Easley, Kiefer, O'Hara & Paperman (1996) proposed one of the first econometric parametrizations of a sequential trade model, henceforth known as the EKOP model. The easiness of its empirical application encouraged numerous studies which review the microstructure of stock markets – especially on stock splits (Easley, O'Hara & Saar (2001)), stock market efficiency (Vega (2006)), on the impact of macro or corporate news announcements on the market (Benos & Johec (2007)), impact of corporate ownership on informed trading (Reza & Wilson (2007)) as well as the fluctuation of selected market liquidity measures (Easley et al. (1996); Brockman & Chung (2000); Easley et al. (2008)). The EKOP model has also been applied in the empirical studies of FX trading by Gençay, Gradojevic & Selçuk (2007) and Gençay & Gradojevic (2008). The first paper examines the trading process on the OANDA FXTrade internet trading platform (electronic market making system), whereas the latter studies EUR/USD interbank trading via the EBS system (Electronic Brokerage Services). In both studies, the authors document the strategic concentration of informed trading on selected days of the week as well as on selected hours of the day.

This paper presents a market microstructure study of the interbank trading of the EUR/PLN currency pair via the Reuters Dealing 3000 Spot Matching System. To our knowledge, this is the first high-frequency study in which the liquidity of the interbank market of the Polish Zloty is being analyzed. The aim of the paper is to present time-varying patterns for the strategic behavior of informed and uninformed traders. We are also contributing to literature on emerging FX markets, which is still very scarce, by analyzing the effect of informed trading on market liquidity. In the first step, we apply the time-varying EKOP model of Easley et al. (2008) in order to describe the process of order submission. With

the application of such a modeling strategy on an intraday basis, we can account for the particular time-varying patterns governing the particular parameters of the EKOP model. The evidence of such an intraday seasonality allows us to deduce the particular strategic behavioral scenarios for informed and uninformed traders. Moreover, dynamic models for the time-varying arrival rates allows us to discover interactions between both types of traders. Moreover, the EKOP model estimates allow us to investigate how the probability of informed trading - which is proxied by the PIN variable - influences selected market features. As forecasted by a work of literature on that topic, e.g. Brockman & Chung (1999); (2000); (2003); Easley et al. (2008); Wong, Tan & Tian (2009); we consider the impact of informed trading on intraday liquidity: the bid-ask spread and the bid and ask depth. Accordingly, we are able to assess how the continually changing 'information state' of the EUR/PLN market impacts the behavior of FX dealers and as a result, how it changes the liquidity of the market.

This paper is structured as follows: In section 2, we describe the interbank EUR/PLN spot market, the trade & order datasets obtained from the Reuters Dealing 3000 Spot Matching System as well as some descriptive statistics for the data aggregated to 15-minute intervals. In Section 3, we present the construction of the EKOP model as well as its refinement used in the empirical analysis. The estimation results of the dynamic EKOP model and its interpretation are presented in Section 4. In Section 5, we test the impact of probability of informed trading on the bid-ask spread and the bid (ask) market depth and volatility. In conclusion, Section 7 sums up the results of the analysis.

2 Market and Data

The FX market of the Polish Zloty is the most liquid among all the currency markets of the Central European emerging economies. According to the survey of the FX market activity conducted by the Bank for International Settlements BIS (2007), the average daily turnover in interbank spot transactions amounted to 4,851 million USD in April 2007. This market is, therefore, nearly two times bigger than the spot market for the Hungarian Forint (where the average daily turnover amounted to 2,959 million USD in April 2007) and about three times more liquid than the market for the Czech Koruna (1,630 million USD). Spot transactions (mainly large ones) can be executed on the OTC market with the application of the Reuters Dealing Direct system, via a voice broker or by telephone. Trades that are rather small in volume (1-5 million EUR) are usually conducted via the Reuters Dealing 3000 Spot Matching System. It is a very liquid and transparent electronic

brokerage system, operating as an order-driven market that can automatically match incoming buy and sell orders, once their prices agree. FX dealers can submit either limit or market orders. Market orders are perceived as liquidity-consuming and aggressive, since they are more immediately executed against most competitive limit orders in the order book. It is estimated that trading via the Reuters Dealing 3000 Spot Matching System accounted for over 40 % of all interbank spot transactions with the Polish Zloty in 2007. Thus, assuming no arbitrage opportunities, this system can be perceived as a representative sample of the interbank activity with respect to Polish Zloty trading.

The datasets used in this study are comprised of all incoming orders and transactions conducted in the entire year of 2007 with the EUR/PLN currency pair via the Reuters Dealing 3000 Spot Matching System. The EUR/PLN exchange rate is quoted as a quantity of Zlotys per one Euro. During the whole year of 2007, the Zloty followed an appreciating trend towards Euro. At the beginning of this period, the Zloty was traded at about 3.83 and during the year under study, the exchange rate fell to 3.61. Since Poland's accession to the EU in May 2004, the EUR/PLN has played a role as the most dominant currency pair in the Polish economy. Trading of the Polish Zloty takes place on offshore markets (i.e. mainly between London banks) as well as in Poland. The datasets cover both of these trading venues. Every transaction is marked with date, exact time, rate and quantity in millions of EUR as well as with a buy/sell indicator. Every order includes an exact date and time of submission as well as execution/cancellation, a firm quote, a size and an indicator for the market side of a quote. The detailed structure of the datasets makes it possible to rebuild the whole order book in each moment of the market activity.

Although trading on the interbank market can potentially take place within 24 hours a day on 7 days a week, it is heavily concentrated on working days from 8.00 to 18.00 Central European Time (GMT+1, with Daylight Saving Time). In order to limit the undesired impact of periods when trading was particularly thin, we exclude observations registered on weekends and on working days between 18.00 p.m. and 8.00 a.m. CET. We also omit days with exceptionally low liquidity due to national holidays. As a result, our sample covers 250 trading days with the data aggregated in 15-minute intervals. The data frequency is chosen as a compromise between the need of observing the intraday instantaneous fluctuation of selected market characteristics and the necessity of avoiding distorted results due to intervals with only a few or even no observations. We identify the following variables:

- Trade imbalance (unbalanced trades) – defined as the absolute difference between the number of all buys (B_t) and sells (S_t), executed between the moments t and

$$t - 1, |B_t - S_t|;$$

- Balanced trades – defined as the difference between the total number of trades, TT_t and the trade imbalance between the moments t and $t - 1$, $TT_t - |B_t - S_t|$;
- Percentage bid-ask spread – defined as the ratio of the difference between the best ask and the bid quote prevailing in the system at time t , and the corresponding mid price, $S_t = \frac{P_t^A - P_t^B}{P_t^m} \cdot 10^4$ (in basis points);
- Market depth on the bid side (ask side)– defined as the quantity of all limit buy (sell) orders in the system order book at time t , D_t^b (D_t^a), in millions of EUR.

The first two variables will be used for the estimation of probability of informed trading and measure market activity. The balanced trades potentially reflect liquidity motivated trading, whereas trade imbalances serve as a preliminary and quite crude measure of trades initiated by an arrival of information signals to the market. The bid-ask spread and the bid-ask depth are chosen as selected market liquidity measures. We defined the bid-ask spread as a percentage of the mid price in order to avoid variations of the variable that can be attributed only to the differences in the EUR/PLN exchange rate level in 2007.

variable	mean	st.dev.	ACF(1)	LB(5) (p-value)	LB(10) (p-value)
balanced trades	12.987	14.266	0.454	4,216.510 (0.000)	4,841.177 (0.000)
unbalanced trades	6.550	6.941	0.164	631.625 (0.000)	792.687 (0.000)
bid-ask spread	3.326	2.473	0.291	2,053.302 (0.000)	2,150.882 (0.000)
ask depth	29.640	17.902	0.822	22,273.959 (0.000)	32,711.186 (0.000)
bid depth	37.226	34.107	0.873	28,536.899 (0.000)	44,972.336 (0.000)

Table 1: Descriptive statistics of variables aggregated in 15 minute intervals. LB(k) denotes Ljung-Box test statistics for autocorrelation, where k is a lag number.

Table 1 presents the descriptive statistics of the obtained time series. We see that the average number of balanced trades (12.99) is nearly twice as large as the value of trade imbalance (6.55) observed during 15-minute-long time spells. Both variables are also slightly overdispersed, as their standard deviations are larger than their means. However, the most striking feature of all the variables is the significant autocorrelation pattern, which should justify the application of the dynamic EKOP model of Easley et al. (2008). In this model the forecasted arrival rates of informed and uninformed trades can be crosscorrelated and depend on the fluctuation of their values in the past.

Large values of ACF(1) coefficients and a slowly decaying autocorrelation function for financial variables which are measured at intraday frequencies have been evidenced by numerous empirical studies in the field of market microstructure (e.g. Manganello (2005); Nolte (2008)). Strong autocorrelation of the variables presented in table 1 will, at a later stage, require adapting an adequate dynamic specification for the econometric models that could satisfactorily describe such clustering effects. To some extent, this autocorrelation can be attributed to the repetitive and deterministic pattern of intraday fluctuations in market activity, referred to as a diurnality pattern or intraday seasonality pattern (e.g. McNish & Wood (1992); Brockman & Chung (1998); Tsay (2005); Heflin, Shaw & Wild (2007)). Diurnality patterns of the percentage bid-ask spread and the joint bid and ask market depth have been depicted in figure 1¹. As it could be anticipated, the widest bid-ask spread can be observed in periods when trading is rather scarce, especially mornings and late afternoons. Two local minima of the seasonality function refer exactly to the highest trading intensity periods during the day – at about 11.00 CET and 15.00 CET. In an overnight period, when the two major headquarters of the Polish Zloty trading are closed, the bid ask spread is wider. This result is in line with many empirical studies on stock markets, which report U-shaped or inverse J-shaped curve for the intraday seasonality of the bid-ask spread (e.g. Brockman & Chung (1998), Nyholm (2002), Nyholm (2003), Ahn, Cai, Hamao & Ho (2002), Giot & Grammig (2006) Heflin et al. (2007)). Intraday seasonality of the market depth is generally inversely related to the one of the bid-ask spread (apart from the morning hours). The market is generally thin overnight, when there are much fewer limit orders posted in the system. It should be noted, that the inverse U-shaped curve for an intraday seasonality of market depth has also been reported in studies (Brockman & Chung (1999)).

¹Intraday seasonality patterns are computed by a kernel regressions of the percentage bid-ask spread or the market depth on a time of a day (cumulative number of seconds from midnight every day). This way of deriving the intraday seasonality pattern has been proposed in Bauwens & Veredas (2004). We used quartic kernel with an optimal bandwidth equal to $2.78sN^{-\frac{1}{5}}$, where s is the standard deviation of the data and N the number of observations.

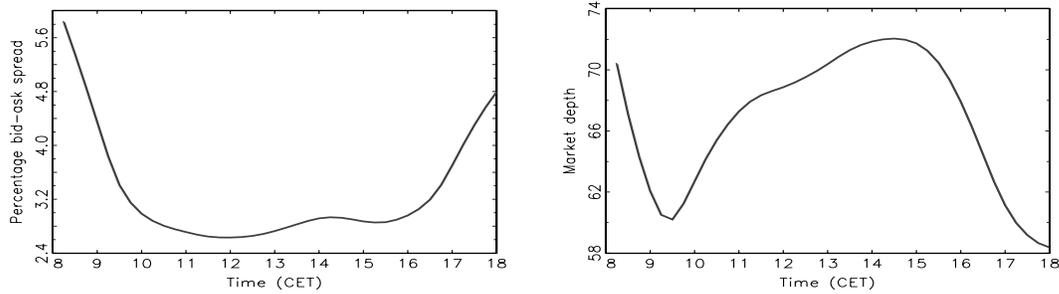


Figure 1: Intraday seasonality patterns for the percentage bid-ask spread (in basis points) – left panel and the market depth (in mln EUR) – right panel.

Assuming that the trading activity patterns of informed/uninformed market participants can also be (partially) explained by such a repetitive intraday diurnality, we aim to augment the dynamic version of the EKOP model of Easley et al. (2008) in order to allow for such a deterministic scenario of traders’ behavior.

3 EKOP Model

In order to deduce some strategic time-varying patterns that govern the behavior of informed and uninformed traders, we apply the dynamic version of the EKOP model (see Easley et al. (2008)). In a shortcut, in the standard version of the EKOP model (see Easley et al. (1996)), all the transactions can be initiated by traders from the bid and ask quotes posted by a single market maker. Numbers of buy and sell transactions are independently Poisson-distributed and their daily arrival rates are $\lambda_{B,t}$ and $\lambda_{S,t}$, respectively. Thus, the model assumes no interdependence between both transaction types. The buy and sell transactions may result from the actions of both informed and uninformed traders. Every day, the informed traders may initiate transactions with the constant arrival rate μ , whereas uninformed – with the constant arrival rate ε .

A diagram of the EKOP model is depicted in figure 2. At the beginning of each trading day, there is an information event with a probability α , or there is no information event with a probability $1 - \alpha$. If the information event occurs, it can be either “bad information” (also described as a “low signal”) with a probability δ or it may be “good information” (“high signal”) with a probability $1 - \delta$. Regardless of whether information arrives or not, uninformed traders always carry out their buy and sell transactions with the expected values of $\lambda_B = \varepsilon$ and $\lambda_S = \varepsilon$, respectively. The behavior of informed traders is different; once they receive information, they want to make use of it and they enter the market. The model assumes that the informed traders are risk-neutral and compet-

itive. On days with bad information, informed traders submit market sell orders (i.e. orders that are immediately executed at the prevailing bid quotes), so they initiate sell transactions because it maximizes their profit. Similarly, on days with good information, they submit market buy orders that result in additional buy transactions. As the arrival rate of informed trades is Poisson distributed, on the low-signal days the buy transactions come only from uninformed traders and occur with an arrival rate $\lambda_B = \varepsilon$; whereas sell transactions, coming from both informed and uninformed market participants, occur with arrival rate $\lambda_S = \mu + \varepsilon$. Similarly, on high-signal days, buy transactions are initiated both by informed and uninformed traders and take place with an arrival rate $\lambda_B = \mu + \varepsilon$, but the sell transactions come only from the uninformed traders with an arrival rate $\lambda_S = \varepsilon$. In the model, the informed traders acknowledge the fundamental value of the financial instrument by observing information signals. If the information is low, they see that the actual price of the asset is overvalued and should fall; whereas if the information is high, they know that the prevailing price is undervalued and should rise. At the end of the day, all the information is eventually impounded into price which converges to the fundamental value of a security.

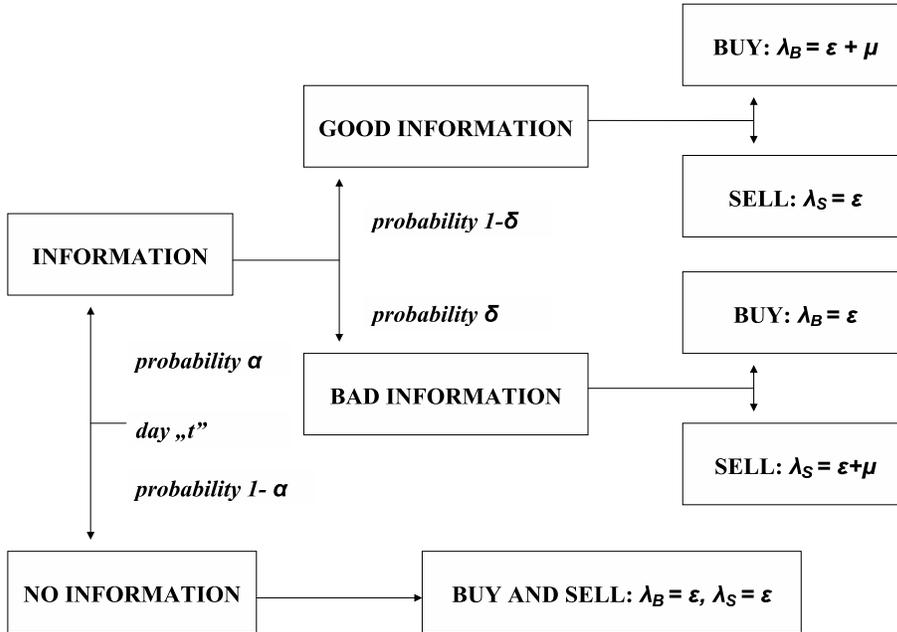


Figure 2: Diagram of the EKOP model.

The market maker cannot observe directly, whether the news arrives to the market or not. He is Bayesian learner and updates his quotes conditionally on the history of submitted buy and sell orders. Hence the price of a security is based on a market maker information set at a particular moment. The market maker quotes ask and bid prices in a way that

protects him from losses incurred due to informed traders, so the bid-ask spread at the market arises solely due to adverse selection protection, for the purpose of mitigating his risks.

In the EKOP model, there are four parameters that fully describe the bivariate distribution of buy and sell transactions at a particular trading period t : α , δ , ε and μ . Let's denote the number of buy (sell) transactions at the day t by B_t and S_t , respectively. From diagram 1 we see that the joint bivariate probability distribution for the buy and sell trades can be given as the mixture:

$$\begin{aligned} P(B_t = b_t, S_t = s_t) &= \alpha(1 - \delta)P_{POI}(z_t, s_t; \varepsilon + \mu, \varepsilon) \\ &+ \alpha\delta P_{POI}(b_t, s_t; \varepsilon, \varepsilon + \mu) \\ &+ (1 - \alpha)P_{POI}(b_t, s_t; \varepsilon, \varepsilon) \end{aligned} \quad (1)$$

where $P_{POI}(b_t, s_t, \lambda_B, \lambda_S)$ denotes joint bivariate distribution of buy and sell transactions with arrival rates: $\lambda_B \in \{\varepsilon + \mu, \varepsilon\}$ and $\lambda_S \in \{\varepsilon, \varepsilon + \mu\}$.

The expected number of informed trades can be derived from equation (1) as $\alpha\delta\mu + \alpha(1 - \delta)\mu = \alpha\mu$ and the total number of trades is: $(1 - \alpha)2\varepsilon + \alpha\delta(2\varepsilon + \mu) + \alpha(1 - \delta)(2\varepsilon + \mu) = \alpha\mu + 2\varepsilon$. The ratio of both of these quantities gives a fraction of informed trades, known also as the probability of informed trading (PIN):

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \quad (2)$$

The initial formulation of the EKOP model is just assumed “to work” and “to fit” the data. Another strand of literature on sequential trade models proposes contributions that refine the model in order to describe the trading process more adequately. The main shortcomings of the EKOP model formulated in this work of literature are: (1) a misclassification bias, (2) a lack of fit and (3) a specification of the information process (see Kokot (2004)). The EKOP model is estimated with the data on numbers of buy and sell transactions within a certain time interval. A misclassification bias arises if the transaction datasets do not contain such information and the classification algorithms must be applied in order to recover an indicator of the trade direction. The most widely-applied algorithm of Lee & Ready (1991) is shown to result in biased estimates of the EKOP model which lead to a systematic distortion of the PIN measure (see Boehmer, Grammig & Theissen (2007)). In our application of the EKOP model to EUR/PLN data, we originally know which side of the market initiated a transaction; because for each case of such an event, we have a buy/sell indicator in the datasets. Thus, we will not obtain biased results due to such a misspecification error. A lack of fit of the EKOP model may arise due to the misspecification of the distribution used for modelling the trade numbers. The last misconception of

the EKOP modelling framework seems to be the assumption that information arrives to the market on a daily basis. According to Easley et al. (1996), there is only one change in the information set of the traders per day. Furthermore, the probability of an information signal arrival is the same during subsequent time intervals, which contradicts the empirical findings on the market behavior, where good or bad news can arrive over a sequence of days. In order to limit this shortcoming, similarly as in Gençay et al. (2007) and Gençay & Gradojevic (2008), we use datasets aggregated on an intraday level. In our setup, the arrival of news may happen at the beginning of each of the defined 15-minute-long time periods. 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 per day. Such a scenario seems much more flexible as it can adjust to changing market conditions more adequately.

The standard version of the EKOP model does not allow parameters and PIN measure to vary. As the assumption seems quite restrictive, Easley et al. (2008) proposed the dynamic specification of the EKOP model in which the arrival rates of uninformed and informed trades follow an autoregressive moving average process. The motivation for such a refinement stems from the belief that the traders themselves observe the order flow scenario and on the grounds of orders composition embark on their trading. In this framework, the arrival parameters ε and μ are updated every day, based on the observed values of buy and sell trades from the previous periods. There is some additional methodological groundwork that underlies this conception. The benchmark model assumes that the number of trades is informative in regard to the arrival rate of uninformed and informed traders. As shown in Easley et al. (2008), the total number of trades per day $TT = B + S$ and the order flow calculated for number of trades $B - S$ have following expected values:

$$E(TT) = \alpha(1 - \delta)(2\varepsilon + \mu) + \alpha\delta(2\varepsilon + \mu) + (1 - \alpha)2\varepsilon = \alpha\mu + 2\varepsilon \quad (3)$$

and

$$E(B - S) = \alpha\mu(1 - 2\delta) \quad (4)$$

The idea of the dynamic observation-driven EKOP specification of Easley et al. (2008) is to model the absolute value of the order flow directly. As the expectation of absolute differences of Poisson variables is approximately equal to $E(|B - S|) = \alpha\mu$, they propose to build the time-varying specification of two components of the TT : (1) the trade imbalance: $E(|B - S|) = \alpha\mu$, and (2) the number of balanced trades: $E(TT - |B - S|) = 2\varepsilon$.

Easley et al. (2008) denote a vector of both arrival rates by $\Psi = [2\varepsilon, \alpha\mu]$ and propose the

dynamic specification:

$$\Psi_t = \omega + \Phi\Psi_{t-1} + \Gamma Z_{t-1} \quad (5)$$

where $Z_t = [TT_t - |B_t - S_t|, |B_t - S_t|]$.

Therefore, in a very close analogy to standard volatility specifications described by GARCH models, there is an autoregressive and an innovation term which drives the arrival rates of uninformed and informed traders. In accordance to GARCH models, the dynamic arrival rates can be transformed to the ARMA specification:

$$\Psi_t = \omega + \Phi^*\Psi_{t-1} + \Gamma\xi_{t-1} \quad (6)$$

where $\xi_t = Z_t - \Psi_t$ is a martingale difference, an innovation which mirrors the unexpected arrivals of uninformed and informed trades between $t - 1$ and t .

In the standard static version of the EKOP model, it is not possible to account for fluctuations of the probability of informed trading (PIN coefficient). As previously mentioned, it may contradict the real scenario of market activity, where the inflow of new information usually clusters and so do the market participants who can make speculative gains out of different pieces of information that they know. Once we obtain time-varying estimates for model parameters, we can easily calculate the corresponding PIN values. The pattern of the changing market information regime, reflected by the behavior of different market participants could be used to explain the fluctuations of different market liquidity measures: the percentage bid-ask spread and the depth of the market.

Application of the dynamic EKOP model to our data is inspired by the studies of Gençay et al. (2007) and Gençay & Gradojevic (2008). In both these studies, the standard static version of the EKOP model of Easley et al. (1996) was reestimated for each day of the period under study in order to achieve time-varying parameters. We decided to use dynamic version of the model since it enables us to make use of the whole data sample, thus making estimates more precise. Second, it allows the model parameters to vary on an intraday basis and not only on a day-by-day basis so we are able to describe intraday fluctuation in arrival rates of informed and uninformed trades and to deduct the interdependencies between them. The FX market is very often perceived as a convincing example of an efficient market and the process of price changes reflecting newly incoming information should be extremely rapid. Therefore we anticipate that suitable adjustments in market participants' behavior must also be very prompt. The interdependencies between the informed and uninformed traders can be much more pronounced on an intraday basis. Third, the time-varying PIN measures allows us to verify how important the uncertainty

and traders' risk aversion are in predicting market liquidity.

We adapted the dynamic version of the EKOP model by Easley et al. (2008) with a slight modification. We introduced two intraday seasonality factors $S(\nu, \tau_t)$ and $S(v, \tau_t)$ as the Fourier flexible forms (FFF). Our intention is to add a diurnal pattern as an additional driving force of the ε_t and μ_t dynamics. Hence, we could account for the deterministic factor in the repetitive day-by-day fluctuations of uninformed and informed trading. Our seasonality factors correspond to parameters ε_t and μ_t and are introduced in an additive way. Thus, the VARMA specification of the model given by equation (5) refers to a *de facto* deseasonalized process of the balanced trades and the trade imbalance. Such an ‘‘augmented’’ specification is as follows:

$$\begin{aligned}\psi_{1,t} &= \omega_1 + \phi_{11}^* \psi_{1,t-1} + \phi_{12}^* \psi_{2,t-1} + \gamma_{11} \xi_{1,t} + \gamma_{12} \xi_{2,t} \\ \psi_{2,t} &= \omega_2 + \phi_{21}^* \psi_{1,t-1} + \phi_{22}^* \psi_{2,t-1} + \gamma_{21} \xi_{1,t} + \gamma_{22} \xi_{2,t}\end{aligned}\quad (7)$$

where the innovations are defined in the following way:

$\xi_{1,t} = TT_t - |B_t - S_t| - \Psi_{1,t-1} - 2S(\nu, \tau_t)$ and $\xi_{2,t} = |B_t - S_t| - \Psi_{2,t-1} - \alpha \cdot S(v, \tau_t)$ and the flexible Fourier forms are:

$$S(\nu, \tau_t) = \nu_0 \cdot \tau_t + \sum_{l=1}^2 \nu_{2l-1} \cdot \sin[2\pi(2l-1)\tau_t] + \nu_{2l} \cdot \cos[2\pi(2l)\tau_t] \quad (8)$$

$$S(v, \tau_t) = v_0 \cdot \tau_t + \sum_{l=1}^2 v_{2l-1} \cdot \sin[2\pi(2l-1)\tau_t] + v_{2l} \cdot \cos[2\pi(2l)\tau_t] \quad (9)$$

The corresponding likelihood function has the following form:

$$\begin{aligned}L(\Theta) &= \prod_{t=1}^T [\alpha(1-\delta)e^{-(\mu_t^* + 2\varepsilon_t^*)} \frac{(\mu_t^* + \varepsilon_t^*)^{B_t} (\varepsilon_t^*)^{S_t}}{B_t! S_t!} \\ &+ \alpha\delta e^{-(\mu_t^* + 2\varepsilon_t^*)} \frac{(\mu_t^* + \varepsilon_t^*)^{S_t} (\varepsilon_t^*)^{B_t}}{B_t! S_t!} \\ &+ (1-\alpha)e^{-(2\varepsilon_t^*)} \frac{(\varepsilon_t^*)^{B_t + S_t}}{B_t! S_t!}] \end{aligned}\quad (10)$$

where $\varepsilon_t^* = \varepsilon_{t-1} + S(\nu, \tau_t)$ and $\mu_t^* = \mu_{t-1} + S(v, \tau_t)$.

Therefore, the awaited arrival rates of uninformed trades $2\varepsilon_t^*$ and informed trades $\alpha\mu_t^*$ are modelled as the sum of two two components: the whole history of balanced and unbalanced trades (composition of buy and sell trades from the past, i.e. up to time point $t-1$) which is reflected in dynamic model (7), and the seasonality factors given by equations

(8) and (9).

As in Easley et al. (2008), from the probability function (10) the corresponding log likelihood function can be derived as:

$$\begin{aligned} \text{Log}L(\Theta) &= \sum_{t=1}^T [-2\varepsilon_t^* + (B_t + S_t)\ln(\mu_t^* + \varepsilon_t^*)] \\ &+ \sum_{t=1}^T \ln[\alpha(1 - \delta)e^{-\mu_t}x_t^{S_t} + \alpha\delta e^{-\mu_t}x_t^{B_t} + (1 - \alpha)x_t^{B_t+S_t}] - \ln[B_t!S_t!] \end{aligned} \quad (11)$$

with $x_t = \varepsilon_t^*/(\mu_t^* + \varepsilon_t^*) \in [0, 1]$. For model estimation, last term $-\ln[B_t!S_t!]$ can be omitted, because it does not vary with model parameters.

The estimates of the model are reported in Table 2. As $\hat{\alpha} = 0.33$, there is a 33% probability that at the beginning of each 15-minute-long time period new information arrives. The value is comparatively smaller than the alpha coefficients of over 40% obtained for the capital market in Easley et al. (2008). Once news arrives it is bad for the EUR (good for the Polish Zloty) with the probability of $\hat{\delta} = 0.48$. As this probability is nearly equal to 0.5, the expectation of the trade imbalance can indeed be well described by the formula (4). The autoregressive matrix Φ^* measures how the current forecasts of uninformed or informed trades are correlated with their previous forecasts, hence it is responsible for the persistency of the arrival rates. All its elements are significantly different from zero, which indicates that the both trader categories interact with each other. As denoted in Easley et al. (2008), if the vector process is stationary, under a linear approximation both eigenvalues of the $\hat{\Phi}^*$ matrix should be less than one. The first eigenvalue of the $\hat{\Phi}^*$ matrix is equal to 0.93 and the second to 0.49, so the system is quite persistent. The diagonal elements of the matrix inform how the awaited rate of the uninformed (informed) trades' arrival depend on its lagged forecasts (lagged awaited rates of uninformed (informed) trades occurrence). The coefficients $\hat{\phi}_{11}^* = 1.20$ and $\hat{\phi}_{22}^* = 0.22$ provide clear evidence of the herding behavior of both types of traders, however the evidence for such a trend following strategy is much more pronounced for the uninformed traders. It must be mentioned that quite similar findings were reported in Easley et al. (2008). The off-diagonal elements of the $\hat{\Phi}^*$ inform how the current forecast of the uninformed (informed) trades' arrival rate is crosscorrelated with the lagged forecasts of informed (uninformed) trades' arrival rates. Thus, it is responsible for interactions between both traders' categories. The fact that $\hat{\phi}_{12}^* = -2.24$ evidences that once there are signals for the informed trading, the amount of transactions executed by uninformed traders significantly declines. Such an interesting result, evidenced also in Easley et al. (2008) can be concluded with a statement that the liquidity traders are very reluctant to submit market orders when the anticipated

probability of informed trading is high and the adverse selection costs increase. Quite opposite conclusions can be drawn from an obtained estimate $\hat{\phi}_{21}^* = 0.08$. The positive coefficient, although small in value, informs that the informed traders prefer to trade in conditions when the trading intensity is generally high. Such a result supports the Admati & Pfleiderer (1988) theoretical model, according to which it is more profitable for informed traders to trade when there are many uninformed traders who do not know the same information as the informed traders do.

The Γ matrix captures the instantaneous impact of the innovations $\xi_{1,t}$ and $\xi_{2,t}$ on predicted rates of the uninformed and informed traders' arrival. As in Easley et al. (2008), the obtained estimates of all elements of the matrix are positive and statistically significant, which indicates that an unpredicted surplus or deficit in quantity of uninformed and informed trades has a significant impact on the forecasted rate of their occurrence. The coefficients $\hat{\gamma}_{11}$ and $\hat{\gamma}_{12}$ are much bigger in value than $\hat{\gamma}_{21}$ and $\hat{\gamma}_{22}$, signalling that innovations to balanced and unbalanced trades have a much more impact on the rate of uninformed trades' arrival than on the forecasted trade imbalance. Thus, as Easley et al. (2008) state, there are fewer premises for the forecastability of informed trading. The obtained relation of $\hat{\gamma}_{11} < \hat{\gamma}_{12}$ is quite unexpected, because it means that the shock to balanced trades has a lower impact on the arrival rate of uninformed traders than the innovation to unbalanced trades has. Therefore, the expected number of balanced trades increases more sharply as a result of an unexpected shock in the number of informed trades. It may be because such initial 'hot-potato' trades induce in the following couple of minutes a wave of trades in which banks rebalance their portfolio inventories with a repeated passing of their portfolio imbalances (see Lyons (1997)). The relation $\hat{\gamma}_{21} < \hat{\gamma}_{22}$ is not counterintuitive, meaning that shocks to balanced trades have a rather small impact on the behavior of informed traders. As opposed to this, the unexpected number of unbalanced trades induces much more of them, which is in line with the effect of herding behavior.

parameters	estimates	st.err.	parameters	estimates	st.err.
ω_1	5.7358	0.4794	ω_2	1.7048	0.0983
ϕ_{11}^*	1.2018	0.0571	ϕ_{21}^*	0.0853	0.0236
ϕ_{12}^*	-2.2412	0.0638	ϕ_{22}^*	0.2230	0.0692
γ_{11}	0.2825	0.0150	γ_{21}	0.0853	0.0236
γ_{12}	0.3771	0.0213	γ_{22}	0.2230	0.0692
ν_0	1.0549	0.1475	ν_0	9.5008	0.6628
ν_1	-0.6543	0.1243	ν_1	-0.4071	0.3508
ν_2	-2.0839	0.1155	ν_2	-0.8716	0.3432
ν_3	-0.3727	0.1784	ν_3	1.6753	0.4991
ν_4	0.2424	0.1297	ν_4	2.3669	0.4613
α	0.3318	0.0074	δ	0.4812	0.0097
<i>LogL</i>	291,553.392				
<i>BIC</i>	29.1354				

Table 2: Maximum likelihood estimates for the dynamic EKOP model parameters.

The five components of the Fourier flexible forms which describe intraday fluctuations of trading activity are jointly statistically significant, so there is an evidence for the deterministic diurnal component in the arrival rates for both trade categories. We plotted the intraday diurnality patterns for the $2\hat{\epsilon}_t$ and $\hat{\alpha}\hat{\mu}_t$ in Figure 3. We can see that the repetitive intraday patternisation of trading activity is not the same for both groups of the market participants. The intraday activity scenario of uninformed trades is presented by a pattern which closely resembles the shape of the letter “M”². Morning and afternoon liquidity of the market is comparatively lower, as the number of both balanced trades and the trade imbalance are very small. The systematic deterioration of market liquidity in the mornings and evenings corresponds to the fact that the trading of the Polish Zloty concentrates mainly in London (offshore market) and in the Polish market. Only when these venues are open, the vast majority of trading can be observed. Another striking feature of the diurnality function is the significant decrease in market participants’ activity around the 12.00-13.00. It can be explained by a well-known phenomenon of the ‘lunch effect’ – a periodic deterioration of liquidity that can simply be attributed to a lunch-time drop in trading intensity. The seasonality function has two evident humps which correspond to the trading hours 10.00-11.00, 15.00-16.00 for uninformed trades and 9.30-10.30, 14.30-15.30 for the informed trades. Hence, the maximum activity of uninformed traders

²M-curved intraday seasonality of balanced trades (an initial proxy for uninformed trading) has been also evidenced by Gençay & Gradojevic (2008) in case of EUR/USD trading in the EBS system

is delayed by about 30 minutes and takes place when informed trading activity is already gradually declining. It seems that on each day, the informed traders reaction to the arrival of news outpaces the arrival of uninformed traders. The obtained results partially agree with the Bloomfeld, O’Hara & Saar (2005) study, where the authors describe the evolution of liquidity on an experimental electronic market. Their results show that informed traders consume liquidity earlier in the day via market orders in order to profit from private information. It is also interesting to note that, in opposite to uninformed traders, the informed really highlight their presence after the London market opens at about 10.00 CET and after New York trading starts at 14.00 CET (GMT+5). They also seem to reinforce their trading intensity in the late afternoon at about 18.00 CET, when the local Polish market is often already closed. This result was also confirmed in Chan (2000) and Angelidis & Benos (2005) for the stock market. Just before closing of the trading session informed traders trade intensively in order to close up their positions, because during non-trading periods open positions can be risky and the superior information devaluates quickly. Such an increase in informed trading can be reflected by larger adverse selection component of the bid-ask spread at the end of a day. Although trading in interbank FX spot market can take place 24 hours a day, the vast majority of transactions is *de facto* executed in hours when banks in London and Poland trade.

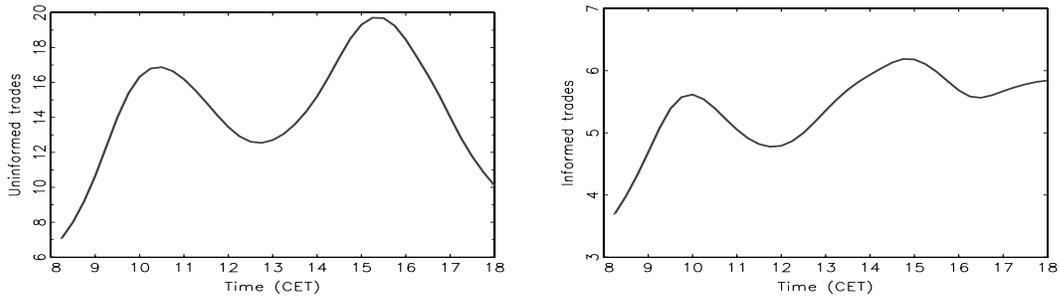


Figure 3: Intraday patterns for the arrival rates of uninformed (left panel) and informed trades (right panel).

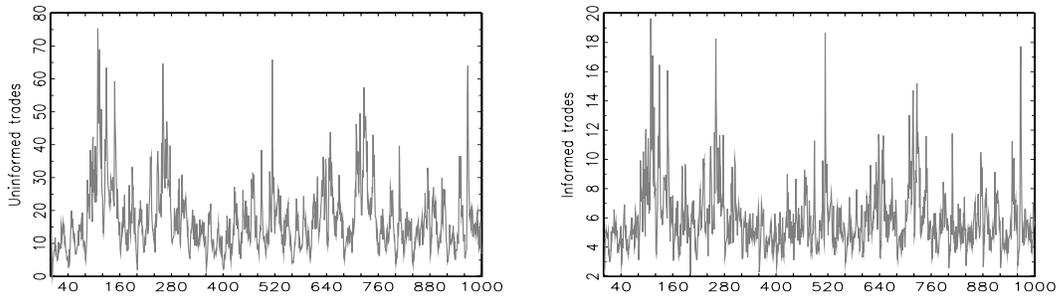


Figure 4: Model estimates of time-varying arrival rates of informed and uninformed trades during the first 1,000 observations of the sample (left panel) and the intraday pattern of the PIN measure.

In Figure 4 we depict a plot of the obtained $2\hat{\varepsilon}_t$ and $\hat{\alpha}\hat{\mu}_t$ coefficients, representing fluctuating arrival rates of uninformed and informed traders, respectively. In order to present a transparent output, we draw estimates for the first thousand observations from the sample. We can see extreme variability behind both arrival rates which, in our setup, can stem either from an additive pattern of intraday seasonality depicted in Figure 3 or from unexpected fluctuations (unpredicted by a seasonality function) in the level of balanced trades and the trade imbalance driven by a VARMA specification given by equation (7). The mean value of the uninformed trade arrival rate amounts to 14.5 and that of informed trades to 5.36. One striking observation from the Figure 4 is that for the balanced trades, much of the variable fluctuations can be attributed to the intraday fluctuation in the banks' activity. On the other side, variability of the informed trades' arrival is much less forecastable on that basis, as the intraday seasonality function may account for an additional four or six trades only. The estimated μ_t coefficient varies inside the [6.3, 59.2] interval. Accordingly, given that the news arrives to the market, the forecasted rate at which informed traders make use of the possessed information by submitting market orders can be very high and it may amount up to 59 trades in an 15-minute interval.

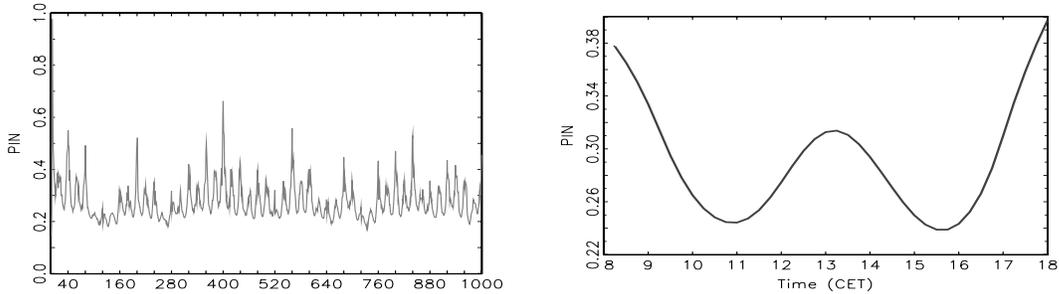


Figure 5: Model estimates of time-varying arrival rates of informed and uninformed trades during the first 1,000 observations of the sample.

On the basis of obtained arrival rates, $2\hat{\varepsilon}_t$ and $\hat{\alpha}\hat{\mu}_t$ with the application of equation (2), we computed time-varying estimates of the PIN variable – the forecasted fraction of the informed trades in the overall number of trades. In Figure 5 (left panel), we plotted of the first 1,000 estimates of the PIN coefficients. The coefficients for the rest of the period behave accordingly in a similar pattern. We can see how unstable the PIN variable is. It varies sharply in accordance to an intraday seasonality in the $\hat{\varepsilon}_t$ and $\hat{\mu}_t$ variables and it is always relatively higher in the beginning of a day at about 9.00 CET, at 14.30 CET (when the New York market opens) and at the end of a day, at 18.00 CET. Irrespective of the intraday seasonality, there are also large variations between PIN variables on different days of the year. The average PIN is about 0.29, so it is much higher than the average probability of informed trading for the stock market reported as having a range of 0.10-0.20

in Easley et al. (2008) and much higher than the PIN of 0.11 which Gençay & Gradojevic (2008) reported for the EUR/USD market. This interesting observation may be justifiable due to lower liquidity of the EUR/PLN market in comparison to the EUR/USD and its much higher sensitivity to short-term speculative behavior.

4 Modeling Market Liquidity

The concept of liquidity is quite elusive and hard to define. There is a kind of consensus in the financial literature that it should be characterized by at least four major dimensions: depth, tightness and resiliency (Kyle (1985)) as well as immediacy (Black (1971)). In the sequel of this paper we focus on explaining the first from the categories mentioned above, namely on the market depth and on the bid-ask spread (as a measure for market tightness).

In the theory of market microstructure, there are three main factors that contribute to bid-ask spread determination: (1) the cost of dealer services, (2) the cost of holding inventory and (3) the cost of adverse selection, e.g. Sarno & Taylor (2001). The cost of dealers' services covers fees charged by suppliers of liquidity (e.g. automated information and trading services). The fee may cover, for example, cost of continuous matching of incoming buy and sell orders. Theoretical aspects on holding inventories has been analyzed by Demsetz (1968), Amihud & Mendelson (1980), Stoll (1978), Ho & Stoll (1981), Ho & Stoll (1983), Biais (1993), among others. Under this viewpoint, dealers are perceived as risk-averse, whereas the cost of holding inventory is the cost for keeping an undesired position in a stock or currency. When changing bid-ask quotes (the bid-ask spread), dealers can encourage their counterparties to submit orders that could rebalance their risky, unwanted positions. The third determinant of the bid-ask spread, the adverse selection costs, can be explained under an information-based modelling setup of the market microstructure. The information models that explicitly characterize bid-ask spread date back to the seminal study of Bagehot (1971), where in the market there are two types of traders: liquidity (uninformed) traders and "insider" (informed) traders, who can make use of the private information at the expense of the 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 that he takes. In the Glosten & Milgrom (1985) model, which also captures a similar notion, a market maker can learn the value of an asset and the probability of informed trading by knowing the direction (buy or sell) of the orders which arrive to the market. The model assumes that the incoming trade itself conveys information. Therefore, each sell transaction can inform that a trader knows bad news and each buy transaction can signal that he knows some good news. A

market maker cannot distinguish liquidity traders from the informed traders. Therefore he adjusts his bid and ask quotes, and so the spread, conditionally on the sign of incoming orders. The model has been additionally developed by Easley & O'Hara (1987), mainly in two dimensions. First, the authors state that, not only the incoming orders' queue, but also their size can signal about the value of a traded asset. Second, an additional uncertainty factor could be introduced: the existence of new information does not have to be assumed *ex ante*, but it also has to be deduced from the sign and the size of incoming orders. Glosten & Milgrom (1985) and Easley & O'Hara (1987) introduced the concept of sequential trading models from which the bid-ask spread resulted in an 'endogenous' manner. Heterogenous traders and asymmetric information obliges dealers to set different ask and sell prices, and the spread arises as a weapon against an adverse selection problem. Accordingly, in many later studies a bid-ask spread was perceived as a measure of information heterogeneity (e.g. McNish & Wood (1992) Foster & Viswanathan (1993a), Foster & Viswanathan (1993b)).

As far as the market depth is concerned, it is not easy to discriminate between liquidity providers and liquidity demanders on the grounds of the information they know. As de Jong & Rindi (2009) state, "the choice between limit and market orders is a strategic element in any trading decision and depends on the relative probability of execution of the two orders, which in turn depends on a variety of factors, such as the asymmetry of the personal evaluations of the risky asset between the agents who submit the orders and those who hit the existing quotes, their degree of patience, their waiting costs and the state of the limit order book". However, the notion that the informed traders are much more likely to use market orders than limit orders is widespread in the theoretical literature (e.g. Glosten (1994), Seppi (1997)). Studies of Angel (1994) and Harris (1998) point out that informed traders can also use limit orders but are much likely to act as liquidity demanders by submitting market orders. However, liquidity traders can be discretionary, which means that they chose the time of trading in order to minimize their costs (Admati & Pfleiderer (1988)). Uninformed traders, being aware of increased adverse selection costs in the periods where informed trading can take place, may prefer to limit the option value of their limit orders. Thus, they may retreat from supplying liquidity to the market, even by cancelling the previously submitted orders. Accordingly, the market depth should deteriorate as a response to signals of informed trading.

In line with the theory of information models, we try to explain the bid-ask spread fluctuations and the market depth by the probability of informed trading (PIN) obtained from the estimated dynamic EKOP model. We treat the PIN as an explanatory variable in an equation describing the conditional expected value of a percentage bid-ask spread or

bid (ask) depth. We use here an Autoregressive Conditional Duration (ACD) model of Engle & Russell (1998). Preliminarily, the ACD models were proposed to describe trading intensity. The model was applied for description of highly autocorrelated durations (time spells) between selected events (e.g. transactions, price or volume changes) that characterize transaction process. Lately, the model was also used in order to successfully describe other financial variables as transaction volumes in Manganelli (2005) or bid-ask spread in Nolte (2008). The ACD model can explicitly capture two specific features of financial variables measured at high frequencies. First, it is designed for variables defined on a strictly positive domain. Second, it can flexibly describe variables that are strongly autocorrelated. Here, we use the logarithmic ACD model of Bauwens & Giot (2000) with the Burr distribution for the error term proposed by Grammig & Maurer (2000). The model for the variable x_t (which can be s_t or d_t^b or d_t^a) is:

$$x_t = \Psi_t \epsilon_t \quad (12)$$

where $\Psi_t = E(x_t|F_t)$ and F_t denotes an information set up to time point t and $\epsilon_t \sim i.i.d. Burr(\kappa, \sigma^2)$. The conditional expected value of the dependent variable x_t is described as:

$$\Psi_t = exp(\psi_t) \quad (13)$$

where:

$$\psi_t = \beta_0 + \beta_1 \psi_{1,t-1} + \beta_2 \ln(x_{t-1}) + \gamma_{TT} TT_t + \gamma_{Vol} Vol_t + \gamma_{PIN} PIN_t + S(\nu^x, \tau_t)$$

and

$$S(\nu^x, \tau_t) = \nu_0^x \cdot \tau_t + \sum_{l=1}^2 \nu_{2l-1}^x \cdot \sin[2\pi(2l-1)\tau_t] + \nu_{2l}^x \cdot \cos[2\pi(2l)\tau_t] \quad (14)$$

The log likelihood function of the ACD model with the Burr distribution of the random term is:

$$LogL(\Theta) = \sum_{t=1}^T \left[\ln \kappa - \kappa \cdot \ln \xi_t + (\kappa - 1) \cdot \ln x_t - \left(\frac{1}{\sigma^2} + 1 \right) \cdot \ln(1 + \sigma^2 \cdot \xi_t^{-\kappa} \cdot x_t^\kappa) \right] \quad (15)$$

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

Application of the logarithmic version for an ACD model makes it possible to add exogenous explanatory variables to the mean equation (see equation 14). Such factors may potentially have a negative impact on the dependent variable, but it does not interfere with the nonnegativity constraint imposed on the conditional mean of the bid-ask spread

or the market depth. The PIN_t variable is a probability of informed trading, forecasted at time point t for the $(t, t+1]$ interval. Apart from the PIN_t variable, we introduced two control variables: the volume of all trades and the proxy for volatility (absolute value of return variable $|r_t|$). As in the Easley et al. (2008) study, the variables “control variations in the spread that are not explained by the proportion of informed trades”. The first one accounts for the impact of trading sizes, while the second one adds the information reflected in variations in the exchange rate. Additionally, we also introduced a seasonality factor with an application of the Fourier flexible form in order to account for deterministic repetitive day-by-day fluctuations in these three liquidity measures.

In the first step of the analysis, we plotted the kernel density functions for the percentage bid-ask spread, market ask depth and market bid depth³. All three variables are defined on the positive domain, but we also can see that the majority of the probability mass is concentrated very close to zero. The shape of the density functions resembles the one characteristic for financial durations (Bauwens, Giot, Grammig & Veredas (2004)). We can also see that the bid and ask depth densities are not identical. The depth on the bid side of the market, where the limit orders to buy the EUR are gathered, is visibly more dispersed than the depth on the ask side.

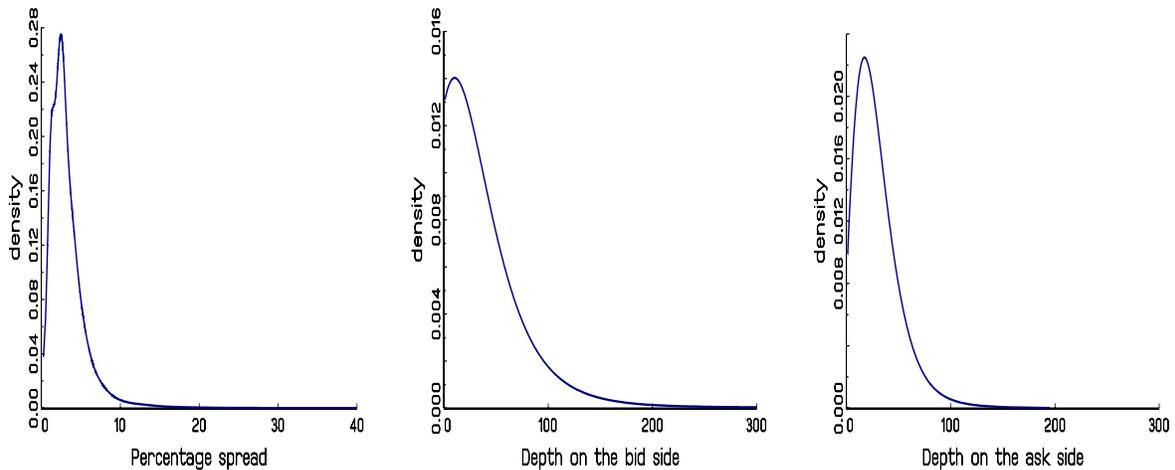


Figure 6: Kernel density estimates for selected liquidity measures.

We report the logarithmic ACD model estimates in Table 3. With reference to the percentage spread model, all explanatory variables are statistically significant. The control

³Kernel density function is produced with the application of gamma kernel as proposed by Chen (2000). Optimal bandwidth is computed as $(0.9\sigma N^{(-\frac{1}{5})})^2$, where σ denotes the standard deviation of the data and N is the number of observations

variables have expected signs. The volume variable has a negative impact on the forecasted bid-ask spread, so the heavier the trading, the more liquid the market and the tighter the bid-ask spread is. The opposite conclusion applies to the volatility component. If the exchange rate is more volatile, the bid-ask spread widens. Volatility is often perceived as a measure of price uncertainty. Due to an adverse selection component of the bid-ask spread determination, it is more costly to place an inside-the-quote limit order, because its option value and the risk of being 'picked off' rises. Previous empirical research on limit order markets also showed that bid-ask spread is inversely related to trading volume and positively related to volatility (see Brockman & Chung (1998); (2000); (2003); Easley et al. (2008)). Apart from the impact of the control variables, we can see that the PIN variable has a significantly positive impact on the value of the percentage bid-ask spread. Accordingly, the dynamic specification of the Easley et al. (2008) EKOP model can additionally explain fluctuations of the bid-ask spread at the intraday frequency. The results show that, as for the stock market behavior examined on the daily frequency, we may apply a similar outlay of the model to study the behavior of the FX market (even if the frequency of observations is very high). Our empirical results agree with Easley et al. (2008) and confirm the information-based models as far as bid-ask spread determination is concerned. The obtained result confirms that on top of the impact of other control variables, if the probability of informed trading forecasted for the next interval is high, the bid-ask spread widens and the instantaneous liquidity of the market deteriorates.

Some interesting conclusions can be formulated with respect to the bid (ask) depth of the market. The depth of the market increases with the volume of executed transactions. In heavy trading periods, liquidity providers are also very active. This scenario is slightly more pronounced for bid market side where orders to buy Euro are allocated. Volatility has a significant negative impact on the bid depth as evidenced by a previous research (Brockman & Chung (2000)). Having controlled for the factors reflected in transaction intensity and price variations, we can also see a significant impact of the PIN variable on the market depth on the ask side. Therefore, an increase in proportion of informed traders in the population of market participants changes the willingness to provide liquidity to the market. We should denote that the reactions on the ask and on the bid market sides are different. The impact of the PIN on the ask depth is significantly negative and on the bid depth it is significantly positive. It is an interesting result, because it may show that market unequally values investments in emerging market currency versus the Euro when it is confronted with new information. The drawback of the ECOP model is that it cannot differentiate between forecasts of informed trading initiated by the arrival of either good or bad information. Nevertheless, if the probability of informed trading increases (which

could be initiated by good or bad news), the quantity of 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. On the contrary, the increase in the probability of informed trading enhances bank dealers to place more buy orders (orders to buy EUR and to sell PLN) in the system. The signs of information trading in the interbank market, irrespectively of whether it was caused by the arrival of good or bad information, encourage banks to secure themselves by buying more EUR via limit orders. Such a result may be due to the submission of stop-loss orders which could be executed once the price moves to a certain undesired level and it can be treated as a weapon against incurring excessive losses. So, if a fraction of traders perceived as 'informed' rises, the uninformed traders are more reluctant to buy Zloty and to sell Euro via limit orders than to sell Zloty and to buy Euro. We could risk a statement that the EUR seems to be perceived as a 'safer' currency when compared to the Polish Zloty. The results show 'the escape to the Euro' in the placement of limit orders once there are premises behind informed trading. It should be remembered, however, that process of liquidity providing, i.e. posting limit orders is not necessarily limited to uninformed traders. Bloomfeld et al. (2005) provide an evidence that informed traders provide even more liquidity than liquidity traders do. 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 proved in the empirical work of Menkoff et al. (2010) devoted to the Russian ruble trading on the Moscow Interbank Currency Exchange.

parameters	percentage spread		ask depth		bid depth	
	estimate	st.err.	estimate	st.err.	estimate	st.err.
β_0	0.0251	0.0084	0.4548	0.0329	0.2612	0.0311
β_1	0.0324	0.0058	0.7093	0.0131	0.7151	0.0154
β_2	0.9495	0.0117	0.1772	0.0148	0.2033	0.0171
γ_{TT}	-0.0026	0.0005	0.0006	0.0003	0.0015	0.0003
γ_{Vol}	0.0151	0.0019	0.0003	0.0012	-0.0054	0.0012
γ_{PIN}	0.5085	0.1333	-0.1765	0.0787	0.2630	0.0832
ν_0^x	-0.2642	0.0474	-0.0261	0.0321	-0.0134	0.0333
ν_1^x	0.2164	0.0099	-0.0211	0.0053	-0.0271	0.0055
ν_2^x	0.1322	0.0113	0.0057	0.0063	-0.0248	0.0066
ν_3^x	-0.1237	0.0174	0.0069	0.0104	0.0081	0.0106
ν_4^x	0.0024	0.0103	0.0084	0.0055	0.0047	0.0054
κ	2.6348	0.0380	5.6673	0.0972	5.7936	0.1103
σ^2	0.5236	0.0265	0.9743	0.0391	1.0845	0.0444
<i>LogL</i>	-18,534.212		-35,040.216		-36,920.206	
<i>BIC</i>	3.7188		7.0200		7.3960	

Table 3: Maximum likelihood estimates for the logarithmic ACD model parameters.

5 Conclusions

The paper presents the empirical application of the sequential trade EKOP model of Easley et al. (2008) to the EUR/PLN interbank spot market in 2007. We proved the existence of the particular intraday seasonality pattern for the arrival rate of uninformed and informed trades. We also discussed some interdependencies in the scenarios of strategic behavior of the uninformed and informed traders. The estimation results served as a premise for recognizing the variation pattern for the probability of informed trading (PIN) variable. In order to measure the effects of the adverse selection costs on market liquidity, we estimated the logarithmic ACD model for the bid-ask spread and the bid (ask) market depth. We proved that the forecasted proportion of informed trades has a significant power in explaining these market liquidity measures. Interestingly, we showed that the investment in Polish Zloty as an emerging market currency is not treated as risky as the investment in Euro, because there is a certain asymmetry in providing liquidity to the ask or bid side of the market once the forecasted probability of informed trading increases.

Our results may contribute to the literature in several ways. This study proved a successful applicability of the dynamic EKOP model of Easley et al. (2008) when describing interbank currency trading and modeling market liquidity on an intraday level. Such results may serve as confirmation of the robustness of the underlying model. With the application of up-to-date EUR/PLN data we also confirmed the results of many previous studies on the relationships between informed trading and market microstructure variables. Apart from seminal contributions of Gençay et al. (2007), Gençay & Gradojevic (2008) and Menkoff et al. (2010) on intraday strategic arrival of informed traders in FX markets, previous studies on that subject have been conducted nearly exclusively for stock markets.

The presented analysis should be perceived as the introductory step in understanding when the information signals migrate to the FX market, how they influence the trading behavior and mirror itself in prevailing market conditions. Future research can be developed in many directions. It would be interesting to apply the dynamic EKOP model not only to the number of trades but also to numbers of orders that are posted inside the best quotes. It may bring more insight into the process in which we deduce the informational content of trading process as the process of liquidity providing can also be information-motivated. Secondly, the impact of the PIN variable should also be tested with respect to more detailed liquidity measures such as bid (ask) quote slope curves or measures of market resiliency. Finally, as we investigate a FX market in which we must pay with the one currency for the other, it could also be of utmost interest to verify whether the distinction between 'bad' and 'good' information (with respect to each of the currencies) has a diverse impact on the instantaneous quality of market liquidity.

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