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Katarzyna Bień-Barkowska[*]

"Does It Take Volume to Move the EUR/PLN FX Rates?" Evidence from Quantile Regressions

A b s t r a c t This study investigates the impact of trading volume on selected quantiles of the EUR/PLN return distribution. Empirical results obtained with the quantile regression approach confirm that an increase in the turnover is associated with a significant increase in the dispersion of the corresponding return distribution. We divided the trading volume into its expected (anticipated) and unexpected (unanticipated) component and found that the unexpected volume shocks have a significantly larger impact on the dispersion of the return distribution. We also observed that the volume-return relationship is nonlinear; the dependence is stronger with more extreme quantiles. Moreover, after accounting for a conditional volatility measure as a controlling explanatory factor for the quantile dynamics, the impact of the expected volume declines yet remains significant especially for the most extreme quantiles.

K e y w o r d s: volume-return relationship, market microstructure, FX trading, quantile regression.

J E L Classification: C22, G15

Introduction

Research on price – volume relationship has a long history in the literature of both theoretical and empirical finance. Positive contemporaneous correlation between trading volume and price volatility is already a well-documented observation with early studies on the topic traced back to the seventies. In this decade, the positive relationship between the selected measures of price variability and trading volume has been demonstrated for stock markets in various publications (Crouch, 1970; Epps and Epps, 1976; Morgan, 1976; Westerfield, 1977, among others). Karpoff (1987) presents a vast survey of the early litera-

[*] Correspondence to: 1. Katarzyna Bień-Barkowska, Institute of Econometrics, Warsaw School of Economics, ul. Madalińskiego 6/8, 02-513 Warsaw, Poland or 2. Katarzyna Bień-Barkowska, Financial System Department, National Bank of Poland, ul. Świętokrzyska 11/21, 00-919, Warsaw, Poland, e-mail: katarzyna.bien@sgh.waw.pl

ture summarizing the results of 19 empirical studies conducted throughout the seventies and eighties focusing on the volume-return relationship evidenced by daily and intraday data from the stock, bond and commodity future markets. Further evidence for this positive relationship can be found in numerous studies from the nineties and more recently (Lamoureoux and Lastrapes, 1990; Gallant et al., 1992; Jones et al., 1994; Bohl and Henke, 2003; Luckley, 2005; Doman, 2008; Doman, 2011; and others). Bessembinder and Seguin (1993) suggest splitting the trading volume into its anticipated and unanticipated component. Given the well documented fact, that the volume is highly autocorrelated, it is also forecastable, hence the authors differentiate its expected and unexpected part and evidence that the unexpected volume shock has between two and thirteen times greater effect on the volatility of stock prices. Different informative meanings of the expected and the unexpected volume have also been found in other studies (Brown-Hruska and Kuserk, 1995; Gurgul et al., 2005; Huang et al., 2006).

There are at least three strands of the literature on market microstructure that could explain the relationship between trading volume and return variability. The first one is known as the sequential information arrival hypothesis (SI-AH) (c.f. Copeland, 1976; Jennings et al., 1981). According to this theory, all traders cannot simultaneously absorb the arrival of new market information. Therefore, a revision of their expectations occurs sequentially and the process in which new information is impounded into the price can spread out over time. Only after all traders are able to react and trade, the final equilibrium price is set; this explains the lead-lag relationship between volatility and trading volume. Accordingly, intensive trading and a high trading volume can help to identify periods where prices continue to adjust to informational shocks.

The second explanation of the positive contemporaneous correlation between return and volume arises from the idea of theoretical information models. In such models traders are allowed to trade different sizes; better-informed traders initiate larger transactions and their activity has an adverse selection effect on the price (c.f., Easley, O'Hara, 1987). In another model, the informational content of trading intensity has been outlined. A long duration between consecutive trades indicates that there was no new information, whereas a short duration increases the probability that better-informed traders have increased the overall trading intensity. Hence, market makers change quoted price by increasing the bid-ask spread as a weapon against an adverse selection risk reflected by an increased number of trades (Easley and O'Hara, 1992). Other information models that predict a positive relationship between trading volume and price volatility are developed in the studies of Admati and Pfleiderer (1988), Blume et al. (1994), Easley, Kiefer and O'Hara (1997), and Malinova and Park (2011).

The third explanation for the significant positive volume-return relationship arises from the mixture of distributions hypothesis (MDH) and has more of a statistical than an economic background (Clark, 1973; Epps and Epps, 1976;

Tauchen and Pitts, 1983). According to the MDH, a bivariate distribution of volume and price change variables is conditional upon an information variable such that both variables react simultaneously to the arrival of news and are driven by this unobservable factor.

The aim of this paper is to shed light on the intraday relationship between return and volatility in the EUR/PLN currency pair on the interbank spot market. We will use trade data from the Reuters Dealing 3000 Spot Matching System, a very popular brokerage trading platform that can automatically match all incoming buy and sell orders once their prices agree.

Inspired by the study of Chuang et al. (2009), we describe the return-volume relationship with the help of quantile regressions (QR). Such an approach allows us to generalize the results of many empirical studies concerning the relationship between trading volume and the measure of price variability. The majority of empirical studies demonstrate that it is common to introduce volume as an additional explanatory factor into the GARCH specification for the conditional variance of the return distribution (Lamoureux and Lastrapes, 1990; Bohl and Henke, 2003; Gurgul et al., 2005; Majand and Yung, 2006; and others). Such a modeling strategy measures only the impact of the trading volume on the second central moment of the conditional return distribution. The QR approach is much different in that it is semiparametric and allows for an analysis of the impact of some explanatory factors on the selected quantiles of the return distribution without making any assumptions about their parametric form (i.e., Gaussian, Student’s t, generalized gamma) or about the parametric specification of its conditional mean and variance.

Models that are members of the GARCH family make an usual implicit assumption about a type of a parametric location-scale distribution for financial returns where the first two moments (i.e., the conditional expectation and the conditional variance) are described in a dynamic fashion. The QR approach does not impose such parametric assumptions but instead concentrates on the quantiles. Accordingly, the QR approach has an obvious upper hand over the standard GARCH approach: the impact of the explanatory variables can be different for different quantiles. An impact of trading volume can be different for the τ-quantile than it is for the $(1-\tau)$-quantile (where τ denotes a corresponding probability level). Hence, we are able to infer whether the arrival of new information has a different impact on the probability of an extreme FX rate increase versus an extreme FX rate decrease. Such a situation could be explained by the possibly of a time-varying skewness and/or kurtosis of the return distribution that could also depend on a latent information arrival variable.

Within this study we decompose trading volume into its expected (forcastable) and unexpected (unpredictable) parts and compare their impact on the selected quantiles of the EUR/PLN return distribution. Moreover, we check to see if the trading volume captures extra information behind the quantile dynamics when confronted with the standard GARCH volatility forecasts as an intuitive and natural explanatory factor.

1. The Econometric Approach

1.1. Trading Volume Decomposition

In order to investigate the volume – return relationship one must typically distinguish between the so-called expected (anticipated) and unexpected (unanticipated) trading volume (Andersen, 1996; Bjonnes et al., 2003). Bearing in mind that the volume variable is highly autocorrelated, the expected volume is the result of more persistent fluctuations in liquidity needs whereas unexpected volume should be unpredictable by traders and should approximate a new information arrival.

Differentiation between what is expected and unexpected volume is typically performed using ARIMA models (c.f., Bessembinder and Seguin, 1993; Hartmann, 1999; Bjonnes et al., 2003). However, such models usually require logarithmic transformation of the volume variable in order to avoid its nonnegativity and/or in order to diminish heteroskedasticity, especially for high frequency data. Such a transformation may distort the potential relationship between the variables and so we propose a different procedure here. In order to preserve an original time series (unchanged due to a logarithmic transformation), we apply the Autoregressive Conditional Duration (ACD) models of Engle and Russell (1998). The ACD were initially used to describe a highly autocorrelated time series of durations (time spells) between selected events (i.e., transactions or price changes). More recently these models were used to describe other financial variables including transaction volume in the studies of Manganelli (2005) and Doman (2008, 2011) or the bid-ask spread in Nolte (2008). The ACD models are well designed for serially correlated variables with a strictly positive domain. Here we have used the ACD (1,1) model with the Burr distribution for the error term proposed by Grammig and Maurer (2000). The model for the trading volume variable vol_t can be written as follows:

$$vol_t = \Psi_t \varepsilon_t, \tag{1}$$

where $\Psi_t = E(vol_t \mid F_{t-1})$, F_{t-1} denotes an information set up at the time point $t-1$ (containing all past realizations of vol_t), ε_t denotes an error term, and $\{\varepsilon_t\} \sim i.i.d.\ Burr(\kappa, \sigma^2)$ such that $E(\varepsilon_t) = 1$. The conditional expectation of the dependent variable vol_t is described as follows:

$$\Psi_t = \beta_0 + \beta_1 \Psi_{t-1} + \beta_2 vol_{t-1}, \tag{2}$$

This model can be estimated using the ML method. The log likelihood function has the following form:

$$LogL(\Theta) = \sum_{t=1}^{N} \Bigg(\ln\kappa - \kappa \cdot \ln\xi_t + (\kappa - 1) \cdot \ln vol_t - \left(\frac{1}{\sigma^2} + 1\right) \cdot \ln(1 + \sigma^2 \cdot \xi_t^{-\kappa} \cdot vol_t^{\kappa}) \Bigg), \tag{3}$$

where $\xi_t = \Psi_t \dfrac{(\sigma^2)^{\left(1+\frac{1}{\kappa}\right)} \cdot \Gamma\left(\frac{1}{\sigma^2} + 1\right)}{\Gamma\left(1 + \frac{1}{\kappa}\right)\Gamma\left(\frac{1}{\sigma^2} - \frac{1}{\kappa}\right)}$, $0 < \sigma^2 < \kappa$ and $\Gamma(\cdot)$ denotes the gamma function.

Accordingly, the expected volume $vol_{\exp,t}$ is defined as an estimate of the conditional expectation $\hat{\Psi}_t$ (i.e., it is conditional upon all past observations of the volume variable) whereas an unexpected volume is defined as the residual $vol_{un\exp,t} = vol_t / \hat{\Psi}_t$.

1.2. Quantile Regressions for the EUR/PLN Returns

Taking the trading volume as an explanatory variable in the QR setup we are able to check its impact on the dispersion of the return distribution in a very explicit manner. In the QR setting we can "jointly" capture the impact that the trading volume exerts on the general shape (i.e., skewness, kurtosis or variance). As mentioned previously, most popular financial econometric models typically neglect the possible effect of explanatory variables on the skewness or kurtosis of the distribution. Furthermore, the popular GARCH models rule out a potential asymmetric impact on the trading volume on the tail probability of a large price upswing versus a large price falls.

In order to check the impact of the trading volume on the selected quantiles of the return distribution we used simple linear QR models where each of them corresponds to a selected conditional quantile $Q_{r_t}(\tau \mid \mathbf{x}_t)$:

$$\begin{aligned} Q_{r_t}(\tau \mid \mathbf{x}_t) &= \alpha_{0,\tau} + \alpha_{1,\tau} r_{t-1} + S(\mathbf{v}_\tau, \upsilon) \\ &+ \gamma_{1,\tau} vol_{\exp,t} + \gamma_{2,\tau} vol_{un\exp,t} + \gamma_{3,\tau} vol_{un\exp,t-1}, \end{aligned} \tag{4}$$

where r_t denotes the logarithmic rate of return on the EUR/PLN exchange rate between the moments t and $t-1$, τ denotes a corresponding probability level and $S(\mathbf{v}_\tau, \upsilon)$ depicts the intraday seasonality factor given as the fast Fourier form (FFF):

$$S(\mathbf{v}_\tau, \upsilon) = \nu_{0,\tau} \cdot \upsilon + \sum_{l=1}^{2} \left[\nu_{2l-1,\tau} \cdot \sin[2\pi l \upsilon] + \nu_{2l,\tau} \cdot \cos[2\pi l \upsilon] \right], \quad (5)$$

where υ denotes a time-of-day variable standardised on the interval $[0, 1]$. $\mathbf{x}_t = [1,\ r_{t-1},\ \tau,\ \sin(2\pi\tau),\ \cos(2\pi\tau),\ \sin(4\pi\tau),\ \cos(4\pi\tau),\ vol_{\exp,t},\ vol_{un\exp,t},\ vol_{un\exp,t-1}]^T$ is a vector of selected explanatory variables. The FFF diurnality component that we apply has been advocated by Andersen and Bollerslev (1996). The diurnality function can therefore be depicted as a number of sine and cosine functions and should smoothly depict the systematic intraday seasonality pattern in the dispersion of the return distribution. This standard methodology assumes a two-step procedure: the intraday returns are first deseasonalized (divided by the obtained seasonality pattern) and then GARCH models are estimated for the filtered returns. We allow for an additive seasonality pattern for each of the estimated quantile regressions, which allow us to capture systematic intraday regularities in the unrestricted shape of the conditional distribution. As previously mentioned, this is done in a semiparametric setup and is much more general such that we can capture different diurnality patterns for different quantile levels. In each of QR regressions given by equation (4) we have also introduced a lagged r_t in order to account for possible autocorrelation. The parameter corresponding to the autoregressive term can be different for different quantiles, as evidenced by Baur et al. (2011).

The suggested model for the conditional quantile of the return distribution can be criticized as being too parsimonious. Given that it contains only the past return, intraday seasonality component and volume variables as the major driving forces[1], its ability to account for the volatility clustering effect may be rather limited. Thus, in the second model that we propose we have included a return volatility forecast as an additional driving factor for the quantile dynamics. Chuang et al. (2009) proposed the addition of a lagged value of r_t^2 as a natural proxy for the volatility. An alternative to this is to account for possible persistency in the conditional quantiles with the application of the Conditional Autoregressive Value-at-Risk (CAViaR) models of Engle and Manganelli (2004). Within this framework quantile dynamics are captured in the form of autoregressive specifications with an absolute value for the past return as new-information variable. However, the application of an autoregressive specification rules out the applicability of standard linear programming algorithms to estimate QR. Accordingly, the estimation process based on the genetic algorithm or the Nelder-Mead simplex algorithm and quasi-Newton method (with the necessity of computing loops for recursive quantile functions) is quite time-consuming. Taking into account that we plan to estimate several quantile re-

[1] The lag structure for the volume variables has been selected on the grounds of their statistical significance.

gression models for several probability levels, this would likely be inefficient. Therefore, we decided to approximate the volatility variable with the conditional standard deviation estimate $\hat{\sigma}_{t-1}$, obtained from the GARCH(1,1) with a Student's t distribution for an error term[2] model. As such, a volatility measure[3] uses whole information from the history of the return process at $t-1$. It is also intended to describe the persistency of the quantile dynamics in a more adequate manner than r_{t-1}^2:

$$\begin{aligned} Q_{r_t}(\tau \mid \mathbf{x}_t) &= \alpha_{0,\tau} + \alpha_{1,\tau} r_{t-1} + \alpha_{2,\tau}\hat{\sigma}_{t-1} + S(\nu_\tau, \tau) \\ &\quad + \gamma_{1,\tau} vol_{\exp,t} + \gamma_{2,\tau} vol_{un\exp,t} + \gamma_{3,\tau} vol_{un\exp,t-1}. \end{aligned} \tag{6}$$

For a given probability τ, QR estimates can be obtained as a minimum of the following objective function of asymmetrically weighted absolute deviations:

$$\hat{\boldsymbol{\gamma}}_\tau = \arg\min_\gamma \sum_{t=1}^{N} \left(\tau - \mathbf{1}_{\{r_t < x_t^T \gamma\}}\right)\left| r_t - \mathbf{x}_t^T \boldsymbol{\gamma}_\tau \right|, \tag{7}$$

where $\boldsymbol{\gamma}_\tau = [\alpha_0, \alpha_1, \nu_0, \nu_1, \nu_2, \nu_3, \nu_4, \gamma_1, \gamma_2, \gamma_3]^T$ denotes a parameter vector and $\mathbf{x}_t = [1,\ r_{t-1}, \hat{\sigma}_t,\ \tau,\ \sin(2\pi\tau),\ \cos(2\pi\tau),\ \sin(4\pi\tau),\ \cos(4\pi\tau),\ vol_{\exp,t}, vol_{un\exp,t},$ $vol_{un\exp,t-1}]^T$ is a vector of the corresponding explanatory variables. Nondifferentiable objective function (7) can be minimized using the linear programming methods described in Koenker (2005, p. 170-202). The limiting covariance matrix of $\sqrt{n}(\hat{\boldsymbol{\gamma}}_\tau - \boldsymbol{\gamma}_\tau)$ takes the form of the Huber sandwich (Huber, 1967):

$$\sqrt{T}(\hat{\boldsymbol{\gamma}}_\tau - \boldsymbol{\gamma}_\tau) \to N\left(0,\ \tau(1-\tau) H_T^{-1} J_T H_T^{-1}\right), \tag{8}$$

where

[2] The volatility estimate $\hat{\sigma}_{t-1}$ refers to deseasonalized returns: $\bar{r}_t = r_t / s_{r,t}$, thus it accounts for the volatility left on top of its cyclical behavior. In our empirical application an intraday seasonality factor $s_{r,t}$ has been estimated with the kernel regression of absolute returns on a time-of-day variable. We use a quartic kernel with bandwidth computed as *2.78sN* $^{-1/5,}$ where *s* is the standard deviation of the data. For details regarding the estimation procedure please refer to (Bauwens and Veredas, 2004). An alternative would be to estimate $s_{r,t}$ by means of cubic splines as suggested by Giot (2005) or by means of the fast Fourier form as suggested by Anderson and Bollerslev (1997).

[3] Introduction of the volatility estimate into the QR model for financial returns has been also adapted in Taylor (1999). Parsimonious GARCH(1,1) specification succeeded to depict the volatility clustering in a satisfactory way.

$J_T = T^{-1}\sum_{t=1}^{T}\mathbf{x}_t\mathbf{x}_t^T$ and $H_T = \lim_{T\to\infty} T^{-1}\sum_{t=1}^{T}\mathbf{x}_t\mathbf{x}_t^T f_t(Q(\tau))$ (Koenker, 2005, p. 74). The term $f_t(Q(\tau))$ denotes the conditional density of r_t evaluated at the τth conditional quantile, $Q(\tau)$.

In order to estimate the matrix H_T, the term $f_t(Q(\tau))$ must be evaluated. It is typically replaced by its consistent estimate $\hat{f}_t(Q(\tau))$ obtained with the help of nonparametric methods. Koenker (2005, p. 80) shows a method to estimate the density function evaluated at a given quantile $Q(\tau)$ with the help of the sparsity estimation methods proposed by Hendricks and Koenker (1991), (i.e., as a difference quotient):

$$\hat{F}_t(Q(\tau)) = 2h_T \big/ \mathbf{x}_t^T(\hat{\boldsymbol{\gamma}}_{\tau+h_T} - \hat{\boldsymbol{\gamma}}_{\tau-h_T}), \tag{9}$$

where h_T denotes a bandwidth ($\lim_{T\to\infty} h_T = 0$); selecting the proper bandwidth is discussed by Koenker (2005, p. 139-140). Another possibility for the covariance matrix estimation, known as a Powell sandwich, would be to estimate H_T via kernel estimation:

$$\hat{H}_t = (nh_T)^{-1}\sum K(r_t - \mathbf{x}_t^T\boldsymbol{\gamma}/h_T)\mathbf{x}_t\mathbf{x}_t^T, \tag{10}$$

where $K(\cdot)$ denotes a proper kernel function (e.g., Powell kernel) (c.f., Koenker, 2005, p. 80).

2. Empirical Results

2.1. Data

An empirical study of the volume-return relationship has been performed with trade data from the Reuters Dealing 3000 Spot Matching System. This is a liquid electronic brokerage system that operates as an order-driven market. It can be estimated that trading with the Reuters Dealing 3000 Spot Matching System accounts for about 60 % of all interbank spot transactions in the Polish zloty market in 2008[4].

The data utilized is comprised of transactions conducted between January-June 2008 with respect to the EUR/PLN currency pair. The EUR/PLN exchange rate is quoted as a quantity of zlotys per one Euro. During the period of study the zloty followed an appreciating trend with respect to the Euro. Each transaction is marked with the date, the exact time, the rate and the quantity (in mil-

[4] Trading of the Polish zloty takes place on offshore markets (mainly between London banks) as well as locally in Poland. The datasets used in this analysis take into account both of these trading venues.

lions) of EUR. Trading on the interbank market is heavily concentrated on business days between the hours of 8:00 and 18:00 Central European Time (CET). 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 have also excluded days with exceptionally low liquidity due to national holidays. For data aggregated in a 15-minute frequency, we define the following variables: (1) vol_t is the trading volume (turnover) between the moments t and $t-1$, expressed in M. EUR, and (2) r_t is the logarithmic rate of return on the EUR/PLN exchange rate defined as $r_t = (ln(P_t^m) - ln(P_{t-1}^m)) \cdot 10^4$ where P_t^m denotes the mid price. The data frequency is chosen as a compromise between the need for observing the intraday instantaneous fluctuation of selected market characteristics and the necessity of avoiding distorted results due to the effects of slow trading periods.

Because trading volume demonstrates strong intraday seasonality we have divided the volume variable by the corresponding seasonality component: $\overline{vol} = vol_t / s_t$. As suggested by Bauwens and Veredas (2004), the intraday seasonality factor s_t has been estimated using the kernel regression of vol_t on a time-of-day variable[5]. Estimation of the Burr-ACD models[6] has been performed on a diurnally adjusted series[7]. With the obtained parameter estimates we defined the expected and the unexpected volume variables. As can be observed in Figure 1, the expected trading volume reflects forcastable fluctuations in the trading turnover whereas the unexpected volume reflects unanticipated volume shocks.

2.2. Modeling the volume-return relationship with the QR

In order to obtain an intuitive picture of the relationship between distinct explanatory variables and EUR/PLN return distribution, in Figure 2 we depict preliminary univariate quantile regressions. In the left upper corner of Figure 2 we present a scatter plot of ($vol_{un\exp,t}, r_t$), as well as the conditional quantile estimates, $\hat{Q}_{r_t}(\tau \mid vol_{un\exp,t}) = \hat{\lambda}_{0,\tau} + \hat{\lambda}_{1,\tau} vol_{un\exp,t}$, for some selected probability levels: $\tau \in \{0.01; 0.05; 0.1; 0.25; 0.5; 0.75; 0.9; 0.95; 0.99\}$. The most striking observation is a strong positive relationship between the unexpected trading volume

[5] We use a quartic kernel with bandwidth computed as *2.78sN* $^{-1/5,}$ where *s* is the standard deviation of the data.

[6] Estimation has been performed in Gauss 8.0 with the application of library maxlik.

[7] The trading volume is stationary. We checked for the presence of deterministic as well as stochastic trends and rejected the null of unit root with the augmented Dickey-Fuller test (p-value=0.0000).

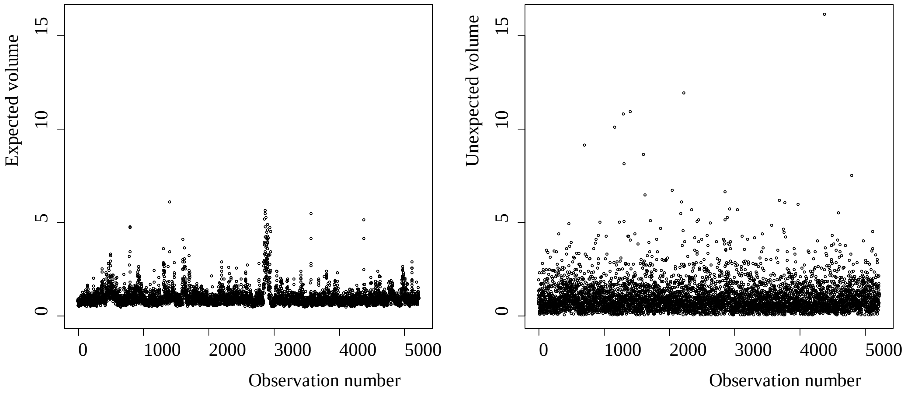

Figure 1. Expected (left panel) and unexpected (right panel) volume

and the dispersion of the return distribution. Moreover, we can also observe that the obtained slope parameter estimates vary across quantiles; such an observation also been found by Chuang et al. (2009). Accordingly, the largest impact on the unexpected volume can be observed with the most extreme quantiles corresponding to the tails of the return distribution. If we turn our attention to the expected volume variable, however, the results seem to be different. Although this variable is also positively linked to the dispersion of the EUR/PLN return distribution, the scale of the effect is much smaller. Thus, the anticipated volume seems to have less of an impact on the probability of large price movements.

In terms of the impact of the lagged return variable, the following tendency is found: after large (positive or negative) returns, the tail probability of observing further large (either positive or negative) movements increases. In order to confirm this effect we applied a nonparametric quantile estimation technique[8]. We can see that the dispersion of the return distribution rises in of the wake of large price movements (upswings or drops). To account for this effect it is reasonable to allow for a forecasted volatility estimate as a factor that is positively related to the dispersion of the distribution.

We estimated the QR models given by equations (4) (model I) and (6) (model II) using the "quantreg" library (version 4.79) written by Roger Koenker under the R[9]. The further inference has also been carried out with the help of these programming codes. QR regressions have been estimated for a dense grid of probability levels ($\tau = 0.01, 0.02, ..., 0.99$); thus, for each model we have

[8] We applied a piecewise cubic polynomial with three knots (Koenker, 2005).

[9] The library can be downloaded from the CRAN website: http://cran.r-project.org.

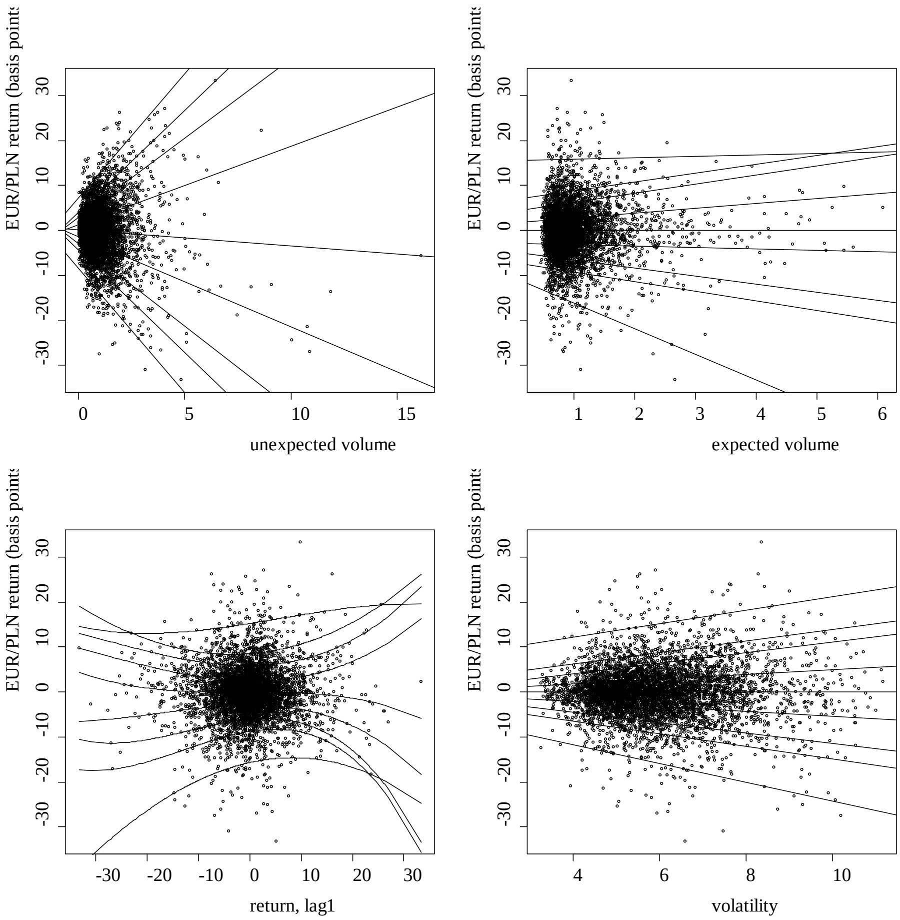

Figure 2. Volume - return relationship. Estimates of quantile regressions for probabilities: $\tau \in \{0.01; 0.05; 0.1; 0.25; 0.5; 0.75; 0.9; 0.95; 0.99\}$

allowed for 99 different vectors of parameter estimates that have been plotted in Figure 3 (model 1) and Figure 4 (model 2). The asymptotic standard errors for each of these specifications have been derived with the help of sparsity estimation methods (see equation (4) and (5))[10]. These equations have been used for the evaluation of the 90% confidence interval for each of the obtained parameter estimates.

As can be anticipated from Figure 3, the seasonality factor of the return distribution is different across the quantiles (in the Figures 3 and 4 the symbols *s*1, *s*2, *s*3, *s*4, *s*5 are defined as $s1 = \tau$, $s2 = \sin(2\pi\tau)$, $s3 = \cos(2\pi\tau)$,

[10] We have also experimented with the Powel kernel and the bootstrap, but it did not influence the further inference.

$s4 = \sin(4\pi\tau)$ and $s5 = \cos(4\pi\tau)$). As the diurnality component $S(\mathbf{v}_\tau, \upsilon)$ seems illegible in Figure 3, we decided to plot the joint diurnality pattern for all of the selected probability levels in Figure 5. As can be seen from the obtained surface, the intraday seasonality pattern is most pronounced for the most extreme quantiles of the return distribution. For the middle quantiles (i.e., quantiles surrounding the median, τ=0.5), humps in the surface are rather negligible and the surface is rather flat. The diurnality pattern for the quantiles corresponding to the lower tail of the distribution demonstrate that the probability of observing large drops in the EUR/PLN rate systematically rises early in the morning (the quantile is "shifted to the left"). This effect is rather symmetric because in the upper quantiles the value of the seasonality function is relatively higher throughout the early morning period (the quantile is "shifted to the right"). What is also striking is the probability of large upswings in the EUR/PLN exchange rate (Polish zloty depreciation) in the late afternoon as the upper tail probability is systematically higher late in the afternoon (just before 18.00 CET).

Concerning the impact of the volume variables, Figure 3 demonstrates that it is the unexpected component of the trading volume that is the most responsible for dispersion of the return distribution. The impact of the unexpected volume is about four times larger than that of the expected volume for the 0.99 quantile and about three times larger for the 0.01 quantile. Therefore, the unanticipated volume brings more information with regards to large upswings of the EUR/PLN exchange rate (i.e., the Polish zloty depreciation). Generally, the impact of the unexpected volume is indisputable as the variable is statistically significant for the probability levels $\tau \in \{0.01, 0.02, ..., 0.51\}$ and $\tau \in \{0.59, 0.6, ..., 0.99\}$ (at a 5% significance level). The effect is also different for different quantiles with the most striking impact placed on the probabilities of the most extreme price movements.

The expected volume was derived as a predictable tendency in the level of a trading volume. At time *t* this variable uses information about the turnover at time *t-1*. Although it is defined for the moment *t*, it is simply an anticipation of the trading volume given the history of its observations. Thus, it can partially capture a potential lead-lag relationships between returns and volumes. If the expected volume is high, the dispersion of the return distribution rises. The impact that this variable exerts on the quantiles of the distribution is significantly different from zero for the probabilities $\tau \in \{0.01, 0.02, ..., 0.19\}$ and $\tau \in \{0.64, 0.65, ..., 0.99\}$. However, the scale of this effect is not as strong as the effect evidenced in the case of unpredictable volume shocks. On top of the expected volume, significant impact on selected quantiles have also lagged unexpected volume shocks (recorded at *t-1*). However, the impact of this variable is significant only for $\tau \in \{0.03, 0.04, ...,0.07\}$.

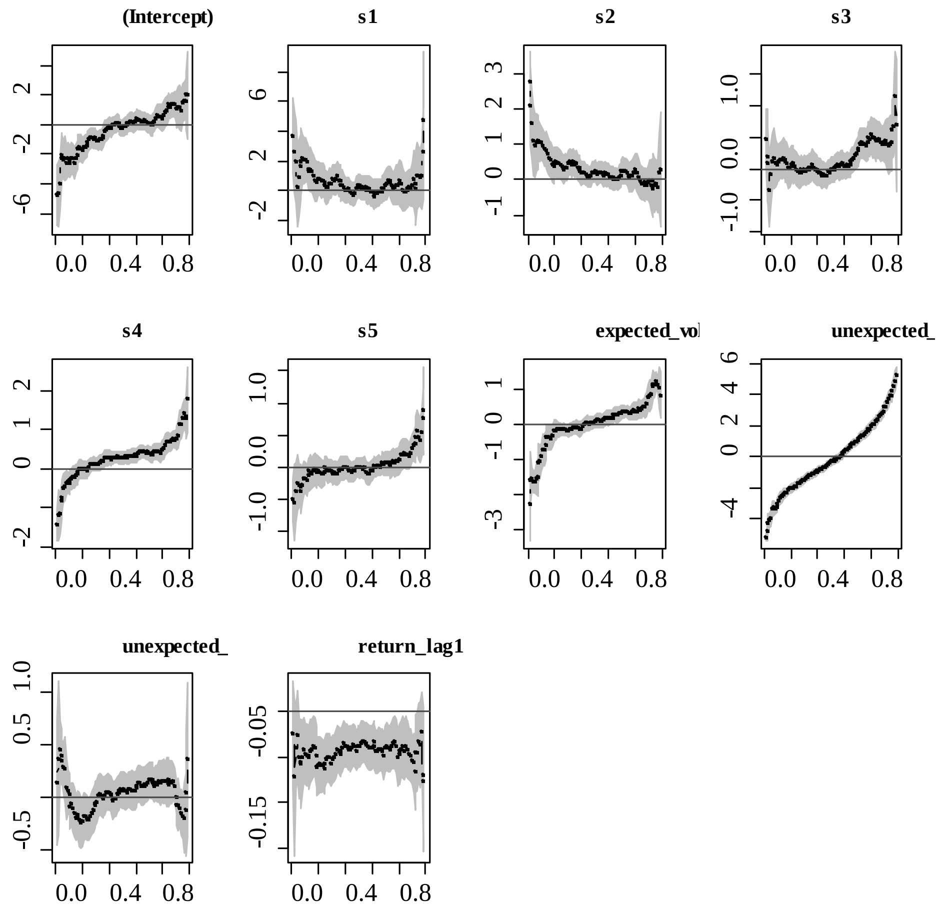

Figure 3. Parameter estimates for quantile regressions (model I). Shaded areas depict the 90% confidence interval

Figure 4 shows that if we account for GARCH-type volatility forecast, $\hat{\sigma}_{t-1}$, as an additional driving force of quantile dynamics, the obtained parameter estimates change. The impact of the unexpected volume remains the same as without the volatile ty variable; however, the role of the expected volume declines in a noteworthy fashion (i.e., it is about two times smaller than in the model I) and it remains significantly different from zero for quantile levels $\tau \in \{0.01, 0.02\}$, $\tau \in \{0.83, 0.84, ..., 0.87\}$ and $\tau \in \{0.93, 0.94, ...,0.98\}$. Findings like this are rather easy to justify. The information contained in the past realizations of the trading volume is, to a large extent, impounded in the FX prices that are set in the market until time *t-1*. Therefore, if these trading volumes are to a large extent reflected by the volatility forecasts $\hat{\sigma}_{t-1}$ (which condition on the information at *t*-1), the amount of information that can be attributed only to the historical volume will significantly decline.

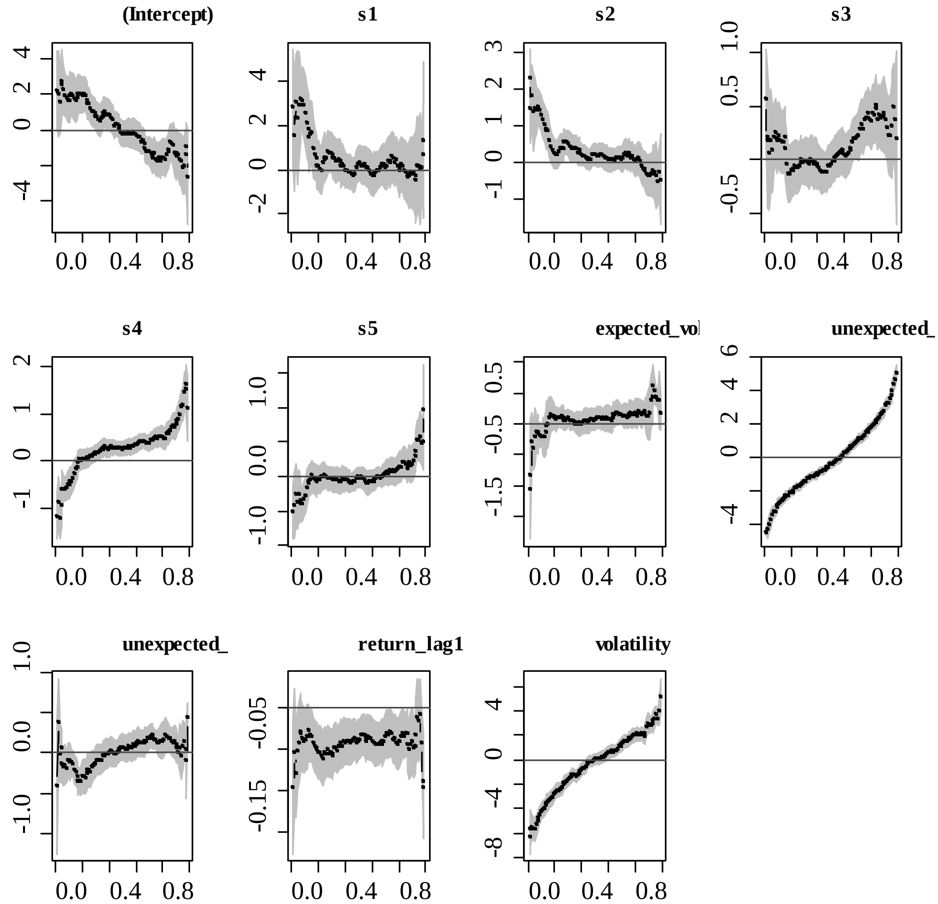

Figure 4. Parameter estimates for quantile regressions (model II). The shaded areas depict the 90% confidence interval

The obtained parameter estimates may also suggest that the return distribution is skewed. This can be observed from the different parameter estimates corresponding to the volatility forecasts that were obtained for lower and upper quantiles (in a symmetric case they should be equal).

Conclusions

The results suggest that trading volume has a significant impact on the variability of the EUR/PLN rate fluctuations. We also show that the unexpected (unanticipated) component of this variable has a significantly stronger impact than the expected (predictable) component. The scale of this impact varies across quantiles and is most pronounced in the tails of the return distribution (i.e., for the most extreme price movements). Our study contributes to the scarce literature on the volume-return relationship in FX markets.

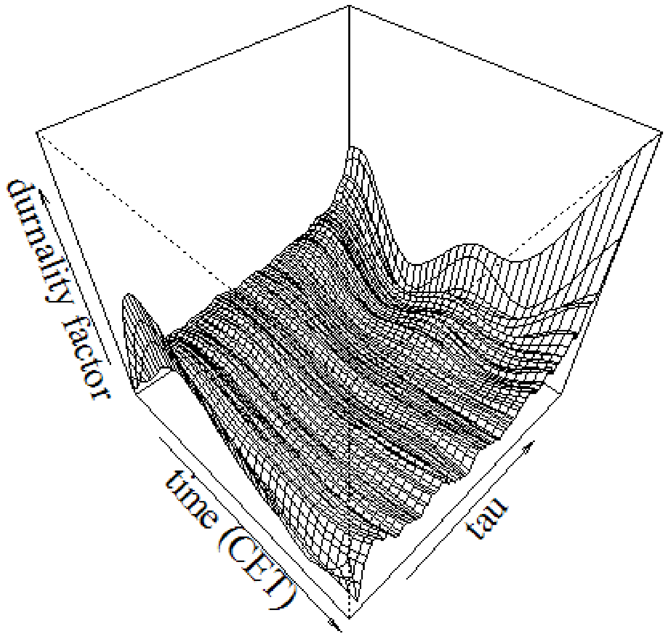

Figure 5. The diurnality pattern for quantiles of the return distribution

Studies on this topic have for the most part been conducted for the lower frequencies including only daily or monthly data. As the FX market is extremely liquid and transparent in comparison to capital markets, the reaction to new information arrival should also be extremely prompt, which justifies the application of high frequency data. Moreover, as outlined by Cheung et al. (2009), applying the QR approach enables one to study the impact of trading on the general shape of the return distribution. Thus, this approach is complementary to the methods based solely on the conditional variance.

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„Czy wolumen transakcji wpływa na zmiany kursu EUR/PLN?” Wnioski płynące z zastosowania regresji kwantylowych

Z a r y s t r e ś c i W artykule dokonano badania wpływu wolumenu transakcyjnego na wartość wybranych kwantyli rozkładu stóp zwrotu z kursu EUR/PLN. Wyniki empiryczne otrzymane na podstawie regresji kwantylowych potwierdziły, że wzrost obrotów ma statystycznie istotny wpływ na dyspersję rozkładu stóp zwrotu. W badaniu dokonano podziału wolumenu transakcyjnego na dwie części: tzw. wolumen oczekiwany przez uczestników rynku i tzw. wolumen nieoczekiwany przez uczestników rynku oraz wykazano, że to wolumen nieoczekiwany ma dużo większy wpływ na dyspersję badanego rozkładu. Zaobserwowano również, że relacja pomiędzy wolumenem a stopą zwrotu ma charakter nieliniowy, tzn. jest najsilniejsza dla najbardziej ekstremalnych kwantyli. Wykazano, że w konsekwencji uwzględnienia miary warunkowej zmienności (jako dodatkowego czynnika wyjaśniającego dynamikę kwantyli stóp zwrotu) wpływ oczekiwanej wartości wolumenu transakcyjnego ulega zmniejszeniu, ale wciąż pozostaje istotny statystycznie, szczególnie dla najbardziej ekstremalnych kwantyli.

S ł o w a k l u c z o w e: relacja wolumen-stopa zwrotu, mikrostruktura rynku, obrót na rynku walutowym, regresja kwantylowa

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