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A comparative study of exchange rates and order flow based on wavelet transform coherence and cross wavelet transform

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A B S T R A C T

Understanding the relationship and behavior of microstructures and exchange rates is an essential discussion for global foreign exchange investors. There are numerous research works regarding the linkage between order flow and exchange rates, yet the exact relationship between the order flow and the market price that indicates whether participants have an impact on the market trend remains undefined. This paper investigates the empirical association and behavior of order flow and the exchange rate movements within the time-frequency space, on three popular currency pairs, using the cross wavelet transform and wavelet transform coherency. The results indicate that order flow has a strong negative correlation and is the leader variable of the exchange rate. A predictor using order flow as an input variable was implemented to forecast the exchange rate direction using the sample data and out-of-sample data. This methodology, which performs with high accuracy and very low drawdown, could be a suitable tool for portfolio managers and forex participants during their trading activities.

1. Introduction

In the traditional theory of exchange rate determination, macrostructural factors, such as inflation rates, interest rates, a country's current account/balance of payments, government debt, and terms of trade, are the basic factors causing exchange rate changes and fluctuations. However, the weak informative power of existing phenomena and theories of nominal exchange rates remain problems in international macroeconomics (Guo, 2017). Based on a large amount of evidence, Meese and Rogoff (1983) stated that the success of forecasting exchange rate changes with economic fundamentals and exchange rate forecasting models was very limited, especially when the forecast horizon is between one month and one year; this tenet has often been cited in subsequent studies (Cheung and Wong, 2000; Evans and Lyons, 2002; Galeshchuk and Mukherjee, 2017). Hence, in the late 1980s, researchers began to consider a new paradigm known as microstructures. The microstructure approach studies the consequences of market configurations, heterogeneous participants with different thinking and strategies, information asymmetry, and limited rationality (Cheung and Wong, 2000). The microstructure method utilizes variables that macroeconomists did not previously consider, the most important of which is order flow, that is, the number of order transactions and the volume of transactions between buyers and sellers, which makes the model understandable and useful. Evans and Lyons (2002a) showed that order flow has strong predictive power for exchange rate movements and, theoretically and empirically, is the driver of price. This is because the order flow consists of current and expected future macroeconomic fundamentals. Therefore, order flow appears to be a predictor of future fundamentals (Rime et al., 2010).

Over the last decade, three approaches have been used to consider the behavior of the forex market. The first is a psychology-based theory called behavioral finance, which defines the behavior of financial participants and their influence on the market (Barberis and Thaler, 2003; Shleifer, 2000). This theory explains some significant psychological behavior of forex market traders, such as the heterogeneous expectations of investors (Frankel and Froot, 1990; MacDonald and Marsh, 1996; Menkhoff et al., 2009), dynamical herding behavior (Kim et al., 2004), and overconfidence leading to high trading levels with poor performance by individual investors (Benos, 1998; Barber and Odean, 2000).

The second approach is the application of empirical microstructure models. Chang and Taylor (2003) considered the effect of Reuter's news arrivals on daily exchange rate movements with the aim of understanding the behavior of participants. Their results suggest that the persistence of

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daily exchange rate volatility is extended by traders' private information in the 15 min following public announcements. In other research, Evans and Lyons (2007) analyzed the association between macro fundamentals, order flow, and exchange rate dynamics. They found that order flow has significant forecasting power for macro fundamentals and future exchange returns.

The third approach is agent-based modeling (ABM), a powerful tool that uses computerized simulations of complex economic phenomena and explores markets and trading behavior by utilizing traders' transactions details, such as opening and closing positions, profit/loss thresholds, traded currency pairs, execution prices, and trade volumes (Farmer and Foley, 2009; Prawesh, 2013; Aloud and Fasli, 2017). Most researchers used simple methods because complexity prevents understanding of the reasons for the emergence of stylized facts. Understanding and discovering some stylized facts (statistical properties) of traders' behavior in high-frequency forex markets is an important aim of ABM methods (Masry et al., 2010; Aloud et al., 2013, 2015; Aloud and Fasli, 2017). The results obtained from this method show that there is a positive linear relationship between the number of buy and sell orders and the number of opening and closing positions (Aloud et al., 2015).

To sum up, there are many methods to study the microstructure of the foreign exchange market, but there is no clear and unified answer about the relationship between order flow (order quantity and transaction volume) and exchange rate. Researches ask whether the order flow guides the market price or the market price guides the market participants. If order flow is a powerful tool to predict the future trend of the foreign exchange market, it will have a significant impact on market participants, and a scientific answer to this question will reveal whether the order flow is an effective means of predicting future forex trends.

However, as an important part of the financial market, the foreign exchange market not only has the general characteristics of the financial market but also has its own characteristics. First of all, the foreign exchange market is a huge, two-tier structure of the trading market; that is, ordinary customers and traders do transactions, so currency transactions can have different prices. Secondly, there is heterogeneity in the foreign exchange market. There is not only information asymmetry among market participants but also different reaction speed to information updating. Even with the same information, different trading behaviors will be produced because of different expectations of future returns. Thirdly, the order flow is different from the usual volume, which means that the positive buying volume and the negative selling volume do not necessarily equal each other, but the trader will adjust the imbalance between the buyer and the seller when they can be compensated. These three characteristics increase the complexity of the foreign exchange market.

The prediction of the market price has been achieved conventionally through different approaches including the statistical models for time series such as autoregressive integrated moving average (ARIMA), autoregressive conditional heteroscedasticity (ARCH), and generalized autoregressive conditional heteroskedasticity (GARCH) models (Montgomery et al., 2015). The time-series regression models have been also used to predict the returns, in which the estimator type plays an important role and needs to account for the predictor persistency and endogeneity, as well as the model heteroscedasticity, such as the generalized least squares estimator (Westerlund and Narayan, 2012, 2015). In addition to traditional forecast methods, the more modern techniques such as stochastic and soft computing based forecasting methods have been also utilized to predict the market price (Mahalakshmi et al., 2016). However, because of the high volatility and market noise, the forecast value of the market price is liable to deviate from the actual value. On the other hand, Forecasting future market trend[3] by utilizing the appropriate analytical tools and methods can reduce the complexity and prediction errors, which may provide a more practical approach compared to predicting the exact price at each time interval (Menkhoff and Taylor, 2007; Özorhan et al., 2018).

In order to clarify the lag-lead relationship between order flow and exchange rate in such a complex environment, we use wavelet analysis in this study. We choose the wavelet analysis method mainly because it has good time-frequency localization and multi-resolution characteristics, as well as the ability to analyze the cross correlation of non-stationary time series considering different time scales and frequency components. This allows researchers to consider the relationship between financial variables and time-varying high, medium and low frequencies, which is useful for short-term and long-term investors interested in short-term and long-term market volatility (Al-Yahyaee et al., 2019). In this respect, the wavelet analysis is obviously superior to the singular spectrum analysis (SSA), which has been favored for time series analysis in recent years. SSA is usually used to eliminate the noise of a univariate time series in empirical analyses of time series lag correlation structures and to determine the main dynamic characteristics inherent in the data (Sharma and Kaw, 2006).

Another interesting and useful feature of wavelets is the fact that its window can be frequently resized. By considering a signal with a small window, only fine features will be viewed whereas by looking at the same signal with a larger window, the coarse features will be viewed (Torrence and Compo, 1998; Madaleno and Pinho, 2014). By using wavelets, we do not need to make any strong hypotheses regarding the data generating process for the series under investigation. Through wavelet analysis, we can simultaneously determine the relationship between variables of different frequencies and discover how the relationship is deduced over time, and also capture non-stationary features. More importantly, inspired by the research results of Torrence and Webster (1999), wavelet transform coherence (WTC), which is good for studying cross correlations, has been widely used in the study of financial market time series. For example, Uddin et al. (2013), Dewandaru et al. (2014), and Yang et al. (2017) applied WTC to the study of the co-variation of stock market returns and exchange rates. Tiwari (2013), Andries et al. (2017), Conlon et al. (2018), and Andries et al. (2014) studied the relationship between price changes and macroeconomic variables (such as inflation and interest rates) based on WTC. However, there is little literature on the application of WTC to the analysis of the microstructure of the foreign exchange market.

In this paper, we apply WTC to consider the relationship between popular currency pairs such as the Euro/US Dollar, UK Pound/US Dollar, and Euro/UK Pound, by analyzing the associated order flows. Therefore, our first contribution is to introduce WTC into the study of the consistency of exchange rate and microstructure variables, such as order flow. This method allows us to measure the cross correlation and phase lag between the two time series by decomposing them with respect to time and frequency (Chang and Glover, 2010; Isbilir et al., 2016). Furthermore, we believe that our study is the first to consider the lag-lead relationship and co-movement between buy and sell position orders and exchange rate price while also demonstrating the predictive power of order flow by applying wavelet transform coherence. Therefore, the second contribution of this paper is the fact that we try to provide advantages to all market participants, such as investors, export and import firms, and especially forex traders to make their own suitable investment decisions. Our prediction method can be executed in real market conditions and does not depend on any special environments such as high-speed trading (algorithmic trading or scalping), low spread brokers (swing trading), or break out, which requires a broker with high execution frequencies at the exact price.

The remainder of this paper is structured as follows. In Section 2, we clarify the procedure and details of obtaining the order flow and exchange rate datasets, and further describe the wavelet coherence approach. Section 3 presents the results for the relationship between two

[3] The trend is the general direction of forex' prices which is upward or downward. Trends may differ in length, from short to intermediate to long term (Kumar et al., 2012).

time series and the associated forecasting accuracy. Section 4 considers backtesting and optimization by using MT4. Finally, this paper finishes with a summary of our conclusions in Section 5.

2. Materials and methodology

2.1. Data background: foreign exchange traders' behavior

In this paper, we choose the wavelet analysis method to analyze the relationship and correlation between exchange rates of three currency pairs of currencies, namely Euro/US dollar, UK Pound/US dollar and Euro/UK Pound, and their order flow. Specific steps are as follows: first, the Pearson correlation and the Spearman correlation are applied to the linear relationship and the monotonic relationship respectively, second, covariance analysis and interactive detection are considered through the cross wavelet transform; then, wavelet coherence is used to identify which time series (exchange rate or order flow) drives or influences the other, and to identify the relative lag between the input signals. MatLab is used to analyze the wavelets. Thereafter, by implementing the order flow and exchange rate dataset as our inputs, we derive an algorithm that predicts the trend in EUR/US Dollar, UK Pound/US Dollar, and EUR/UK Pound exchange rates. Therefore, in our algorithm, the first thing to consider is buying and selling positions separately for each currency pair.

As far as a suitable currency transaction is concerned, if we want to buy (sell) in the context of a pair of currencies, the best way is to implement short (long) position orders for buy (sell) positions. Unfortunately, as Yahoo Finance[4] has pointed out, most traders lost more money on their losing trades (average of 83 pips) from February 2014 to January 2015 than they won on their winning trades (average of 48 pips), which shows that traders keep their losing orders for a long time, hoping for a reversal in the market, but close their winning orders quickly. Aloud et al. (2015) found a linear correlation between buying and selling orders and the number of opening and closing positions.

Take the Euro/US dollar currency pair as an example. To determine the reversal of the trend towards buying Euro, the previous trend should be downward so that more Euro selling orders can be obtained after the reversal of the trend. Once the overall trend of the exchange rate changes, the selling position of the euro begins to decrease, thus the cumulative amount of the selling position of the euro increases more smoothly.

The second variable is the proportion of buy position orders and sell position orders, both of which cause changes in the direction of exchange rate movements.

An uptrend reversal is predicted, when the total ratio number of buy positions exceeds the total number of sell positions, and vice versa for a sell trend reversal. The normalized ratio of buy and sell positions against normalized exchange rate price is shown in Fig. 1.

The final variable implemented in our method is the moving average of price changes. Moving average methods are generally used to smooth and remove noise from time series data and predict future trends. However, when using the moving average method to predict, the result depends on the period value (i.e., n value). Increasing the value of n will make the predicted value more insensitive to the actual change of data and make the fluctuation smoother. For this reason, we simulated several moving averages with higher period to smooth the data and several moving averages with lower period to recognize the reversal of direction earlier and optimize the system based on the lowest drawdown, the highest profit, and the most winning trades.

The moving average with period value of 72 h (three days) was selected in this paper to show the main trend, and the 8-h period was selected to indicate the short-term trend of price with lower lag and lower smoothness. A strong trend often serves as intraday support (Weatherford et al., 2003), and demonstrates the latest trend in price changes. In the process of predicting a buy trend reversal, the two moving averages due to the lag with the current price should be trending downward and tend to zero with decreasing slope, and vice versa for a sell trend reversal.

Our buy or sell positions take place when all the conditions mentioned above occur at the same time.

2.2. Data

The quantity of data collection and the quality of the extracted data are crucial in exchange rate predictions (Einav and Levin, 2014). For instance, in machine learning, a small amount of data with large numbers of parameters can cause over-fitting (Yosinski et al., 2014). Our method does not require a huge dataset, but a large amount of data allows us to optimize our methodology to obtain more reliable conclusions.

For estimation purposes, we collect an hourly time-frequency data on the three exchange rate prices EUR/USD, GBP/USD, and EUR/GBP, with the corresponding order flow data. Due to the limitation of time span, with maximum 1000 order flow history data, and lack of access to extract the data, the only way to collect the data was hourly recording which lasted from May 1 to October 31, 2018; the total was 6 months, corresponding to 132 working days (Monday to Friday) or 3168 h. All exchange rates were collected by recording the data reported by Meta Trader 4 (MT4) during the same time period of order flow data. The order flow data is taken from myfxbook, which is a social forex community with a huge number of traders' accounts covering funds of more than $1.6 billion. This dataset provides volumes and the number of long and short positions in the order flow data for different currency pairs.

The main reason that we choose the 1 h time frame is that the lower time frames, such as 1 min, 5 min, or 15 min, cannot visualize the main direction of the exchange rate, and a 30-min time frame contains more noise and includes half of time span history data of 1 h. The higher time frames such as 4 h and daily are not selected because the 4-h time frame needs 4 h to create the data and the daily time frame needs one day to create the data; during this time, many opportunities will be missed, which means traders cannot take a position at the beginning of the directional change.

We choose EUR/USD and the GBP/USD as the major forex currency pairs and the EUR/GBP as a minor forex currency pair based on the hourly frequency. The major currency pairs are those with the US Dollar and are frequently traded. The minor or cross currency pairs do not include the US Dollar. The reason why we chose these three currency pairs is that, in theory, any one of these currency pairs is derived from the other two currency pairs. For instance, Euro/US Dollar is equal to Pound/US Dollar times Euro/UK Pound. That is, the analysis results of these currency pairs are related to each other and allow us to find the most powerful and weakest currency among them. US Dollar against Japanese Yen is not considered because of the low transaction amount of participants, which renders it an improper indicator of sample data.

To collect data for analysis, we must first consider the intraday seasonality of trading activity over 24 hourly intervals, namely the trading activity during intraday trading hours of the forex market to obtain the start and end times of the full trading day. We aggregate the number of trading activities per hour and divide it by the total number of trading activity days in the dataset to obtain a general overview of trading activity for the whole of our dataset.

Fig. 2 shows the total trading activity of our dataset for EUR/USD, GBP/USD, and EUR/GBP over 24-h intervals based on Greenwich Mean Time. An interesting result from Fig. 3 is that the number of trading activities increases and decreases synchronously for these three currency pairs. The fewest positions occur at 19:00 GMT and 21:00 GMT, which are respectively 3 h and 1 h before the Tokyo session starts.

In their study, Andersen et al. (2001) chose 21:01 GMT and 21:00 GMT as the start and end of daily periodicity. Due to the weekly closing of market on Fridays at 20:59 GMT and opening of market on Sundays at 21:01 GMT based on the Pepperstone broker, and the lowest activities of traders in this time, we consider the start and close of market trading

[4] Yahoo Finance https://finance.yahoo.com/news/why-many-forex-traders-lose-214500903.html.

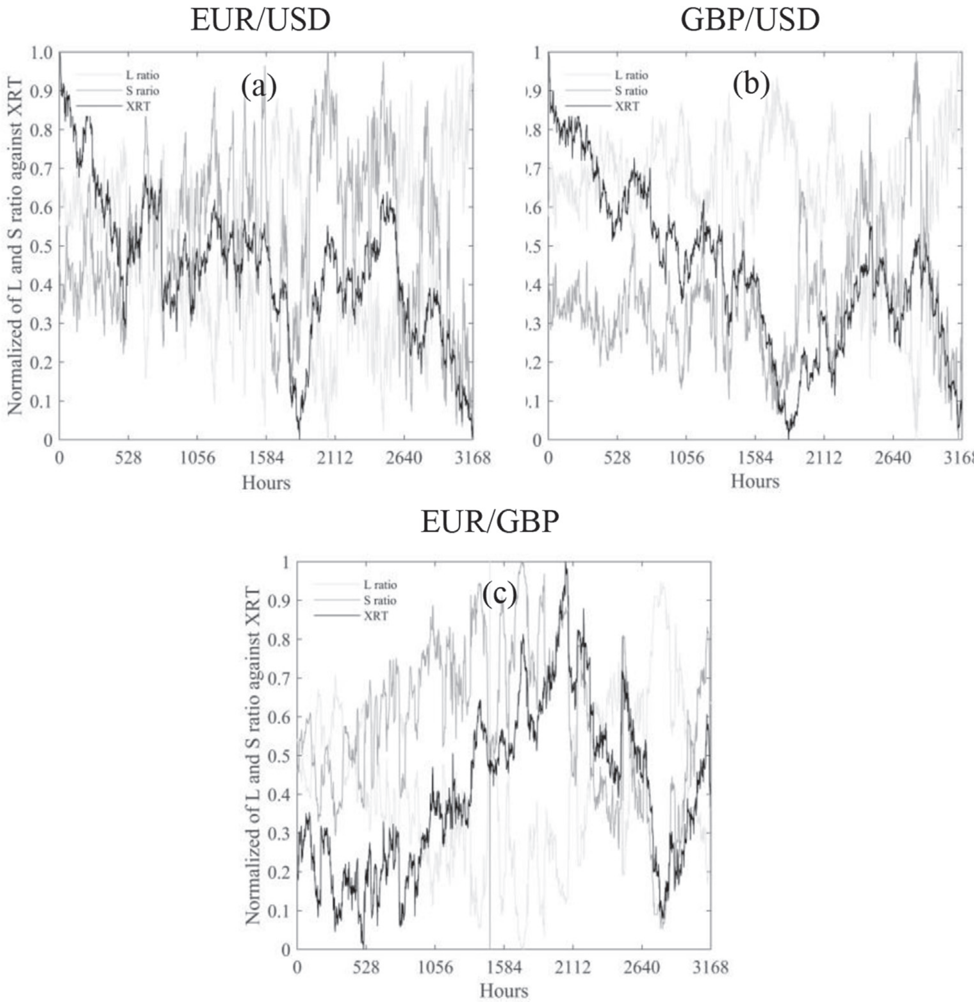

Fig. 1. Normalized of total long position orders ratio (L ratio) to total buy and sell position orders and short position orders ratio (S ratio) to total buy and sell position orders against normalized exchange rate price (XRT).

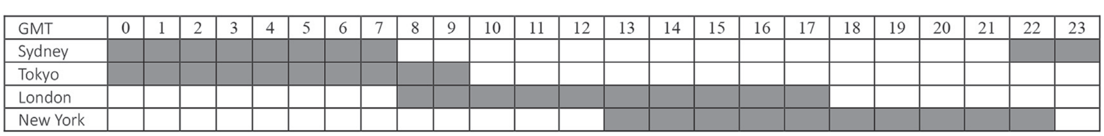

Fig. 2. Open and close times for each forex session based on GMT.

from 21:01 to 20:59 as a full day of trading activity. The most trading positions occur at 05:00 and 06:00 GMT, three and 2 h respectively before the opening of the London session, and at 11:00 GMT, 2 h before the opening of the New York session. Another notable aspect of Fig. 3 is the sudden reduction in the number of trading positions at 12:00 GMT, 1 h before the New York session opens.

The raw datasets of the order flow of long positions, short positions, and the difference between them with the exchange rates of these three currency pairs are shown in Fig. 4. In the next section, we describe the preparation of the data and the inputs.

2.3. Data preparation

The exchange rate price samples collected from MT4 include open, high, low, and close rates of hourly data. We choose the close rate versus long- and short-traded orders as the input to the wavelet coherence, and use the two most common moving averages (the simple moving average (SMA) and the exponential moving average (EMA)) with 72-h periods to show the long term price change trend; we also use 8-h periods to indicate the short term price change trend. As explained in Section 2.1, the choice of the 72-h and 8-h periods is based on the lowest drawdown, highest profit, and most winning trades, and is ultimately determined by system optimization after many attempts. The order flows of long and short positions should reflect the reverse trend in the exchange rates. The SMA is given by:

$$SMA_m = \frac{CR_m + CR_{m-1} + \ldots + CR_{m-(n-1)}}{n} \tag{1}$$

$$SMA = \frac{1}{n}\sum_{j=0}^{n-1} CR_{m-i} \tag{2}$$

where CR_m represents the present closing.

The EMA is calculated based on the following formula:

$$EMA = ((Current\ exchange\ rate - \mathrm{Previous}\ EMA) \times \alpha) + \mathrm{Previous}\ SMA \tag{3}$$

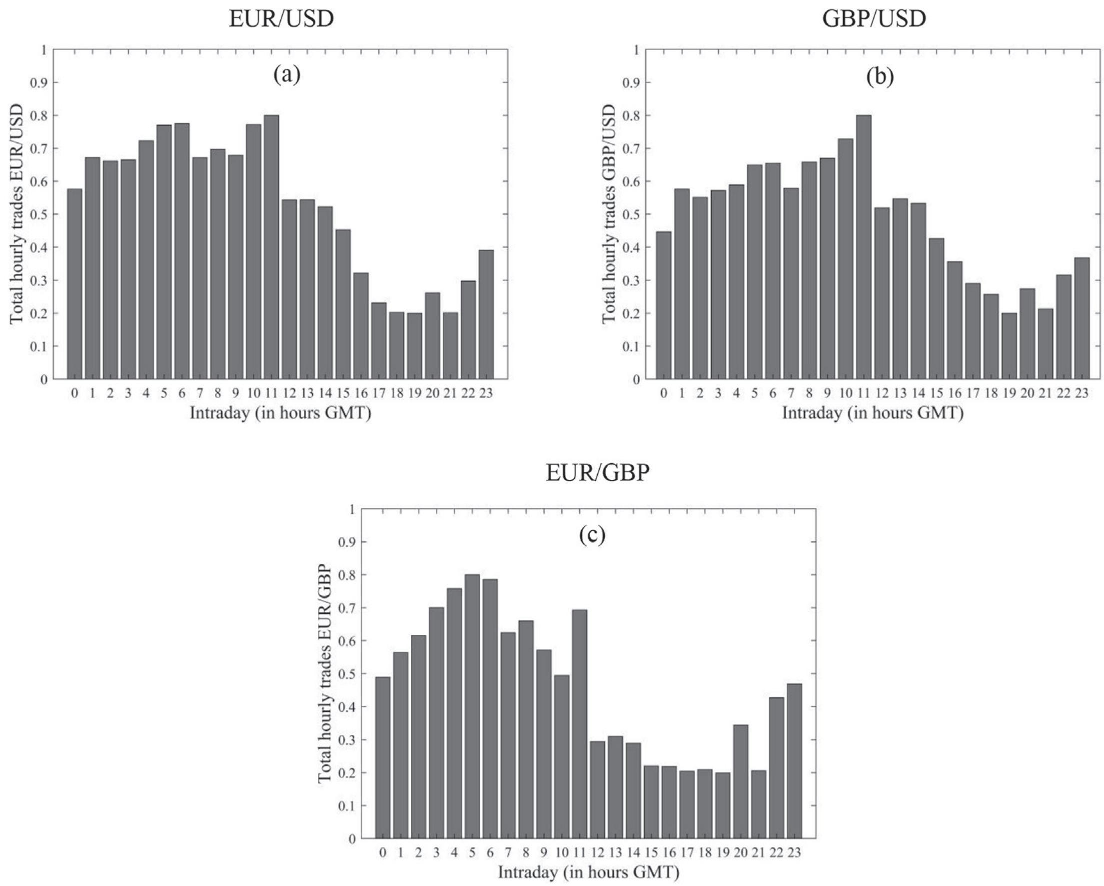

Fig. 3. Total intraday seasonality of EUR/USD, GBP/USD, and EUR/GBP trading activity based on GMT.

where α is a smoothing factor (or multiplier). To reflect that the market is more sensitive to new information, we give more weight to the recent price, that is, $\alpha = 2/(n\text{-}1)$, where n is an index of the time period. Once the multiplier is known, we can calculate the EMA.

To get the first EMA value, we use the SMA for the same period, as the previous EMA is not available. At this moment, all requirements for having optimal data are satisfied; hence, in the remainder of this section, we briefly describe continuous wavelet transform (CWT), cross wavelet transform (XWT), wavelet transform coherency (WTC), and the cross wavelet phase angle.

2.4. Wavelet

The wavelet transform is a powerful signal processing tool consisting of a zero-mean function that is localized in time (Δt(and frequency (Δω or bandwidth) (Tiwari et al., 2015). The wavelet function (daughter wavelet) is defined as (Ko and Lee, 2015):

$$\tilde{\psi}_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), \quad s,\tau \in \mathbb{R}, s \neq 0 \tag{4}$$

Wavelet functions are formulated based on location, scale parameters, and a mother wavelet function. The mother wavelet ψ draws out frequency information with some dilation or compression corresponding to a variety of frequencies in the time series. The scale parameter s considers the extent of the dilation or compression, and τ is the translation parameter that determines the position of a specific wavelet function in the time series. There are several types of wavelets with diverse characteristics that are suitable for different purposes (Dogra, 2017). The mother wavelet implemented in our method is the Morlet wavelet introduced by Goupillaud et al. (1984), which is the most appropriate for identifying oscillatory components of a signal. The Morlet wavelet, which has no scaling function, can be written as:

$$\psi^{Morlet}(t) = \frac{1}{\pi^{1/4}} e^{i\omega_0 t}\, e^{-t^2/2} \tag{5}$$

where t is the normalized time and ω_0 is the frequency. Based on the classical Heisenberg uncertainty principle, there is always a trade-off between time and frequency localization. By selecting $\omega_0 = 6$, the Morlet wavelet balances the localization of time and frequency, giving the optimal wavelet for feature extraction purposes (Saiti et al., 2016), which is a good choice for our study. The other advantage of the Morlet wavelet is that information is obtained based on the amplitude and phase of waves, which are substantial when analyzing the synchronization of the movement of exchange rates and order flows (Aloui et al., 2015; Vasquez et al., 2018).

Following the guidelines of Grinsted et al. (2004), we use the Monte Carlo method to calculate the statistical significance level of wavelet transform coherence.

2.5. The continuous wavelet transform (CWT)

The continuous wavelet transform (CWT) offers good time and frequency resolution at high and low frequencies, respectively (Haris et al., 2017). Also, CWT retains phase information and exhibits adaptive frequency resolution. The CWT equation for a time series x(t) is given by:

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t)\tilde{\psi}^*_{\tau,s}(t)dt, \quad s,\tau \in \mathbb{R},\ s \neq 0 \tag{6}$$

where $\tilde{\psi}$ indicates the daughter wavelet from equation (4), $\tilde{\psi}^*$ is the

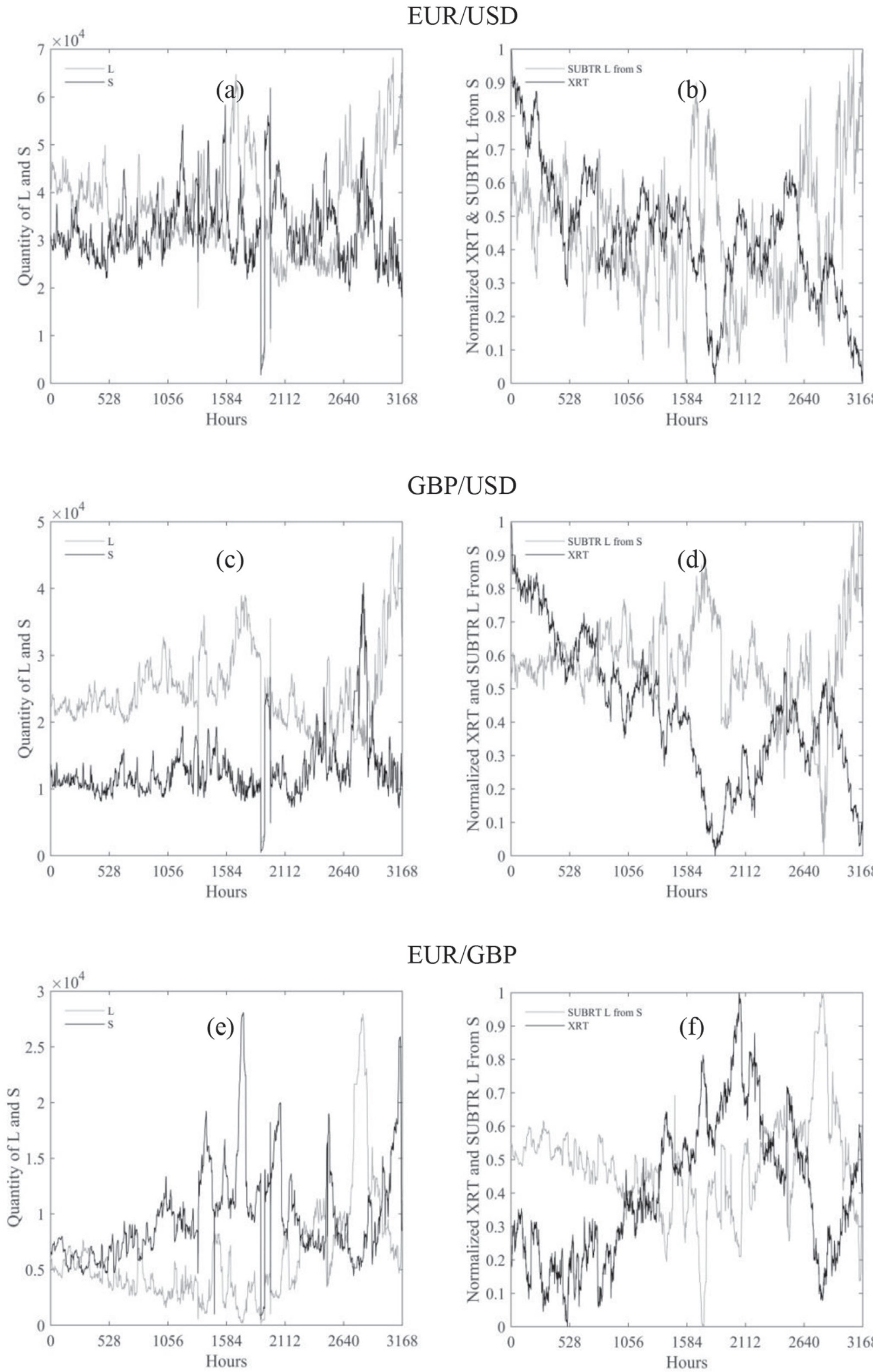

Fig. 4. Raw data of exchange rates and order flow (long and short positions) of EUR/USD, GBP/USD, and EUR/GBP. Note: (a), (c), (e) show long (L) positions vs short (S) positions; (b), (d), (f) show exchange rate (XRT) vs difference between L and S positions.

complex conjugate of $\bar{\psi}$, τ is the translation parameter, and s is the scaling factor.

The main purpose of our study is to identify the relationship between two time series, x(t) and y(t), which can be considered by the cross wavelet transform.

2.6. The cross wavelet transform (XWT)

The cross wavelet transform (XWT) was developed to investigate the relationship between two nonstationary time series and determine their powers and phase difference in time-frequency domains. Thus, XWT can be used to define the covariance between the two time series (Yu and Lin, 2015).

The wavelet transforms of the time series x(t) and y(t) are denoted by W_x and W_y, respectively, and their XWT is defined as:

$$W_{xy}(\tau, s) = W_x(\tau, s) W_y^*(\tau, s) \tag{7}$$

where W_y^* is the complex conjugate of W_y. The wavelet power spectrum is simply defined as $|W_x|^2$, which gives us a measure of the local variance of a time series and the cross wavelet power. The local covariance between the two time series is defined as $|W_{x,y}|$ (Qin et al., 2014).

2.7. Wavelet transform coherence (WTC)

The wavelet transform coherence (WTC) can be used to analyze the localized correlation coefficients and phase relationships of two time series that contain nonstationary powers at many different frequencies (Nourani et al., 2016). Wavelet coherence analysis can identify information about the dependencies and correlations between the data from two time series (Ahn and Park, 2016). The WTC (Torrence and Webster, 1999) has the specific form:

$$R_{xy}(\tau, s) = \frac{|S(W_{xy}(\tau, s))|}{\sqrt{S(|W_x(\tau, s)|^2).S(|W_y(\tau, s)|^2)}} \tag{8}$$

where S is a smoothing operator applied to both time and frequency (without S, the wavelet coherency would equal 1 at all scales and times) and R_{xy} takes values between 0 and 1. Values closer to 1 provide evidence of a stronger correlation, and values closer to 0 indicate a weaker correlation (Akoum et al., 2012). The smoothing operator S is given by the convolution in time and scale:

$$S(W) = S_{scale}(S_{time}(W(s))) \tag{9}$$

where S_{scale} and S_{time} denote smoothing along the wavelet scale axis and in time, respectively. The time convolution is performed with a Gaussian operator, and the scale convolution is performed with a rectangular window (for details, see Torrence and Compo, 1998).

The wavelet coherence analyzes lags in the oscillation of two time series x = $\{x_n\}$ and y = $\{y_n\}$. The angle ϕ_{xy} is called the phase difference; it reflects the lags and the lead relationship between x and y, allowing us to distinguish whether the dependence of wavelet coherence is positive or negative (Owusu Junior et al., 2018). As the CWT is complex, it can be divided into real and imaginary parts based on the mother wavelet (the Morlet wavelet). The phase difference is defined as:

$$\phi_{x,y} = \tan^{-1}\left[\frac{\mathrm{Im}\{W_{x_n,y_n}\}}{\mathrm{Re}\{W_{x_n,y_n}\}}\right], \phi_{x,y} \in [-\pi, \pi] \tag{10}$$

where Im and Re denote the imaginary and real parts of the smooth power spectrum, respectively.

We consider the eight phase angle conditions denoted by the arrows in Fig. 5. In this figure, the angles are measured counterclockwise. In the first condition, the arrow points to the right and the phase difference is zero, indicating that the time series' movements are synchronized and there is a positive correlation at the given time frequency. The arrow pointing to the left indicates that the two variables are out of phase by 180° and have a negative correlation. Upward and downward arrows have phase differences of π/2 and -π/2, respectively, and indicate that the second variable leads the first or that the first variable leads the second, respectively. Phase angles $\phi_{x,y} \in \left(0, \frac{\pi}{2}\right)$ or $\phi_{x,y} \in \left(-\pi, -\frac{\pi}{2}\right)$ show that the second variable is leading the first, whereas $\phi_{x,y} \in \left(-\frac{\pi}{2}, 0\right)$ or $\phi_{x,y} \in \left(\frac{\pi}{2}, \pi\right)$ represent the first variable leading the second (Fattouh, 2016).

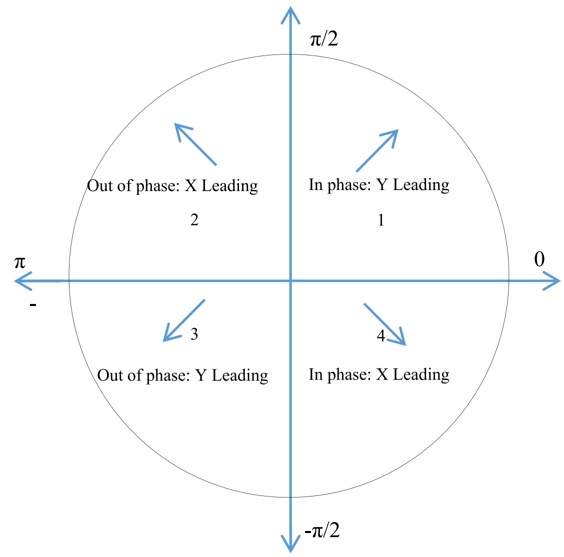

Fig. 5. Representation of phase angles.

3. Results and discussion

Table 1 shows the statistical characteristics of each pair of currency samples, in which the standard deviation measures the volatility of the time series data. Comparing them, we can find that the EUR/USD market has the highest volatility, and EUR/GBP has the lowest volatility. Note also that the normal distribution occurs when the skewness is zero or near zero. None of the return series obey a normal distribution, and all exhibit positive skewness except for the subtraction of long positions from short positions for GBP/USD; the positive skewness indicates that the data are skewed to the right.

Next, statistical analysis was performed to determine the correlations between the exchange rates of all currency pairs and their own order flow data, such as long positions, short positions, and the difference between the two. This analysis examined the linear association and rank correlation coefficients through the Pearson and Spearman correlations, respectively, at 95% confidence intervals, which is the area below the histogram graph with two standard deviations of the mean. The results are presented in Table 2.

From the analysis results in Table 2, it can be seen that the correlation coefficients reveal that the exchange rate is negatively correlated with the difference of buy position orders minus sell position orders. The price change and order flow datasets for EUR/USD and EUR/GBP exhibit a large negative correlation, whereas the price change and order flow for GBP/USD have a smaller negative correlation. The p-values are extremely small, which means that the results are highly significant, and the probability of unrelated variables producing the same correlation is very low. Therefore, the Spearman and Pearson coefficients can be employed to consider the correlation between long positions and short positions. The results in Table 3 indicate that there is a strong negative correlation between long positions and short positions for EUR/USD and EUR/GBP, and GBP/USD.

Next, as described in Sections 2.4-2.6, CWT was applied to determine the co-movement between the price change and order flow data, so that the dynamic linkage between these two time series can be analyzed; WTC is measured to observe how the order flow and price changes change over time and across frequencies. WTC can be used to investigate regions with a high common power and explain the phase relationship (Madaleno and Pinho, 2014). Fig. 6 shows the results of cross wavelet analysis per hour, on average for each trading day of price changes and order flow of the three currency pairs, that is, the local covariance between these two time series at each time and frequency, which indicates that the relationship between exchange rate price and order flow returns is influenced by

Table 1
Descriptive statistics of the raw data of exchange rates and order flow (long and short positions) of EUR/USD, GBP/USD, and EUR/GBP.

Currency Pairs	Data Types	min	max	mean	median	mode	Variance	Standard deviation	Kurtosis	Skewness
EUR/USD	*Long Positions*	2317	68,234	36,844	36,043	30,039	9.94×10^{7}	9969	3.8004	0.3605
	Short Positions	1757	61,888	32,036	31,220	33,946	5.17×10^{7}	7153	5.4173	0.2232
	Close Rate	1.1302	1.2079	1.1645	1.1649	1.1665	2.01×10^{-4}	0.0142	3.3146	0.1644
	LongPos-ShortPos	−30,779	46,743	4807	4225	23,854	2.03×10^{8}	14,254	2.7537	0.2937
GBP/USD	*Long Positions*	845	47,758	24,671	23,605	17,418	3.75×10^{7}	6121	5.5142	0.5275
	Short Positions	489	40,841	12,857	11,712	24,643	2.17×10^{7}	4657	11.7031	2.3787
	Close Rate	1.2668	1.3769	1.3145	1.3142	1.3142	5.11×10^{-4}	0.0226	2.4802	0.1348
	LongPos-ShortPos	−24,467	38,468	11,814	11,654	−7225	7.21×10^{7}	8490	4.9745	−0.4260
EUR/GBP	*Long Positions*	134	27,972	6022	4639	21,667	2.17×10^{7}	4654	9.8388	2.3352
	Short Positions	498	28,088	9679	8500	5159	1.81×10^{7}	4254	6.1662	1.5163
	Close Rate	0.8699	0.9095	0.8859	0.8848	0.8789	6.93×10^{-5}	0.0083	2.3806	0.3800
	LongPos-ShortPos	−27,724	22,367	−3657	−3319	16,508	5.30×10^{7}	7277	5.3464	0.3166

Table 2
Pearson and Spearman correlations of exchange rates against order flow.

		Long Positions				Short Positions				LongPos - ShortPos			
		R	RL	RU	p-value	R	RL	RU	p-value	R	RL	RU	p-value
EUR/ USD Price	Pearson	−0.3543	−0.3844	−0.3235	2.3×10^{-94}	0.2924	0.2602	0.3239	1.8×10^{-63}	−0.3946	−0.4236	−0.3647	1.6×10^{-118}
	Spearman	−0.3756	−0.4005	−0.3502	1.0×10^{-106}	0.3691	0.3436	0.3941	8.1×10^{-103}	−0.3940	−0.4184	−0.3690	3.7×10^{-118}
GBP/ USD Price	Pearson	−0.3698	−0.3995	−0.3394	3.0×10^{-103}	0.0560	0.0212	0.0907	1.6×10^{-05}	−0.2973	−0.3287	−0.2652	1.1×10^{-65}
	Spearman	−0.3308	−0.3566	−0.3045	9.2×10^{-82}	0.0862	0.0571	0.1151	1.2×10^{-06}	−0.2729	−0.2997	−0.2456	3.3×10^{-55}
EUR/ GBP Price	Pearson	−0.3228	−0.3536	−0.2912	9.9×10^{-78}	0.6326	0.6113	0.6531	~0	−0.5762	−0.5990	−0.5525	1.0×10^{-279}
	Spearman	−0.3069	−0.3331	−0.2802	4.6×10^{-70}	0.7073	0.6924	0.7216	~0	−0.5547	−0.5746	−0.5341	3.9×10^{-255}

Note: R is the correlation coefficient of Pearson and Spearman correlations. RL and RU give the lower and upper limits of the confidence interval at the 95% level, respectively.

Table 3
Pearson and Spearman correlations of long positions, short positions, and the difference between them.

EUR/USD	Long Positions		Short Positions		LongPos - ShortPos	
	Pearson	Spearman	Pearson	Spearman	Pearson	Spearman
Long Positions	1	1	−0.3688	−0.5939	0.8845	0.9187
Short Positions	−0.3688	−0.5939	1	1	−0.7598	−0.8462
LongPos - ShortPos	0.8845	0.9187	−0.7598	−0.8462	1	1
GBP/USD	**Long Positions**		**Short Positions**		**LongPos - ShortPos**	
Long Positions	1	1	−0.2277	−0.3408	0.8454	0.8928
Short Positions	−0.2277	−0.3408	1	1	−0.7121	−0.6600
LongPos - ShortPos	0.8454	0.8928	−0.7121	−0.6600	1	1
EUR/GBP	**Long Positions**		**Short Positions**		**LongPos - ShortPos**	
Long Positions	1	1	−0.3337	−0.4342	0.8345	0.8173
Short Positions	−0.3337	−0.4342	1	1	−0.7979	−0.8265
LongPos - ShortPos	0.8345	0.8173	−0.7979	−0.8265	1	1

long-term changes more than by short-period movements.

In the nine subfigures of Fig. 6, the left-most three figures are based on the exchange rate against the difference between buying and selling positions; the middle three figures are based on the exchange rate against buying positions; and the right three figures are based on the exchange rate against selling positions. The arrows in the figure represent the relative phase relationship. The horizontal axis represents the (days) data index; 1, 22, 44, 66, 88, 110, and 132 under the horizontal axis represent May 1, May 30, June 29, July 31, August 30, October 1, and October 31, respectively. The vertical axis represents the frequency/scale.

In the furnace charts of Fig. 6, the first time series x of CWT is the exchange rate price, and the second time series y is the order flow. The Morlet wavelet was used as the mother wavelet in XWT. The thick black contours represent the 5% significance (95% confidence) level against red noise, as estimated through Monte Carlo simulations. The cone of influence (COI) separates the plot into dependable (full colors) and undependable (pale colors) regions, indicating the zones affected by edge effects, and is drawn as a thin black line. The color bar to the right of the XWT results depicts the steep power gradient of the significant contours. The areas with warmer colors have powerful interrelations, whereas areas with colder colors have less correlation and interrelation among time and frequency. Blue indicates the lowest power (no correlation) and red denotes the highest power (highly correlated) distributed according to the frequency intervals.

An interesting observation is that the direction of arrows at different frequency bands remains almost the same over the study period, indicating that the exchange rate moves opposite to the order flow. In Fig. 6(a), (d), and (g), those regions of the plot with stronger powers (yellow, orange, and red colors) have arrows directed down and to the left. This reveals that the exchange rate and the order flow have a negative correlation with 180° phase difference beyond 4 days. For the majority of points in the plots, the order flow is the leader variable. Out of the thick black contours with low correlation power, the exchange rate was the leader variable in currency pair EUR/USD from late July to mid-August between 9 and 12 scales. For GBP/USD, the order flow was always the leader, and for EUR/GBP, the order flow was the leader variable

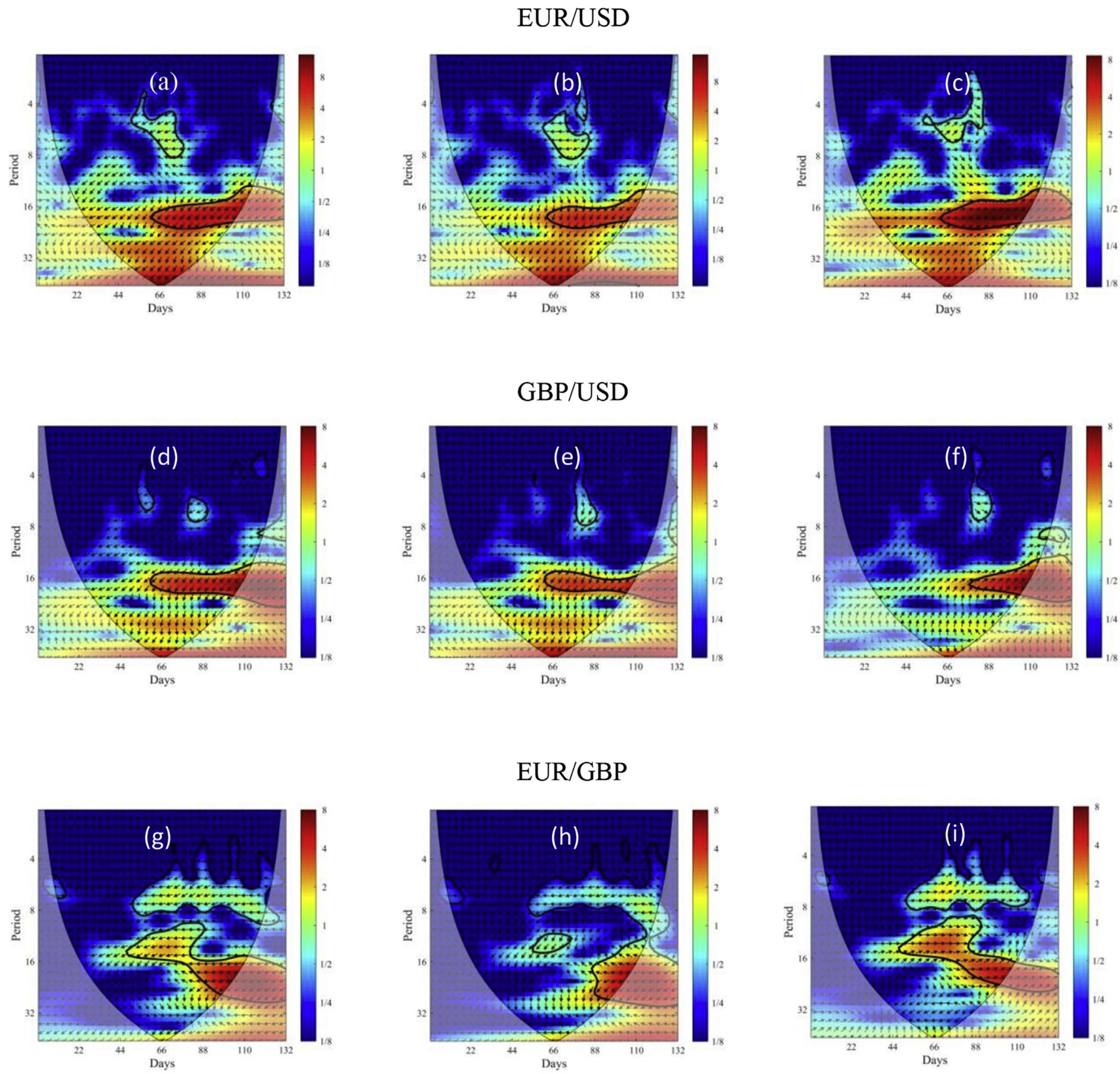

Fig. 6. Cross wavelet transform of the standardized exchange rate price and order flow time series for EUR/USD,GBP/USD, and EUR/GBP. Note: In the nine subfigures, the left-most three figures (a), (d), and (g) are based on the exchange rate against the difference between buying and selling positions; the middle three figures (b), (e), and (h) are based on the exchange rate against buying positions; and the right three figures (c), (f), and (i) are based on the exchange rate against selling positions. The arrows in the figure represent the relative phase relationship.

except from mid-July to early August in out of the thick black contours with low correlation and period of 30.

Note: In the nine subfigures, the left-most three figures (a), (d), and (g) are based on the exchange rate against the difference between buying and selling positions; the middle three figures (b), (e), and (h) are based on the exchange rate against buying positions; and the right three figures (c), (f), and (i) are based on the exchange rate against selling positions. The arrows in the figure represent the relative phase relationship.

We can also draw some conclusions with respect to phase (indicated by the arrows). Information on the phases shows that the relationship between the exchange rate and order flow is almost homogeneous across scales because those arrows in most of times pointed in one direction and in a few scales we can see heterogeneity. Moreover, the cross wavelet coherency is high at high scales (low frequencies), higher than 4 scales of all, and the coherence results out of the cone influence are not statistically significant.

Note that CWT does not normalize the common power of the two processes into a single wavelet power spectrum, thus failing to accurately analyze the correlation and relationship between the two time series; this is a disadvantage of CWT (Tiwari et al., 2015). The reason it is used in this study is to obtain a deeper analysis than linear correlations and find out the high and low coherency frequencies. At the same time, in order to analyze the coherence more deeply and understand the coherence more clearly, WTC is applied to the exchange rate and order flow datasets to examine the coherency between the two time series for different frequency bands and time intervals.

The correlation between the exchange rate and order flow of different currency pairs based on WTC is shown in Fig. 7. The meanings of color, line thickness, and other features in this figure are the same as those in Fig. 6.

The phase difference in Fig. 7 represents the lead-lag relationship of the two series at different scales, so the correlation between exchange

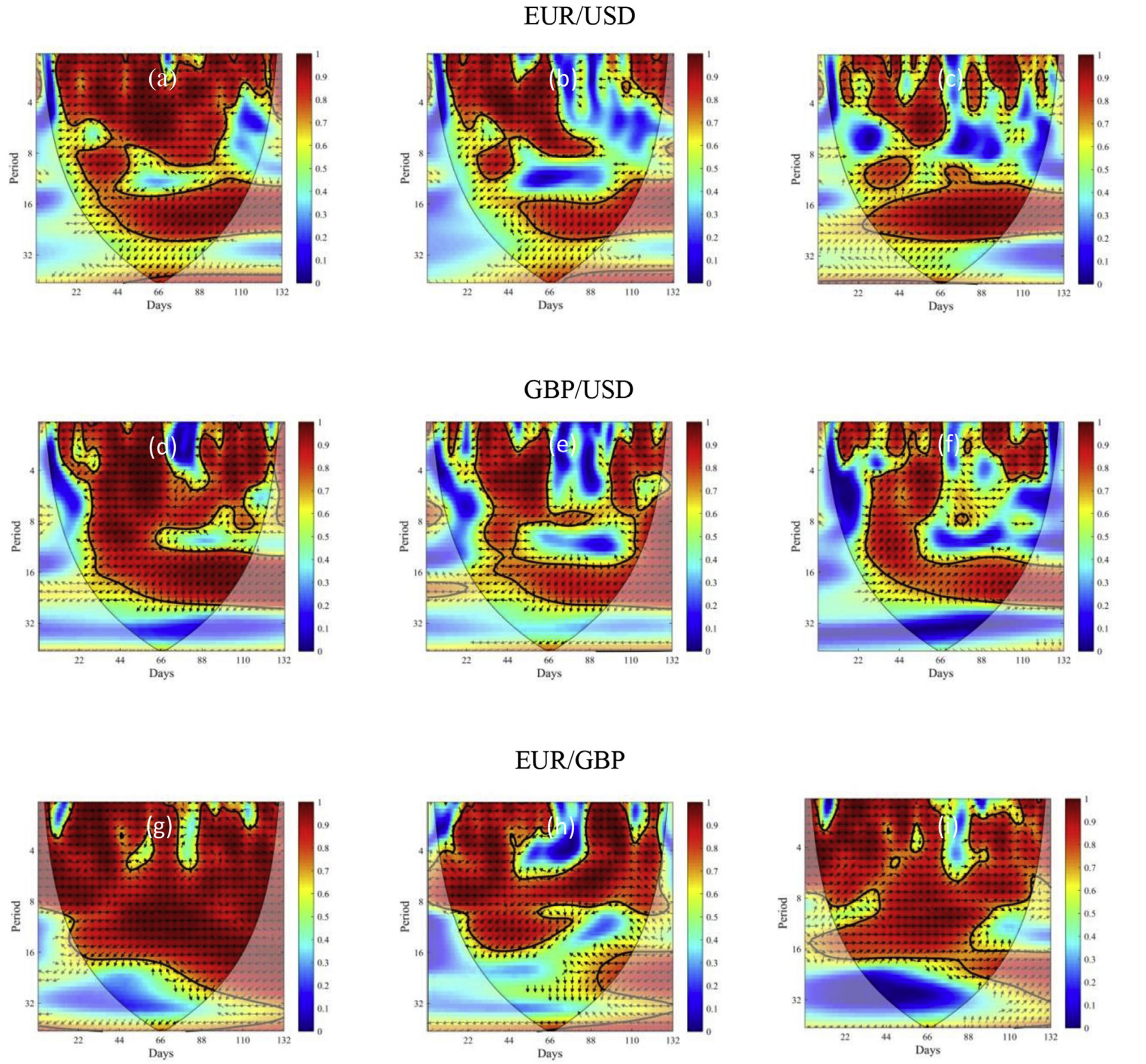

Fig. 7. WTC of the standardized exchange rate price and order flow time series of EUR/USD, GBP/USD, and EUR/GBP. Note: In the nine subfigures, the left-most three figures (a), (d), and (g) are based on the exchange rate against the difference between buying and selling positions; the middle three figures (b), (e), and (h) are based on the exchange rate against buying positions; and the right three figures (c), (f), and (i) are based on the exchange rate against selling positions. The arrows in the figure represent the relative phase relationship.

rate and order flow is much more significant in Fig. 7 than in Fig. 6. For all three currency pairs, there is a negative correlation between the exchange rate price and the difference between buy and sell positions from 0 to 2. Moreover, sometimes the arrows are pointing up and to the left and sometimes the arrows are pointing down and to the left, which suggests that sometimes the exchange rate is the leader variable and sometimes order flow is the leader variable. From 2 to 32 periods for EUR/USD and 2–24 periods for the other currency pairs, the arrow is pointing down and to the left in most regions indicating that the order flow was the leader variable.

4. Backtesting and optimization by using MT4

In summary, the order flow appears to be the leader of the exchange rate in most situations. Hence, this could be a powerful tool for predicting the market. Based on our methodology, we constructed an expert advisor using the mql4 programming language for trading strategies in MT4, a trading platform that is widely used by forex traders. Data with 99.9% similarity to the real market movements were extracted from Strategy Quant, a free historical tick data downloader, and then imported to Tickstory Lite, which is linked to MT4. This allowed MT4 to show the price rate of each tick of the market with 99.9% accuracy. Our mql4 codes linked the exchange rate and order flow data, and then the "backtest" feature of MT4 was applied.

The positioning of long orders take place in the opening of a new hourly candle in the case that, three conditions be taken at the same time. The first condition is that the total amount of buy position orders exceeds the total sell position orders, which can change the price direction. The second condition is that the downward trend direction of sell positions breaks and becomes an upward trend, and the accumulation of short position orders increases. The third condition is that the exchange rate moving average with a period of 8-h takes an upward arc and also the

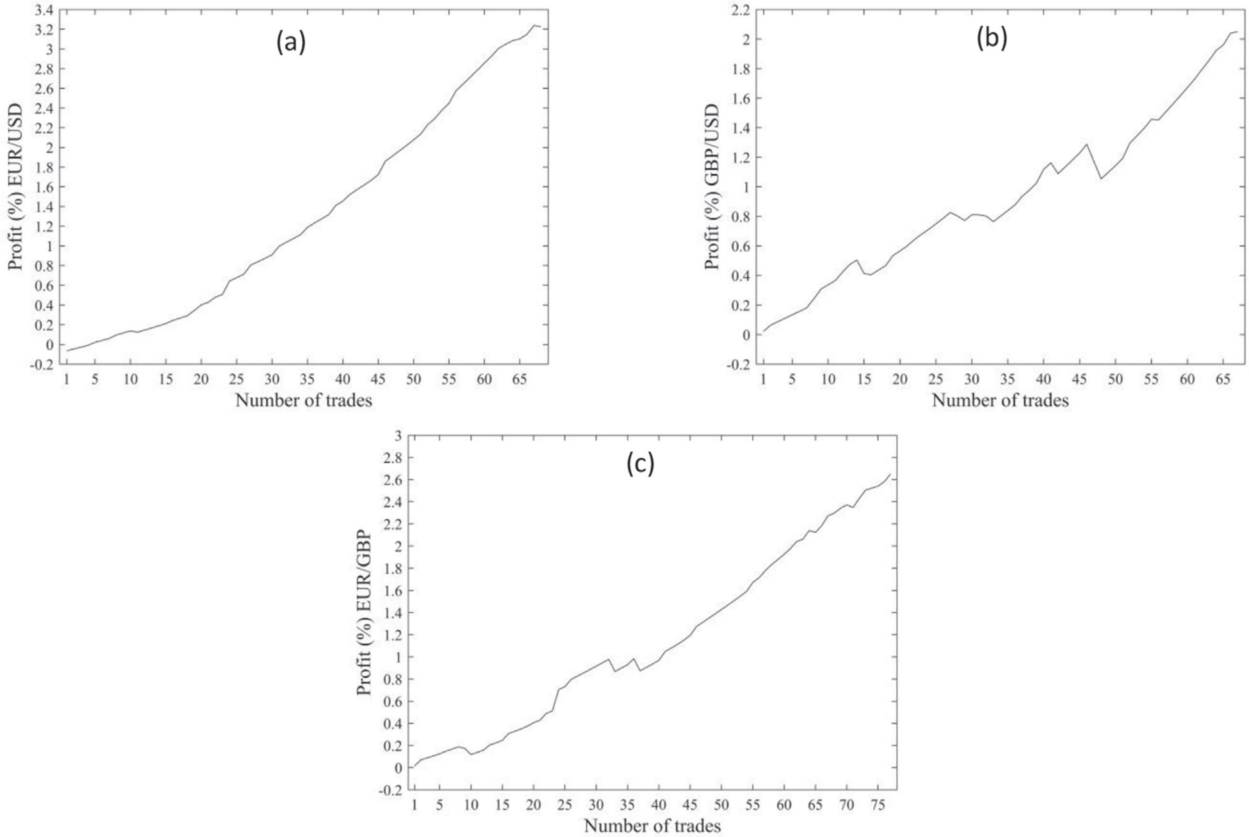

Fig. 8. Profit based on percentage gain in the specified period from May/01/2018 to October/31/2018. Note: In the three subfigures, the figure (a) is the percentage gain on EUR/USD; the figure (b) is the percentage gain on GBP/USD; and the figure (c) is the percentage gain on EUR/GBP.

downward slope of moving average with a period of 72-h decreases, and vice versa for taking short position orders. The open position orders hold for a minimum of 1 h and a maximum of the holding time until the end of the day's trading activity, which is 21:00 GMT. If the exchange rate moves in the desired direction of our position order, with the minimum positive movement of 10 pips after an hour, the system automatically closes that order; if not, this order will be held until the market moves in the desired direction or hits the stop loss of 40 pips; otherwise, the position closes at 21:00 GMT except Fridays the position closes at 20:59 GMT. The backtest results using our method for a sample with the volume trade of 20% of the balance for each trade are shown in Fig. 8.

Statistical details of the backtest results for EUR/USD, GBP/USD, and EUR/GBP are presented in Table 4. The most profitable currency pair was EUR/USD, with 68 trades over the period from May 1 to October 31, 2018, producing an accuracy and total profit of 95.59% and 322.60%, respectively. The maximal drawdown (MDD), which indicates the downside risk over a specified time period, was 14.32%, and the lowest relative drawdown (RDD), which is the ratio between the maximal drawdown and the value of the corresponding local maximum of the equity, was also 14.32%. The profit factor, which represents the gross profits divided by gross losses, reached a maximum of 37.26. Over the same period, the second most profitable currency pair was EUR/GBP, with the lowest MDD of 10%, a low RDD of 17.69%, high accuracy of 92.20%, total profit of 265.02%, and a profit factor of 9.01. The least profitable was GBP/USD, with an MDD of 15.4%, an RDD of 21.75% and a profit factor of 5.01, which achieved a total profit of 205.13% and accuracy of 83.58%.

The results presented above are limited by the amount of order flow data. Thus, out-of-sample testing is preferred to demonstrate the empirical benefits of our methodology in real markets. Out-of-sample tests were conducted for the period from November 14 to December 18, 2018, with an initial amount of $508.72. In our real account, because the system compounds investments, the profit is added to the capital and the lot size increases. Therefore, to understand the performance of our methodology, we used a fixed lot size of 20% of the initial capital. The value of one pip in the EUR/USD and GBP/USD markets (pips measure changes in currency pair rates in the forex market) for a 0.1 lot size was equal to $1, and the value of one pip in the EUR/GBP market for a 0.1 lot size averaged $1.29 during our out-of-sample testing. Data for the buying and selling positions on EUR/USD and EURGBP markets are presented in Tables 5 and 6. The GBP/USD market did not offer the opportunity to take any positions, so we could not check the out-of-sample performance of this currency pair. The overall results for EUR/USD and EUR/GBP, such as the total amount of pips, accuracy, and profit return, are listed in Table 7. The live trading buying and selling positions for EUR/USD and EUR/GBP are shown in Figs. 9 and 10, respectively, where the blue

Table 4
Statistical details of the backtest results for the three currency pairs.

Currency pairs	Total trades	Profit trades	Loss trades	Profit factor	MDD (%)	RDD (%)	Total profit (%)	Accuracy (%)
EUR/USD	68	65	3	37.26	14.32	14.32	322.60	95.59
GBP/USD	67	56	11	5.01	15.4	21.75	205.13	83.58
EUR/GBP	77	71	6	9.01	10	17.69	265.02	92.20

Table 5
EUR/USD trading history from November 14 to December 18, 2018 (GMT).

EUR/USD Trading						
Date	Open Time (GMT)	Close Time (GMT)	Order Type	Lot Size	Pips	Return U.S Dollar
2018.11.14	14:00:00	14:28:08	Buy	0.1	12.0	$12.0
2018.11.14	14:28:08	14:48:30	Buy	0.1	12.4	$12.4
2018.11.14	14:48:31	14:53:33	Buy	0.1	16.1	$16.1
2018.11.14	14:53:33	14:54:15	Buy	0.1	12.5	$12.5
2018.11.14	14:54:16	21:00:00	Buy	0.1	−23.5	$-23.5
2018.11.14	15:00:00	20:05:27	Buy	0.1	8.9	$8.9
2018.11.14	14:00:00	17:14:23	Buy	0.1	9.0	$9.0
2018.11.14	17:00:00	19:12:14	Buy	0.1	10.0	$10.0
2018.11.14	18:00:00	18:51:57	Buy	0.1	12.1	$12.1
2018.11.14	18:51:58	19:11:53	Buy	0.1	8.5	$8.5
2018.11.14	19:00:00	19:12:13	Buy	0.1	12.7	$12.7
2018.11.14	19:12:14	19:51:15	Buy	0.1	12.0	$12.0
2018.11.14	19:51:15	20:15:00	Buy	0.1	8.9	$8.9
2018.11.27	12:00:37	13:00:38	Buy	0.1	8.9	$8.9
2018.11.28	19:00:00	21:00:00	Buy	0.1	−5.7	$-5.7
2018.12.11	15:00:00	15:35:06	Sell	0.1	12.2	$12.2
2018.12.11	15:35:07	16:37:00	Sell	0.1	9.3	$9.3
2018.12.11	16:00:14	16:40:59	Sell	0.1	4.0	$4.0
2018.12.18	10:00:00	10:22:35	Buy	0.1	12.0	$12.0
2018.12.18	10:22:35	11:05:38	Buy	0.1	9.0	$9.0
2018.12.18	11:00:00	11:07:20	Buy	0.1	11.8	$11.8

Table 6
EUR/GBP trading history from November 14 to December 18, 2018 (GMT).

EUR/GBP Trading						
Date	Open Time (GMT)	Close Time (GMT)	Order Type	Lot Size	Pips	Return U.S Dollar
2018.11.14	06:02:29	08:03:09	Buy	0.1	6.9	$8.9
2018.11.14	07:00:00	08:00:02	Buy	0.1	11.6	$14.9
2018.11.14	08:01:09	08:12:30	Buy	0.1	8.6	$11.1
2018.11.15	05:06:02	07:28:24	Buy	0.1	7.3	$9.4
2018.11.15	06:00:00	07:28:03	Buy	0.1	7.0	$9.03
2018.11.15	07:00:00	07:38:52	Buy	0.1	12.0	$15.5
2018.11.20	13:27:27	13:56:53	Sell	0.1	12.0	$15.5
2018.12.04	13:27:04	21:00:00	Sell	0.1	−11.4	-$14.7
2018.12.11	12:01:45	12:25:25	Sell	0.1	9.5	$12.2
2018.12.12	05:57:18	08:23:02	Sell	0.1	8.1	$10.4
2018.12.12	06:00:19	08:23:03	Sell	0.1	6.0	$7.7
2018.12.12	07:20:25	08:23:03	Sell	0.1	6.8	$8.8
2018.12.13	11:26:25	12:26:32	Sell	0.1	7.2	$9.3
2018.12.13	12:00:00	12:45:25	Sell	0.1	16.3	$21.0

Table 7
Statistical details of EUR/USD and EUR/GBP out-of-sample testing.

Currency Pair	Sell Orders	Buy Orders	Total Orders	Win Trades	Loss Trades	Total Pips	Total Accuracy %	Total Return %
EUR/USD	21	18	3	19	2	346.2	90.4	69.24
EUR/GBP	14	6	8	13	1	107.9	92.8	27.84

arrows denote buying orders, and red arrows denote selling orders. The blue lines and redlines indicate that the trading positions are closed with positive and negative results, respectively. For instance, in Fig. 9(a), the blue arrows represent the buy trading position orders on EUR/USD, all but one of which achieved positive results, and in Fig. 9(c), the red arrows represent the selling orders on EUR/USD, all of which closed with positive results.

Note: The blue and red arrows represent the buy and sell position orders. The blue and red lines indicate the positive results and negative results of trading orders.

Note: The blue and red arrows represent the buy and sell position orders. The blue and red lines indicate the positive results and negative results of trading orders.

5. Conclusions

Under the floating exchange rate regime, the dramatic changes in the price of foreign exchange market often make the investment decisions of foreign exchange assets confused and illusory, but it also provides profitable opportunities for the general public. Seeking to improve the

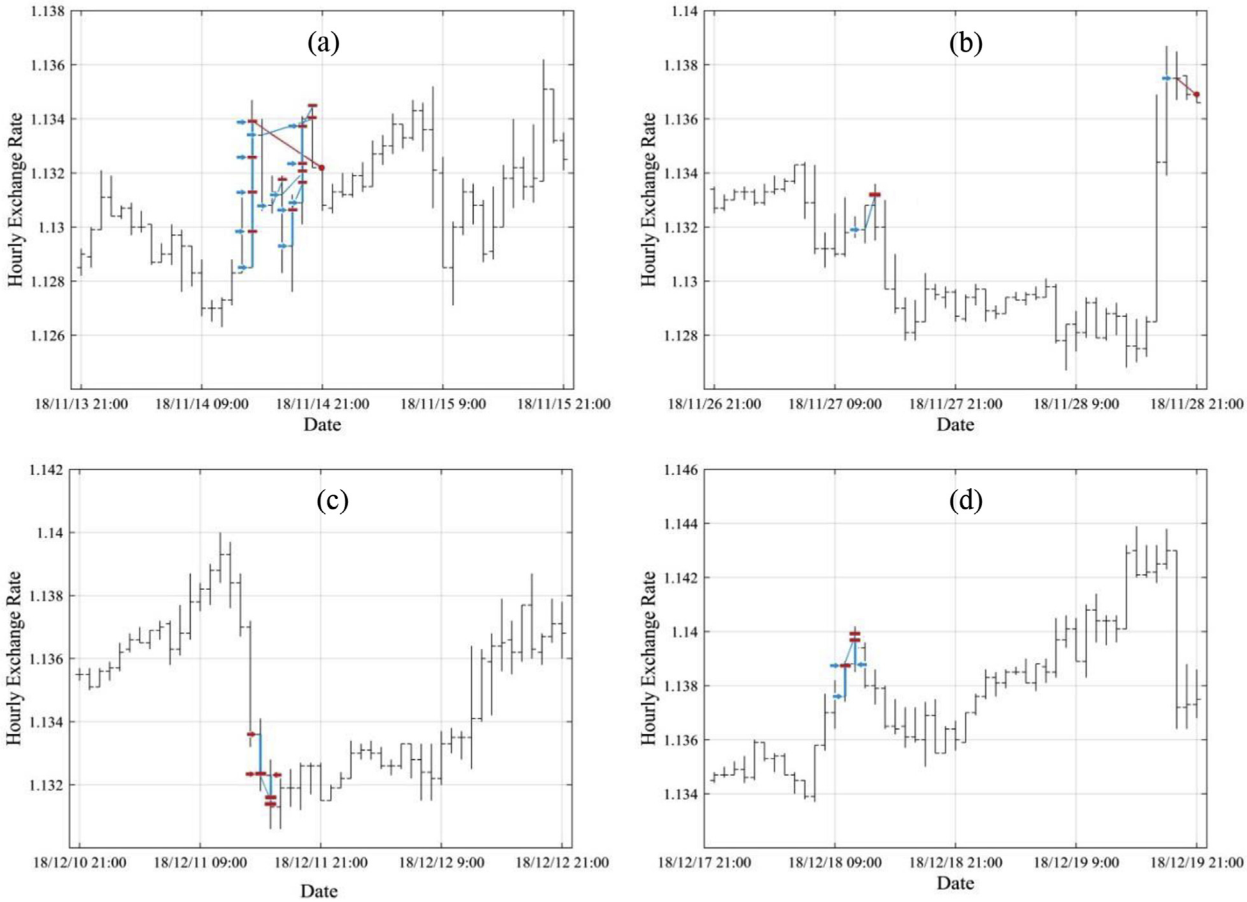

Fig. 9. EUR/USD live out-of-sample trading. Note: In the four subfigures, the figure (a) is the buy positions on November 14th; the figure (b) is the buy positions on November 27th and 28th; the figure (c) is the sell positions on December 11th; and the figure (d) is buy positions on December 18th.

accuracy of exchange rate forecasting and the efficiency of foreign exchange investment (hedging), it is necessary to clarify the relationship between order flow and price in foreign currency exchange markets. In this paper, we apply wavelet transform coherence analysis to the study of the relationship between three pairs of currencies (EUR/USD, GBP/USD and EUR/GBP) and their order flows.

Our findings include the following conclusions:

First, wavelet transform coherence analysis yields a clear view of the co-movement between two time series and improves the forecasting ability for forex markets. However, the exchange rate trend itself is vague and ambiguous at many times, so the method presented in this paper (1) uses a moving average 72-h period to de-noise the exchange rate data and detect the main direction of market, and (2) uses an 8-h period to detect the short-term directions of price exchange rates.

Secondly, for foreign exchange market traders, the volume and direction of order flow are very important information. Our analysis shows that the order flow guides the exchange rate in most time periods, and there is a significant negative correlation between them. This result proves that order flow contains much public and private information and is a powerful tool for forecasting exchange rates. Previously, however, only foreign exchange brokers access enough forex market data to check the order flow. The popularity of networks now enables general retail traders to get the needed data from several online trading platforms.

Thirdly, whether from Table 3 or the results of wavelet coherence analysis, the three pairs of currencies in the selected sample clearly show that there is a highly negative correlation between long positions and short positions. Therefore following the market principle, the net position (i.e. order flow) of a currency is an important variable reflecting the overall trend of the market.

Fourthly, the pairs of currencies we choose are strictly interrelated in theory, but the results of standard deviation analysis show that the most volatile exchange rate is the EUR/USD, followed by the GBP/USD, and then the EUR/GBP. Moreover, this is confirmed by the correlation between order flow data and price changes. Among them, EUR/GBP has the highest negative correlation (about −60%), followed by EUR/USD (−40%) and then GBP/USD (−30%). The reason may lie in two aspects: First, most of the order flow is generated by major currency pairs, such as brokers who also trade GBP/USD, but EUR/USD orders offset GBP/USD orders. Second, the economic development of Europe and the United States shows different trends, and the corresponding monetary and fiscal policies run counter to each other. Therefore, when making foreign exchange investments, it is very important to bring together orders in the same direction at the micro-level and pay attention to the economic situation and policies of the relevant countries at the macro-level.

In addition, the surprising accuracy of forecasting the exchange rate according to order flow shows that there is a way to predict the forex market without changing the original data or using machine learning to forecast future trends. Out-of-sample testing achieved 90.4% accuracy on EUR/USD and 92.8% accuracy on EUR/GBP, with 69.24% and 27.84% return on capital, respectively, which confirms the in-sample backtest results. Therefore, policymakers can anticipate investor behavior as a result of machine learning and improve the effect of policy intervention in the market.

This paper's findings pave the way for a variety of new research

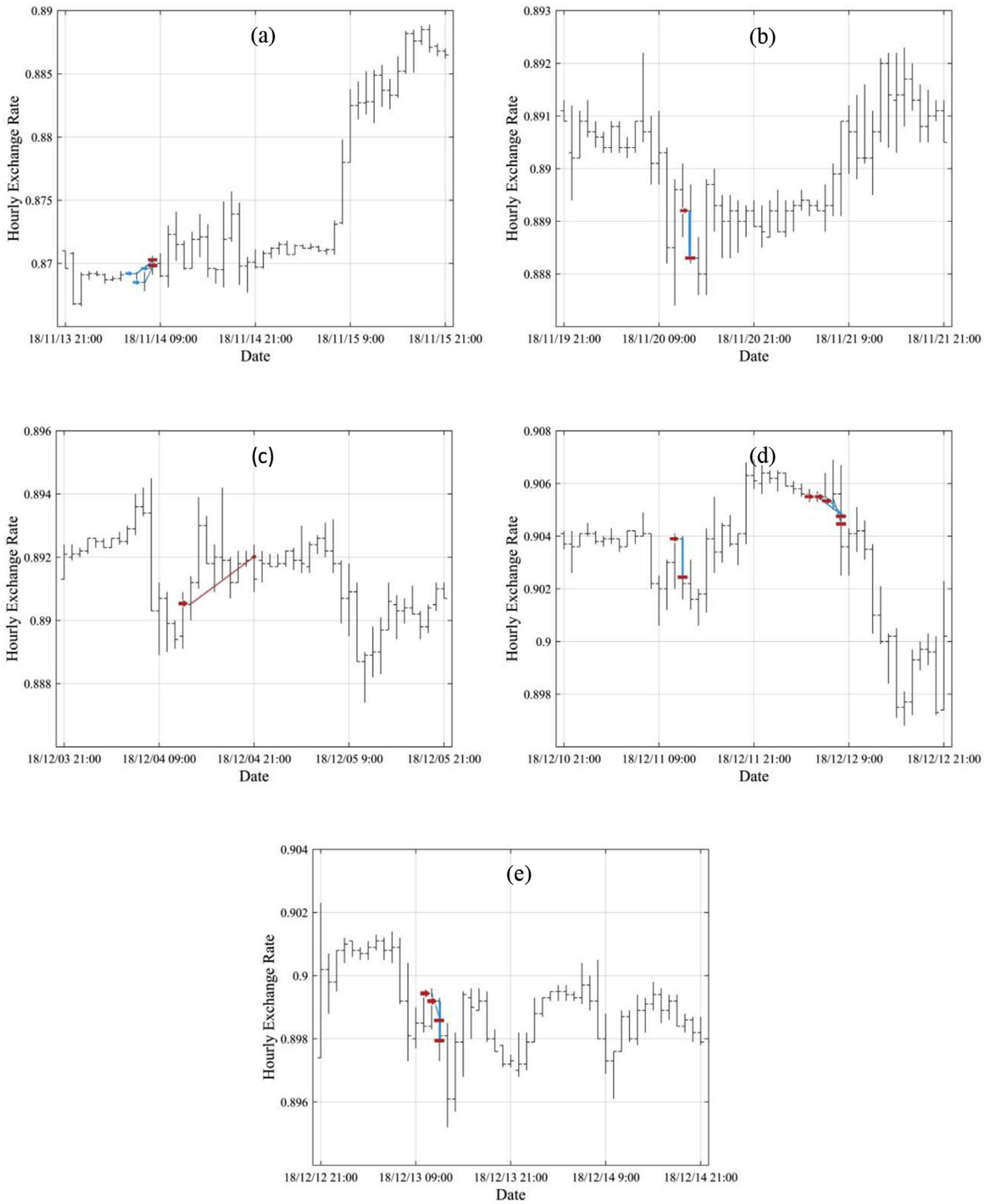

Fig. 10. EUR/GBP live out-of-sample trading. Note: In the five subfigures, the figure (a) is the buy positions on November 14th; the figure (b) is the buy position on November 20th; the figure (c) is the sell position on December 4th; the figure (d) is sell positions on December 11th and 12th; and the figure (e) is sell positions on December 13th.

efforts. Firstly, it is interesting to apply wavelet coherence analysis to other currency pairs in different time periods. Second, our results may be useful for analyzing other currencies or other financial markets, such as the stock market. Thirdly, our wavelet consistency results and order flow analysis provide knowledge of the dominant variables in forex markets, which can be applied to machine learning methods, such as in-depth learning to forecast future order flows and predict exchange rate changes. Finally, our results are useful for portfolio managers and foreign exchange participants who want to make clear decisions about their trading activities and use order flow tools in conjunction with their own strategies and order flows.

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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