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DETECTING "FAKE" PRICE MOVEMENTS: A CONVERGENCE/DIVERGENCE INDICATOR

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Abstract

This paper develops a new pair trading method to detect "fake" price movements and arbitrage opportunities that is based on a convergence/divergence indicator (CDI) belonging to the oscillatory class. The proposed technique is applied to a cross-currency pair (EURAUD, 2010-2015), and trading rules based on CDI signals are obtained. The CDI indicator is shown to outperform others of the oscillatory class and to generate profits (in the case of EURAUD) without the need for incorporating additional algorithms in the trading strategy. The suggested approach is of general interest and can be applied to different financial markets and assets.

Keywords: *Pair trading; oscillator; trading strategy; convergence/divergence indicator (CDI).*

JEL classification: *G12, C63*

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1. Introduction

Pair trading is a technique often used by practitioners to predict short-term price movements and detect arbitrage opportunities. It searches for statistically linked asset pairs and any mispricings that can be exploited through arbitrage trading until the divergence in prices disappears.

This paper develops a new pair trading method to detect "fake" price movements and arbitrage opportunities that is based on a convergence/divergence indicator (CDI) belonging to the oscillatory class. The proposed technique is applied to cross-currency pair (EUR-AUD, 2010-2015) and trading rules based on CDI signals are obtained. The suggested approach is of general interest and can be applied to different financial markets and assets.

The basic idea is as follows: the degree of correlation between financial assets varies over time, and can be very high in certain periods. For example, the average correlation between EURUSD and AUDUSD in 2015 has been higher than 0.9 at the daily frequency, and in the range [0.8 – 0.9] if considering hourly intraday data, but at times the hourly correlation has dropped below 0 and even below -0.5 before reverting to "normal" values. We investigate the reasons for such abnormal situations in the case of the FOREX market using a convergence/divergence indicator (CDI) and show its efficiency in comparison to other popular methods.

The layout of the paper is as follows. Section 2 briefly reviews the literature on technical analysis. Section 3 describes the data and outlines the methodology. Section 4 presents the empirical results, while Section 5 offers some concluding remarks.

2. Literature Review

Forecasting asset price movements is a challenging task. According to the Efficient Market Hypothesis (EMH - see Fama, 1970), prices should follow a random walk.

However, several studies have tried to detect exploitable profit opportunities which would constitute evidence of market inefficiencies. Statistical arbitrage is a very popular trading strategy that was first used by Morgan Stanley in the 1980s (see Gatev et al., 2006 for details). It can be described as follows: the investor selects a pair of assets for which the mean spread between prices is relatively constant, and in case of deviations from this value he keeps selling one asset and buying the other till the spread reverts to its equilibrium level; then opened positions are closed.

This method was subsequently analysed in academic studies (Burgess, 1999; Bondarenko, 2003; Hogan et al.2004; etc.), mainly for stock markets (Hong and Susmel, 2003; Nath, 2003; Gatev et al., 2006; Perlin, 2009; Do and Faff, 2010; Avellaneda and Lee, 2010; Broussard and Vaihekoski, 2012 and others). There is plenty of evidence that pair trading allows to generate abnormal profits in various financial markets, for instance in the US (Gatev et al., 2006) and Finnish (Broussard and Vaihekoski, 2012) stock markets. This approach was further investigated by Enders and Granger (1998), Vidyamurthy (2004), Dunis and Ho (2005), Lin et al. (2006), Khandani and Lo (2007) among others. A variety of methods have been used for statistical arbitrage, including: cointegration analysis; correlation analysis; regression analysis; neural networks; pattern recognition methods; factor models; subjective approaches (when the trader/investor selects pairs based on their fundamentals or other characteristics which make them "similar" - see Vidyamurthy (2004) for details).

Standard cointegration tests (see Engle and Granger, 1987 and Johansen, 1988) are frequently carried out to devise trading strategies based on long-run linkages between asset prices. However, these might not be particularly useful in the presence of structural change. For instance, the correlation between oil and EURUSD was -0.7 in 2005, but 0.9 in 2007-2008, the average for the period 2005-2008 being in the 0.7-0.8 range. Clearly, statistical arbitrage based on cointegration analysis will not work in such a case. In fact

Capocci (2006) found that during the financial crisis of 2007-2009 funds employing a pair trading strategy did not perform well. One possibility is to use in periods of instability the Kalman filter (see Dunis and Shannon, 2005). The alternative is correlation analysis focusing on the short-run statistical properties of asset prices (see Alexander and Dimitriu, 2002).

Once profitable trading strategies become well-known to the financial community, they cease to generate profits (see Chan, 2009). Indeed Gatev et al. (2006) have shown that returns from pair trading strategies have been declining over time. Thus, it is important to develop new techniques, which is the aim of this paper.

3. Data and Methodology

Correlation analysis is a very popular method in financial markets, especially in stock markets (the degree of correlation between the S&P 500 and Dow Jones indices is higher than 0.9), less so in the FOREX market because linkages between currency pairs are much more volatile, as can be seen in Figures 1 and 2 in the case of EURUSD and AUDUSD in 2014.

Figure 1 – Daily data, EURUSD, 2014

Figure 2 – Daily data, AUDUSD, 2014

However, this was not the case in 2013 (see Figures 3 and 4). .

Figure 3 – Daily data, EURUSD, 2013

Figure 4 – Daily data, AUDUSD, 2013

Annual correlations are reported in Table 1.

Table 1: Correlations between EURUSD and AUDUSD in 2004-2014

Year	Correlation
2004	0.71
2005	0.81
2006	0.78
2007	0.88
2008	0.96
2009	0.98
2010	0.58
2011	0.81
2012	0.47
2013	-0.41
2014	0.76

As can be seen, the two series are generally positively and strongly correlated, but their correlation can suddenly become negative as it did in 2013, when it dropped to -0.41. Correlations for other financial assets are reported in Table 2, which confirms that from time to time divergence can occur (more information about correlations between financial assets can be found in Plastun and Kozmenko, 2011). The question arises whether this type of information can be used to predict future price movements.

Table 2: Correlation analysis for different financial assets in 2005 and 2008

Financial assets	EURUSD		USDJPY		AUDUSD	
	2005	2008	2005	2008	2005	2008
Oil futures	-0.66	0.82	0.62	-0.55	-0.37	0.84
Gold spot	-0.63	0.27	0.83	-0.49	-0.56	0.39
US Stock market (Dow Jones Index)	-0.13	0.11	0.26	0.32	-0.11	0.15

Let us consider first the dynamics of EURUSD and AUDUSD over the period 20-23 February 2015 (see Figure 5). The daily correlation between the two series was more than 0.9 (see Figure 6) and positive, but on 20 February, at 8pm prices started to move in the opposite directions, before converging again on 23 February at 3am. Specifically, the hourly correlation dropped to -0.8 before reverting a few hours later to its "typical" range 0.8-0.9 (see Figure 7).

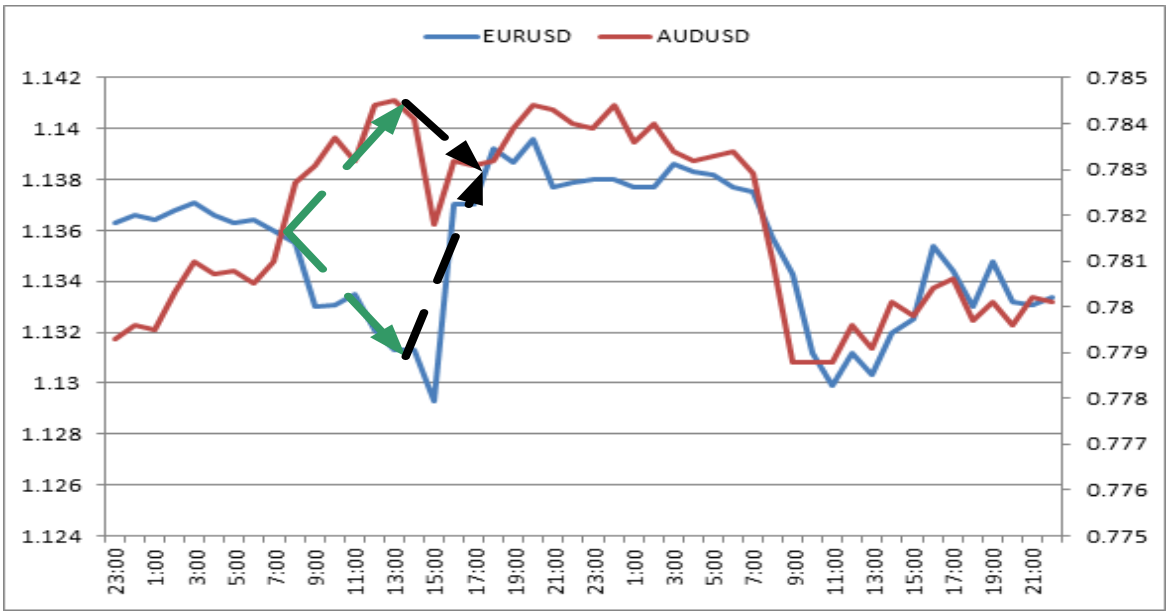

Figure 5 – Hourly price dynamics of EURUSD and AUDUSD on 20-23 February 2015

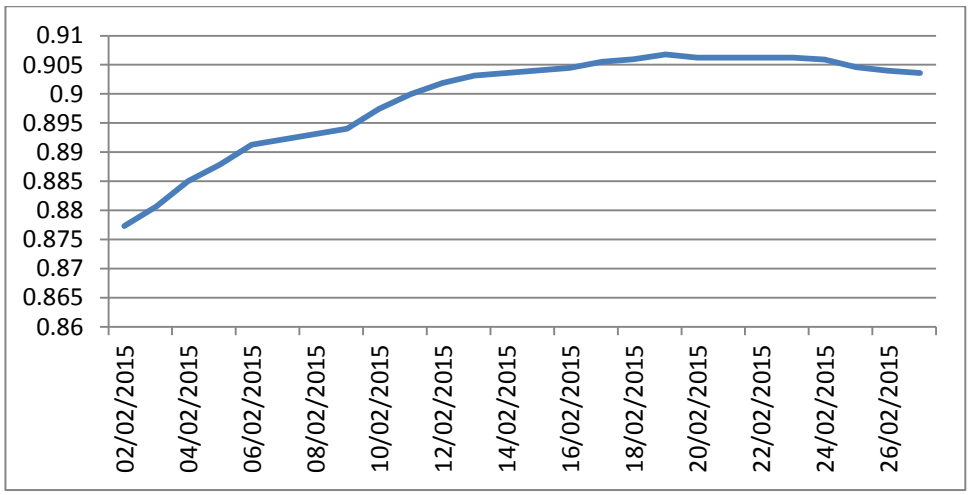

Figure 6 – Daily correlation between EURUSD and AUDUSD in February 2015 (period 90)

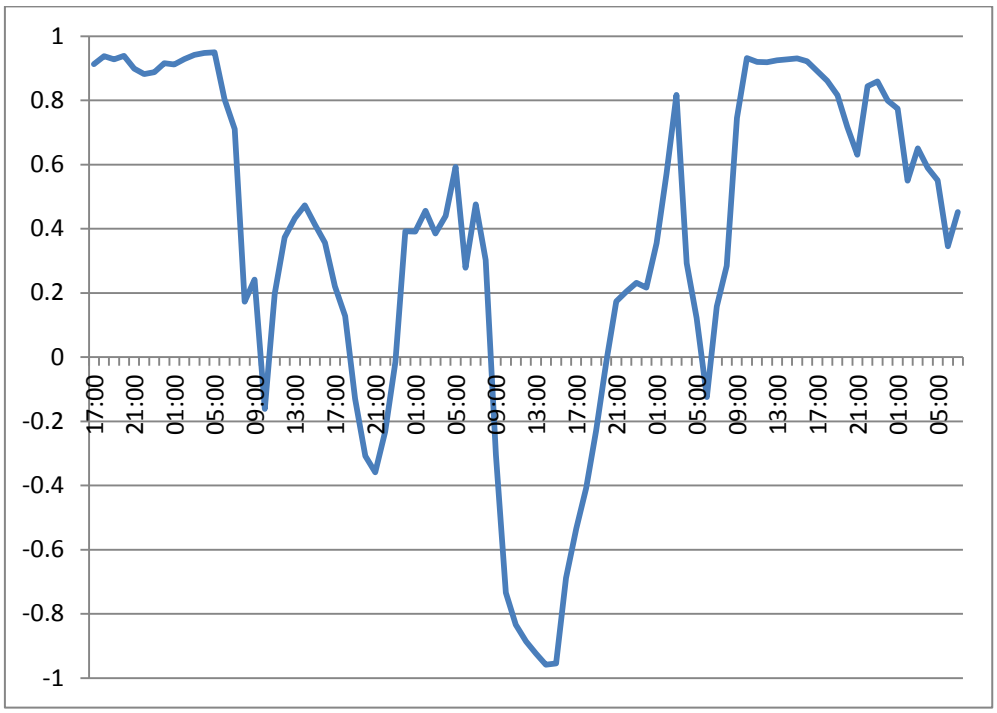

Figure 7 – Hourly correlation between EURUSD and AUDUSD on 20-23 February 2015 (period 12)

The biggest negative hourly correlation (-0.96) occurred at 2pm on 20 February, the daily correlation being instead strongly positive (0.9 - see Table 3 for details). During this period EURUSD fell and AUDUSD rose. This would suggest that a trader should buy EURUSD at 1.1313 and sell AUDUSD at 0.7841 till the anomaly disappears (at 3am on 23 February), and then any open positions should be closed by closing EURUSD at 1.1386

and AUDUSD at 0.7834. This generates a profit of +0.65% for EURUSD and +0.09% for AUSUSD, and therefore an aggregate profit of +0.73%.

Table 3: Data for analysing the anomaly which appeared on 20.02.2015

date	Time	EURUSD	AUDUSD	Hourly correlation (period=12)	Daily correlation (period=90)
20.02.2015	7:00	1.136	0.781	0.48	0.90
20.02.2015	8:00	1.1355	0.7827	0.30	0.90
20.02.2015	9:00	1.133	0.7831	-0.30	0.90
20.02.2015	10:00	1.1331	0.7837	-0.73	0.90
20.02.2015	11:00	1.1335	0.7832	-0.83	0.90
20.02.2015	12:00	1.1321	0.7844	-0.89	0.90
20.02.2015	13:00	1.1313	0.7845	-0.92	0.90
20.02.2015	**14:00**	**1.1313**	**0.7841**	**-0.96**	**0.90**
20.02.2015	15:00	1.1293	0.7818	-0.95	0.90
20.02.2015	16:00	1.137	0.7832	-0.69	0.90
20.02.2015	17:00	1.137	0.7831	-0.53	0.90
20.02.2015	18:00	1.1392	0.7832	-0.41	0.90
20.02.2015	19:00	1.1387	0.7839	-0.23	0.90
20.02.2015	20:00	1.1396	0.7844	-0.01	0.90
20.02.2015	21:00	1.1377	0.7843	0.17	0.90
20.02.2015	22:00	1.1379	0.784	0.20	0.90
23.02.2015	23:00	1.138	0.7839	0.23	0.90
23.02.2015	0:00	1.138	0.7844	0.22	0.90
23.02.2015	1:00	1.1377	0.7836	0.35	0.90
23.02.2015	2:00	1.1377	0.784	0.57	0.90
23.02.2015	**3:00**	**1.1386**	**0.7834**	**0.82**	**0.90**
23.02.2015	4:00	1.1383	0.7832	0.29	0.90
23.02.2015	5:00	1.1382	0.7833	0.12	0.90

Let us consider next the EURAUD dynamics in the period 20-23 February 2015 (see Figure 8). EURAUD dropped sharply in the early morning of 20 February, but reverted to a more typical value a few hours later.

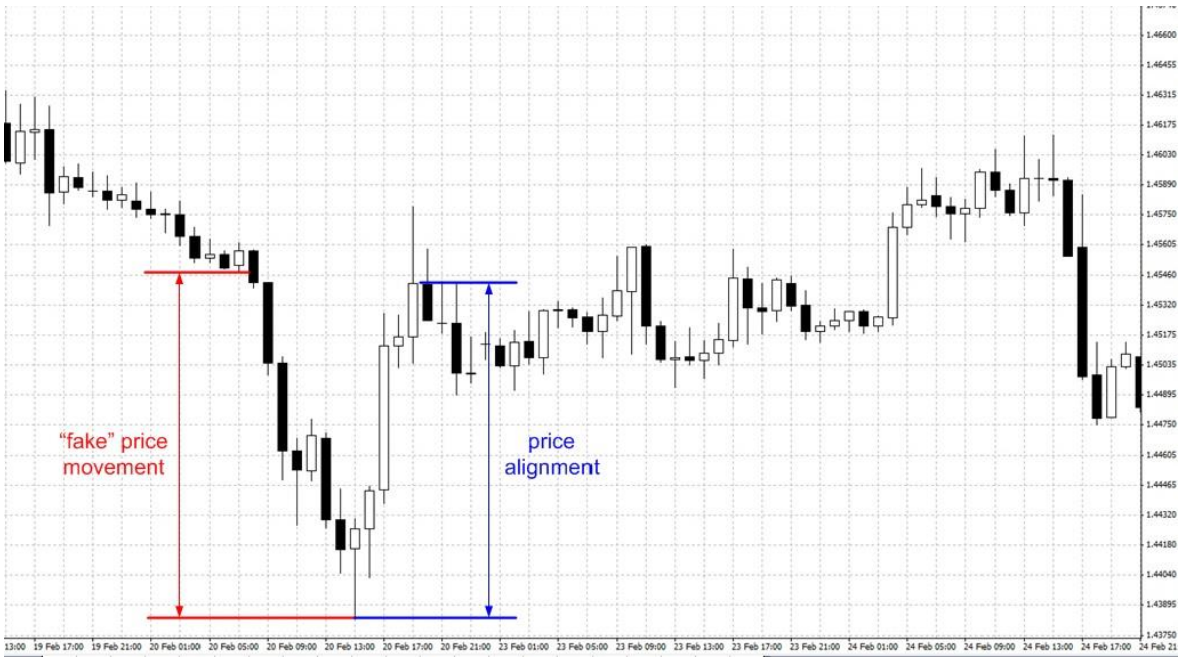

Figure 8 – EURAUD dynamics on 20-23 February 2015

Let us see how this was reflected in the hourly correlation between EURUSD and AUDUSD (see Figure 9): this dropped to -0.8 from its daily average of +0.9, which suggests that double correlation (daily and hourly) analysis as a criterion for convergence/divergence can be useful to detect "fake" price movements.

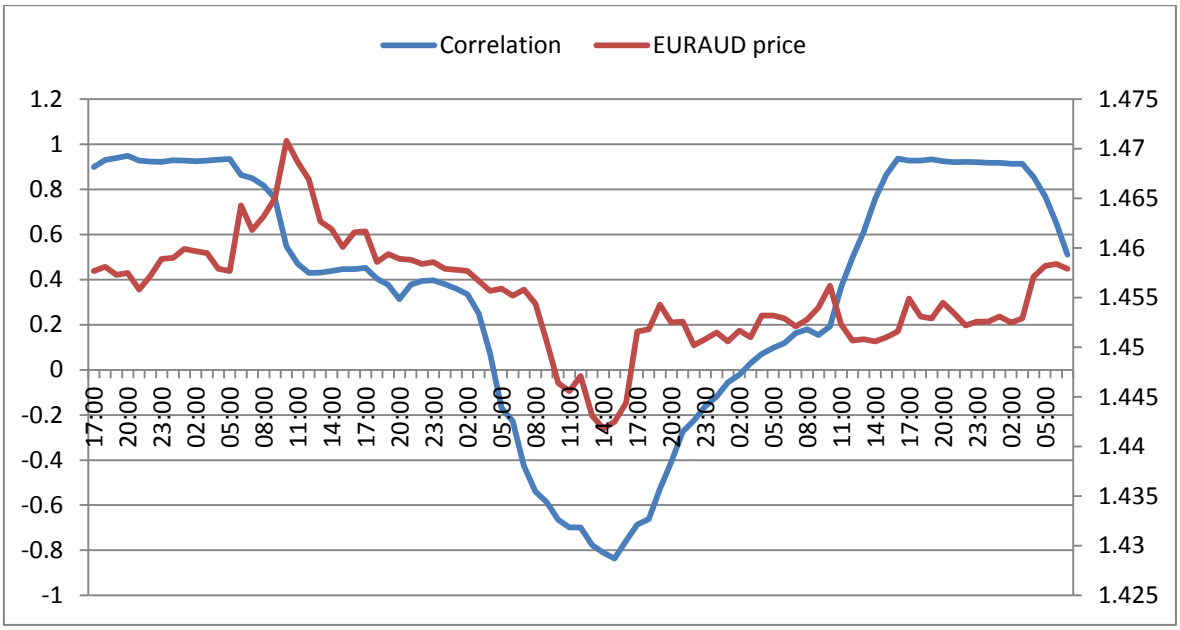

Figure 9 – EURAUD dynamics and hourly correlation between EURUSD and AUDUSD (period 24) on 20-23 February 2014

Specifically, we propose first to measure the average correlation using daily data over different time periods (30, 60, 90 days etc. – the correlation could change significantly) – we define this "slow"correlation. Values higher than 0.5 indicate synchronisation. Then we use as an indicator of convergence/divergence the correlation coefficient computed with intraday data – the "fast" correlation. A degree of “slow” correlation above 0.5 combined with one of “fast” correlation below zero can be interpreted as a clear signal of divergence, which implies that positions should be opened. When after some time the degree of "fast" correlation reverts back to that of “slow” correlation, then open positions should be closed.

Figure 10 shows that the shorter the period is, the more volatile daily correlation is. We use the more stable 90-day average.

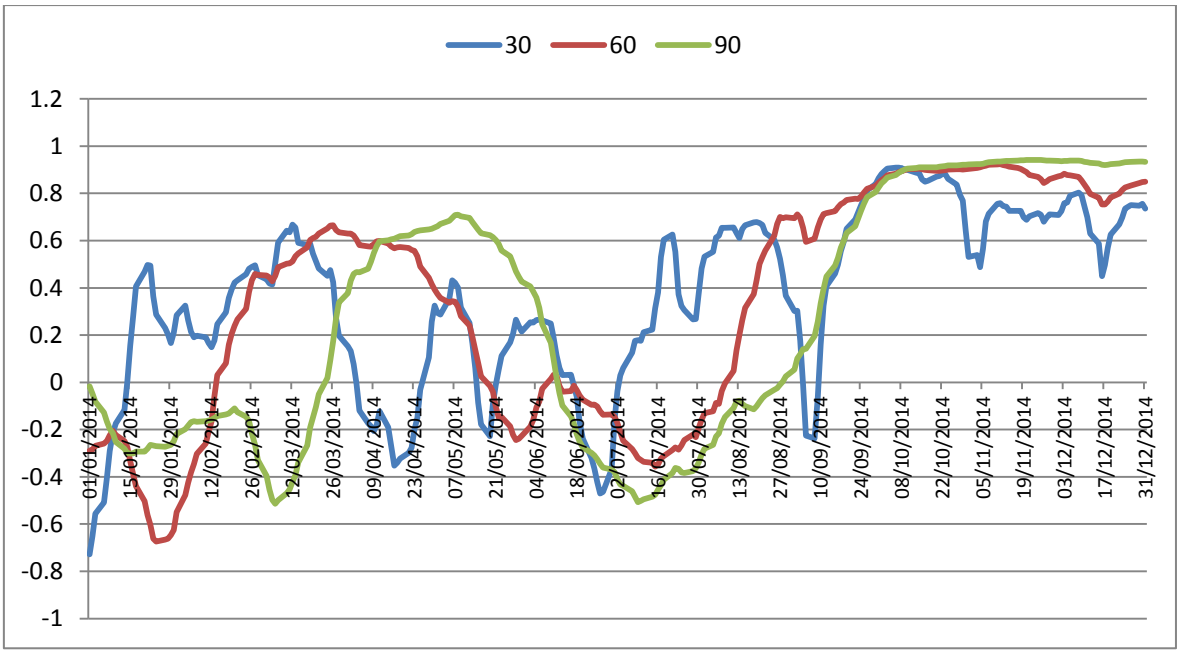

Figure 10 – Dynamics of daily correlation between EURUSD and AUDUSD during 2014 (periods 30, 60 and 90)

The same is true of hourly correlation (see Figure 11). We use the measure based on 24 hours.

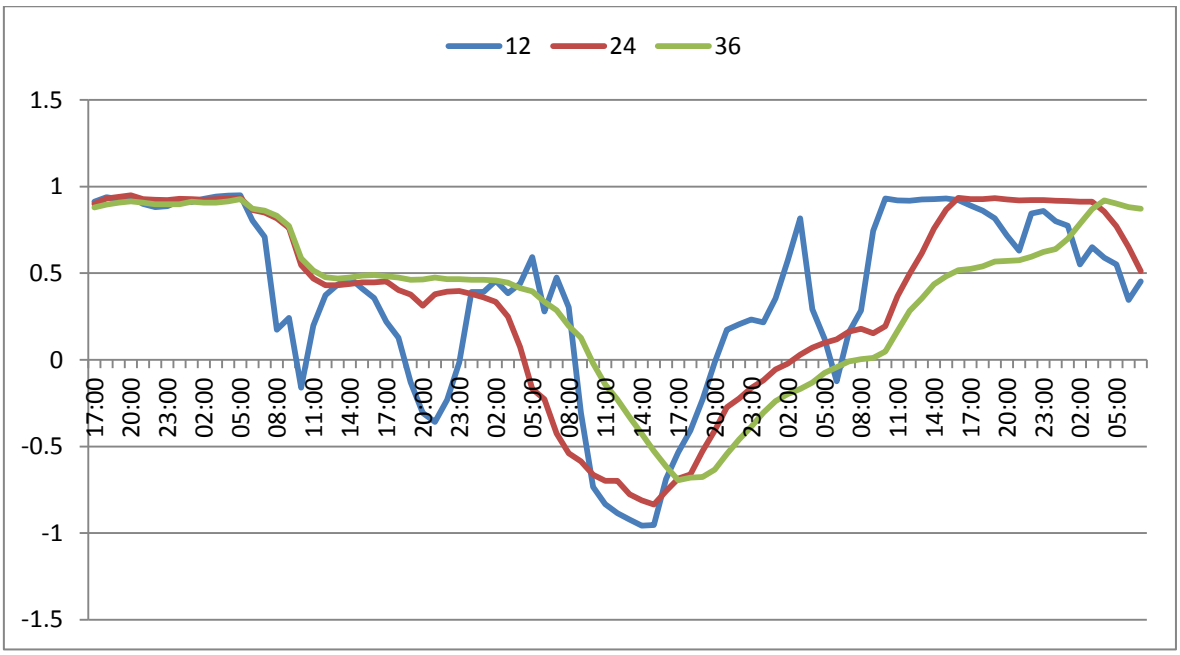

Figure 11 – Dynamics of hourly correlation between EURUSD and AUDUSD during 2014 (periods 12, 24 and 36)

Such anomalies are not specific to the EURUSD and AUDUSD co-movement, but can be detected, for instance, in other cross-currency pairs such as EURGBP, CHFJPY etc. As a tool for easy detection of such divergence/convergence situations ("fake" price movements) we propose to use a new Convergence/Divergence indicator (CDI) of the oscillatory type, programmed using the MetaQuotes Language 4 (MQL4). This is a language for programming trade strategies built in the client terminal. The syntax of MQL4 is quite similar to that of the C language. It allows to programme trading robots that automate trade processes and is ideally suited for the implementation of trading strategies; it can also check their efficiency using historical data. These are saved in the MetaTrader terminal as bars and represent records appearing as TOHLCV (HST format).

The trading terminal allows to test experts by various methods. By selecting smaller periods it is possible to examine price fluctuations within bars, i.e., price changes will be reproduced more precisely. For example, when an expert is tested on one-hour data, price changes for a bar can be modelled using one-minute data. The price history stored in the client terminal includes only Bid prices. In order to model Ask prices, the strategy tester

uses the current spread at the beginning of testing. However, a user can set a custom spread for testing in the "Spread", thereby approximating more accurately actual price movements.

The algorithm for CDI is as follows:

1. The daily correlation with period 90 (default value) is calculated
2. The hourly correlation with period 24 (default value) is calculated
3. Different colours are used to display them.

The results are shown in Figure 12 (this is a screenshot from MetaTrader 4).

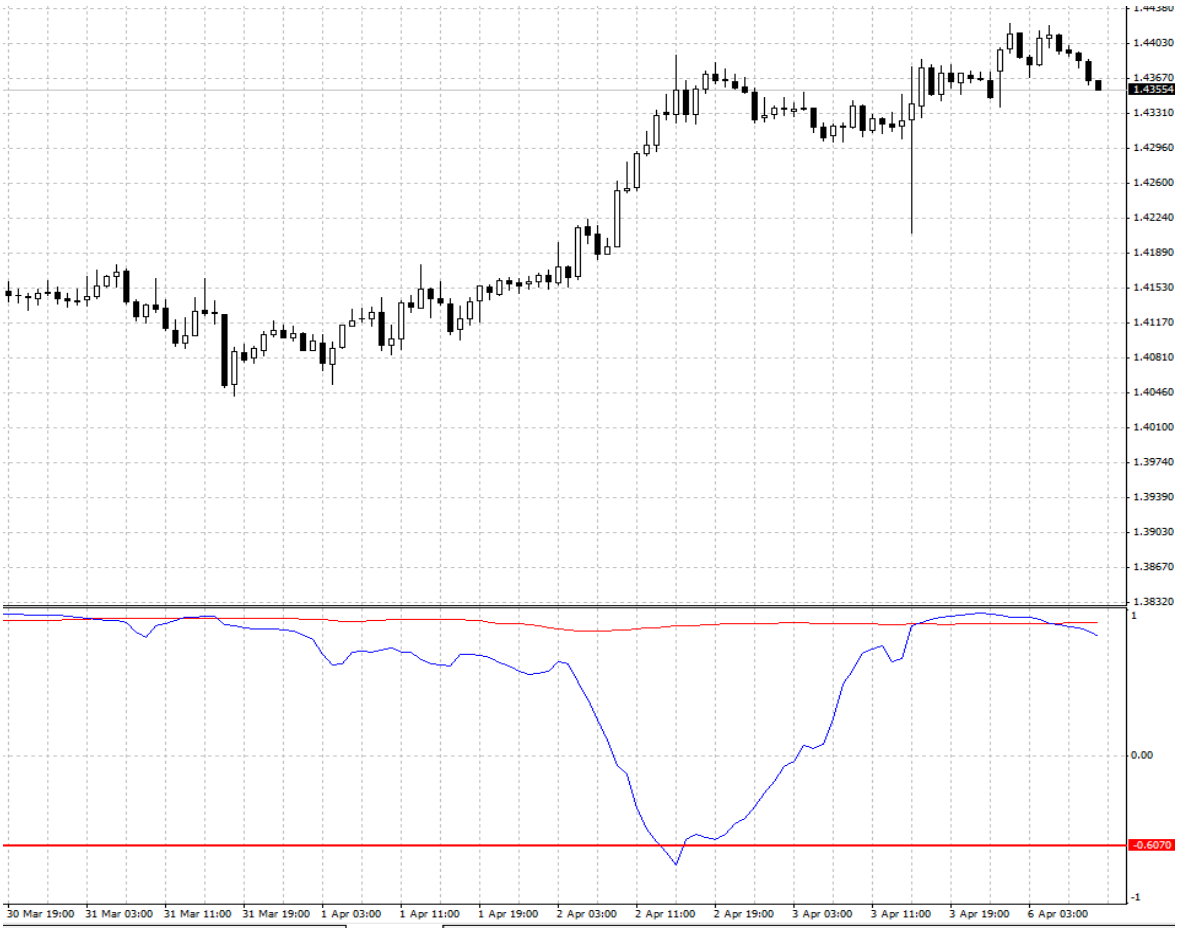

Figure 12 – Indicator CDI (screenshot from the MetaTrader 4 trading platform; the price is shown in the top half and the Indicator in the bottom half of the chart).

The indicator consists of two lines:

- Red line – it shows the daily correlation dynamics (the period can be set by the user, the default value is 90);

- Blue line – it shows the hourly correlation dynamics (here the default value for the period is 24).

More lines can be added (see the red line in the indicator window) to help interpret the divergence zones.

The inputs of CDI are presented in Figure 13 (screenshot of the input parameters of CDI from MetaTrader 4).

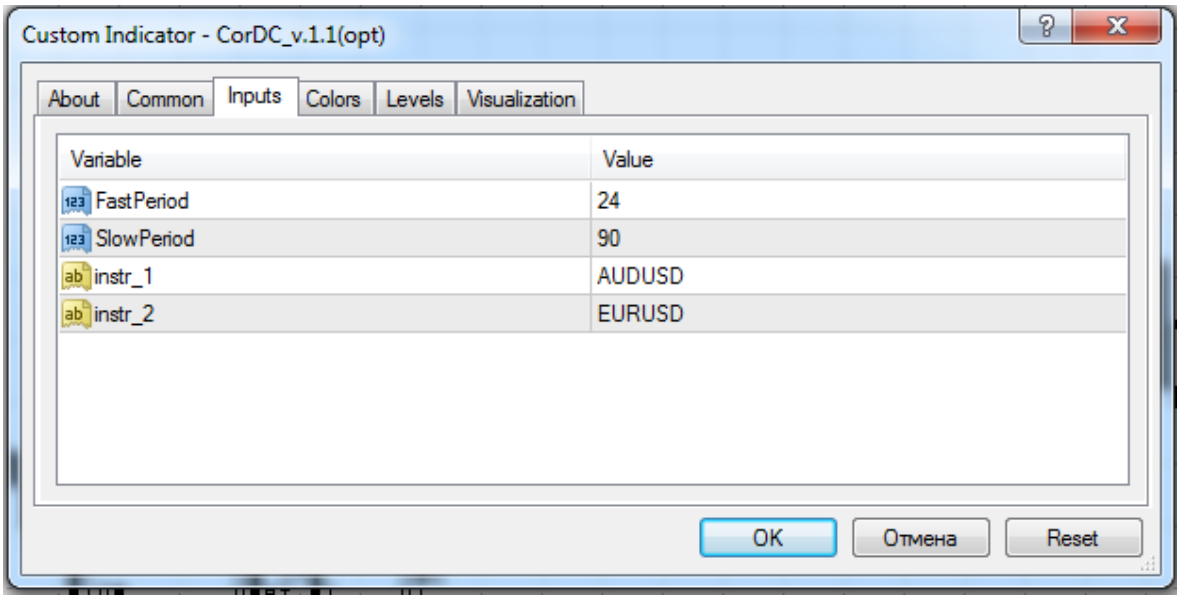

Figure 13 – Input parameters of CDI (screenshot from the MetaTrader 4 trading platform)

4. Testing the CDI

Preliminary testing is carried out to determine the basic parameters of the indicator to detect the divergence/convergence zones (the sample is 2010). The results of the optimisation of hourly correlation (in order to find the entry and exit criterions to open and close positions) are presented in Figure 14.

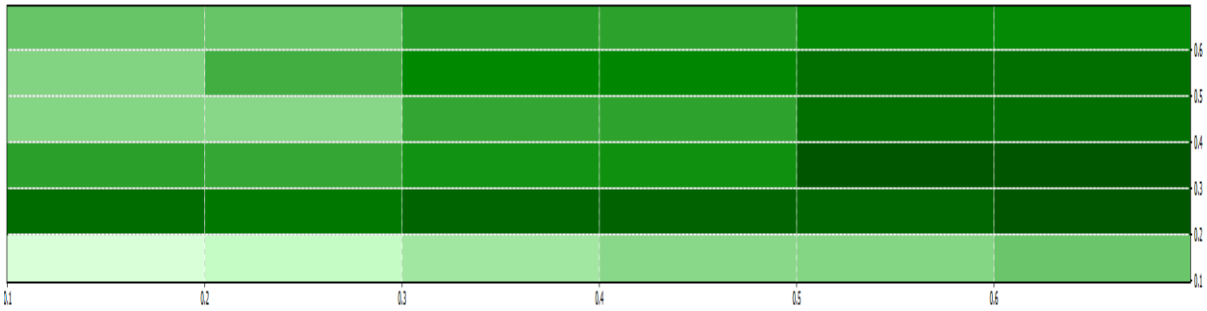

Figure 14 – Testing results for the convergence/divergence parameters*

* Axis X – Hourly correlation value (it should be multiplied by -1) for anomaly detection (extreme level of divergence)

Axis Y – Hourly correlation value for detecting the disappearance of the anomaly (convergence level)

The darker the green is, the better the trading results are. As can be seen, the following intervals for hourly correlation can be used as basic parameters for convergence/divergence:

- Divergence – [(-0.5)-(-0.7)];
- Convergence [0.3-0.6].

In the next round of testing we search for the most appropriates periods for the daily and hourly correlation calculations. The results are presented in Figure 15.

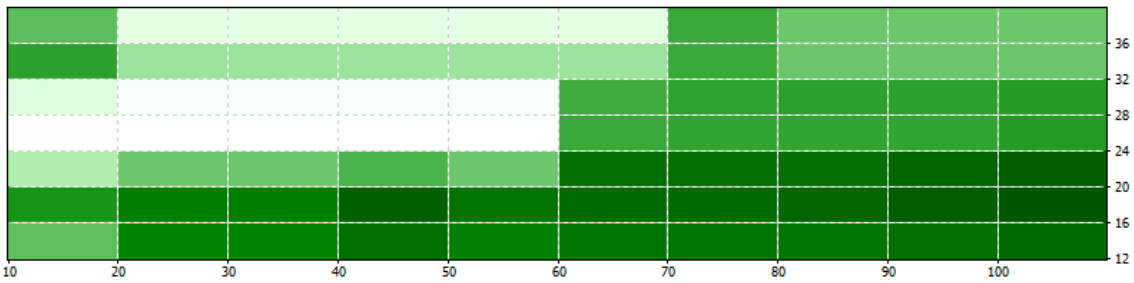

Figure 15 – Testing results for the daily and hourly correlation periods*

* Axis X – daily correlation period

Axis Y – hourly correlation period

As can be seen the best periods are:

- for daily correlation: [60-90];
- for hourly correlation: [12-20].

We carry out both within-sample (2010) and out-of-sample (2011-2015) testing (for the full sample results, 2010-2015, see Appendix A) using the following parameters: daily correlation period = 90, hourly correlation period = 12, divergence criterion = - 0.5, convergence criterion = 0.5, criterion of "equality" of assets daily correlation > 0.7.

CDI vs RSI

Next we compare the performance of CDI to that of the Relative Strengthen Index (RSI – one of the most popular indicators of the oscillatory type) in the case of the EURAUD pair during 2010-2014. For RSI we build standard trading algorithms: sell in the overbought zone (when the RSI value is 70 or above), buy in the oversold one (when the RSI value is 30 or below). Positions should be closed in the opposite zone. Short positions are closed near the oversold zone, when the RSI value reaches 40, long positions in the overbought zones, when the RSI value reaches 60. The period is 14, as recommended for the RSI indicator by its developer (see Wilder, 1978). The CDI trading parameters are as follows: daily correlation > 0.7, hourly correlation < -0.5 (for open), hourly correlation > 0.5 (for position close). The daily correlation period is 90, and the hourly one is 12.

We trade 0.1 standard lot (this is trade size; it represents 100,000 units of currency used to fund the trading account). The minimum deposit for this volume is USD200, but we use a USD10,000 deposit to cover all possible losses during testing and to avoid possible margin calls because of lack of money (in the case of unprofitable trading, there may be insufficient funds to trade and as a result the testing process could be stopped).

Detailed test results for CDI and RSI are presented in Appendices A and B, whilst some key results are displayed in Table 4.

Table 4: Testing results for RSI and CDI: case of EURAUD 2010-2014

Parameter	CDI	RSI
Total net profit	500.5	-6373
Profit trades (% of total)	77%	58%
Total trades	26	457
Average profit trade	35.5	40
Average loss trade	-35	-89

It can be seen that CDI generates 20 times less signals than RSI, but leads to profits 77% of the times. RSI exhibits the main problem of oscillatory indicators: in the case of a trend they generate losses, and should be used only with additional trend indicators. CDI manages to avoid this trap by detecting "fake" price movements. Of course it is impossible to generate 100% profitable trades because the daily correlation is not 1, and also there are losses if market behaviour changes when the correlation begins to fade. Therefore it is necessary to carry out additional checks to make sure that the daily correlation during the last few days was not falling constantly.

Trading Rules

The above analysis suggests adopting the following trading rules:

1) positions should be opened in zones of divergence;
2) positions should be closed in zones of convergence;
3) to open trading the daily correlation should be >0.7;

4) the daily correlation during the last few days should have been increasing;

5) positions should be opened in the opposite direction to "fake" movement (a "fake" price movement occurs when there is divergence)

An example is shown in Figure 16.

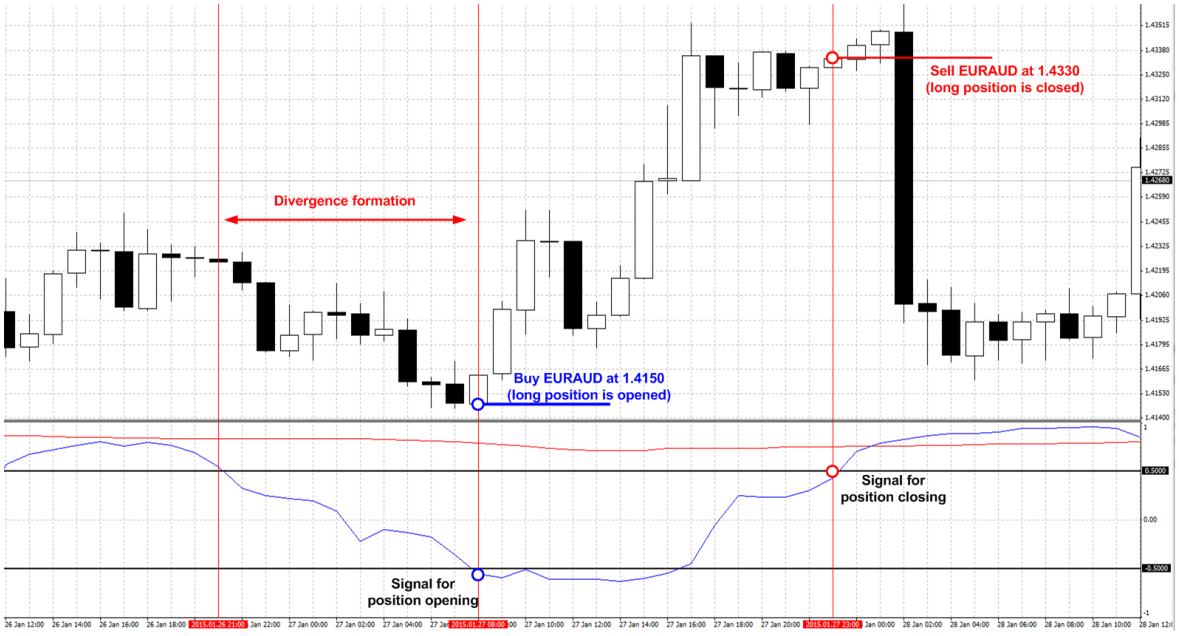

Figure 16 – Illustration of CDI trading rules work in practice (screenshot from MetaTrader 4)

A divergence situation in the EURAUD dynamics appeared on 26 January 2015. The hourly correlation dropped below -0.5, whilst the daily correlation was > 0.8. At 8am CDI generated a signal for opening a long position at 1.4150. The divergence disappeared at 11pm when the hourly correlation reached +0.5; at that time the position should be closed at 1.4330. The net profit from trading would then exceed 1%.

5. Conclusions

In this paper we develop a new approach to detecting "fake" price movements based on double correlation analysis of financial asset dynamics. Daily correlations are taken to represent the "normal" behaviour of asset prices, whilst hourly correlations are used to detect divergence/convergence and devise appropriate trading strategies.

The general rule is as follows: if the daily correlation between two assets is higher than 0.5-0.7, they are considered to be diverging if their hourly correlation is lower than -0.5 and converging if it is higher than 0.5. On the basis of this rule we construct a new technical indicator (convergence/divergence indicator or CDI), which visualises both types of correlation (daily and hourly) and provides the user with information about the current state (divergence/convergence). Divergence is defined as a "fake" price movement. This indicator is shown to outperform other indicators of the oscillatory class and to generate profits (in the case of the EURAUD pair) without the need for incorporating additional algorithms in the trading strategy.

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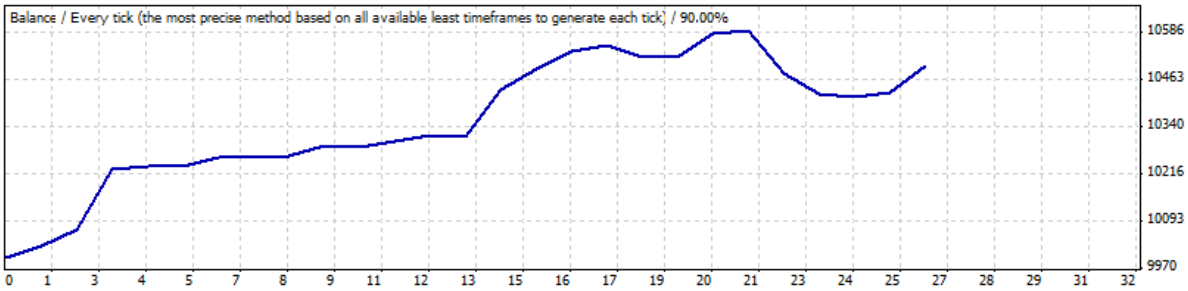
Appendix A

Test results for the CD indicator: EURAUD, 2010-2014

Strategy Tester Report

Symbol		EURAUD (Euro vs Australian Dollar)			
Period		1 Hour (H1) 2010.01.04 00:00 - 2014.12.30 23:00 (2010.01.01 - 2014.12.31)			
Model		Every tick (the most precise method based on all available least timeframes)			
Parameters		period1=90; period2=12; instr_1="EURUSD"; instr_2="AUDUSD"; instr_3="EURAUD"; cor_day=0.7; cor_in=0.5; cor_out=0.5;			
Bars in test	31921	Ticks modelled	80597401	Modelling quality	90.00%
Mismatched charts errors	0				
Initial deposit	10000			Spread	Current (7)
Total net profit	500.51	Gross profit	710.22	Gross loss	-209.71
Profit factor	3.39	Expected payoff	19.25		
Absolute drawdown	15.74	Maximal drawdown	205.46 (1.94%)	Relative drawdown	1.94% (205.46)
Total trades	26	Short positions (won %)	14 (71.43%)	Long positions (won %)	12 (83.33%)
		Profit trades (% of total)	20 (76.92%)	Loss trades (% of total)	6 (23.08%)
Largest		profit trade	157.82	loss trade	-112.85
Average		profit trade	35.51	loss trade	-34.95
Maximum		consecutive wins (profit in money)	9 (292.18)	consecutive losses (loss in money)	3 (-175.30)
Maximal		consecutive profit (count of wins)	292.18 (9)	consecutive loss (count of losses)	-175.30 (3)
Average		consecutive wins	4	consecutive losses	2



Appendix B

Test results for the RSI oscillator: EURAUD, 2010-2014

Strategy Tester Report

Symbol		EURAUD (Euro vs Australian Dollar)			
Period		1 Hour (H1) 2010.01.04 00:00 - 2014.12.31 19:00 (2010.01.01 - 2015.01.01)			
Model		Every tick (the most precise method based on all available least timeframes)			
Parameters		periodRSI=14; oversold=30; overbought=70; deltaRSI=10;			
Bars in test	31932	Ticks modelled	81725196	Modelling quality	90.00%
Mismatched charts errors	0				
Initial deposit	10000			Spread	Current (7)
Total net profit	-6373.1	Gross profit	10604.96	Gross loss	-16978.06
Profit factor	0.62	Expected payoff	-13.95		
Absolute drawdown	6690.67	Maximal drawdown	6927.11 (67.67%)	Relative drawdown	67.67% (6927.11)
Total trades	457	Short positions (won %)	221 (59.28%)	Long positions (won %)	236 (57.20%)
		Profit trades (% of total)	266 (58.21%)	Loss trades (% of total)	191 (41.79%)
	Largest	profit trade	144.66	loss trade	-644.62
	Average	profit trade	39.87	loss trade	-88.89
	Maximum	consecutive wins (profit in money)	13 (532.21)	consecutive losses (loss in money)	7 (-355.40)
	Maximal	consecutive profit (count of wins)	532.21 (13)	consecutive loss (count of losses)	-1187.32 (4)
	Average	consecutive wins	2	consecutive losses	2