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Resistance Levels for Three Foreign Exchange Rates

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Abstract

Academic research on chartist methods has dealt mainly with trading rules. This paper innovates by considering resistance levels for foreign exchange rates that are called thresholds in the technical literature. However, unlike the literature, these thresholds are taken to be at fixed and round figures: 2 for the British pound, 200 for the Japanese yen and 2 for the Swiss franc. The null hypothesis of one regime is rejected for the alternative hypothesis of two regimes. The three foreign exchange rates follow a very strong mean-reverting process in the upper bands, while mean reversion is fairly strong in the lower bands. Market timing rules are proposed for these three foreign exchange rates.

Introduction & Literature Survey

Chartist and technical methods are oftentimes used by analysts for the purpose of forecasting prices in the financial markets, most notably in very short-run trading. This behavior has perplexed academicians who believe in market efficiency, especially weak-form efficiency, which states that past prices do not help in predicting future prices (Fama, 1970, 1991). Otherwise, risk-less profit opportunities are left unexploited, which ought to be eliminated by profit-seeking traders. The proponents of behavioral finance think differently. Profit opportunities exist but they are risky because of noise trading, marking-to-market and margin requirements, in addition to delivery conditions in short sales. All of this prevents fundamentalists from taking consistently a position against the trend, especially if adjustment to fundamentals takes time to happen and if investors are handicapped by certain psychological traits (Bodie, Kane, and Marcus, 2007, pp. 242-268). Other explanations for trading profits are herding behavior, or band-wagon effects, and market power. Herding behavior occurs when investors rush, like herds, to take the same position in the market in order not to be left out from the 'wagon', and this behavior causes prices to be positively serially correlated, thereby creating structure and non-randomness in prices. Market power arises when listed company shares are held by a small number of investors who can manipulate prices, and is especially prevalent in financial markets of emerging nations.

Technical and chartist methods are not only seen in stock markets but they are also frequently observed in foreign exchange markets (Park and Irwin, 2007, p. 787). This is the market that is studied in this paper. Three foreign exchange rates are analyzed: the US price of the British pound (GBP), the yen price of the US dollar (JPY), and the Swiss franc price of the US dollar (CHF). This differential pricing is due to the way these exchange rates are quoted in international financial markets. The choice of these three rates is based on two factors: data availability, and a relative absence of heavy official intervention that is known to distort prices (Sweeney, 1986, Davutyan and Pippenger, 1989, and Park and Irwin, 2007). The Deutsche mark is not considered because it was recently replaced by the Euro exchange rate, and hence there is a break in the series. The French franc is not considered because it also was replaced recently by the Euro exchange rate, and because, during its modern history, was rigged by heavy official intervention in order to keep prices within pre-specified bands in the European Exchange Rate Mechanism.

The early literature has tested whether filter trading rules are profitable. Sweeney (1986) was among the first to subject filter trading rules in foreign exchange markets to statistical significance, and he found evidence of risk-adjusted profits. Usually a filter works as follows. When prices go up by a certain specified percentage, this is a signal to buy because the trend becomes upward; and when prices go down by the same percentage, this is a signal to sell because the trend becomes downward. It is as if price movements are *filtered* around the specified percentage. Sometimes a contrarian policy is adopted: when prices go up (down) by a specified percentage, this is a signal to sell (buy) and not to buy (sell). Filter trading rules are based on price patterns that will recur in the future. Other trading rules are as follows. Crossing of short run with long run moving averages from below is a signal to buy, and crossing from above is a signal to sell (Chang *et al*., 2006). The presence of a significant negative serial correlation, due to liquidity effects, can initiate trading decisions (Avramov *et al*., 2006). Trading volume could affect prices (Chen and Li, 2006). Momentum and contrarian premiums may exist (Boyton and Oppenheimer, 2006, Balsara *et al*., 2007). Forecasting prices by price-earnings ratios and dividend yields may be possible (Fisher and Statman, 2006). Finally adding technical variables, like lagged prices and dummies for superior and inferior performance to fundamental variables, can help in improving forecasts (Bettman, 2007). Qi and Wu (2006) study 2,127 different trading rules in foreign exchange markets and conclude that trading profits tend to disappear in the more recent period. The same opinion is held by Park and Irwin (2007) which is also a survey of the literature on the profits of trading rules.

Another approach has modeled the behavior of technical analysts and has incorporated such behavior in the determination of foreign exchange rates. One of the oldest models is in Frankel and Froot (1990), who assume that chartists follow a band-wagon feedback reaction. A more recent model which focuses on noise trading is found in Mark (2001, pp. 152-158). According to Park and Irwin (2007) the most recent theoretical model is Slezak (2003) who gives to noise traders a dominant role even in the long run.

The findings in the literature are in the majority in support of the existence of trading profits (Park and Irwin, 2007). However there are two problems. The first is that insignificant findings are hardly published, and only studies that find significant trading profits are published. The second problem is data-snooping, or the fact that significant results are found just by luck. And since most trading rules are chosen *ex post* then the risk of data-snooping is high. Some authors have used robust methods to such a problem (Qi and Wu, 2006).

This paper innovates in the literature by studying another facet of chartism which is the presence of resistance and support bands in foreign exchange prices. It is true that the subject matter has been studied by Brock *et al.* (1992), Sullivan *et al.* (1999) and Qi and Wu (2006), but their definition of the bands is different from the definition in this paper. See, for example, Qi and Wu (2006, p. 2139 and p. 2155). When the price exceeds the maximum price over the previous n days by b% the foreign currency is bought, where b is a pre-specified percentage. When the price goes below the minimum price over the previous n days by b% the foreign currency is sold. In this paper a resistance level to prices is defined when an upper limit is reached that will signal a sell rule which will activate in the aggregate a downward movement: the price is resistant to further upward movement. A support level to prices is defined when a lower limit is reached that will signal a buy rule and which will activate in the aggregate an upward movement: the price is resistant to further downward movement. Prices are expected to revert to a mean below the resistance level and to another mean above the support point. For simplicity this paper assumes the same price for both resistance and support, which means that the statistical series have two different regimes, one above the threshold and one below it. Below this threshold prices tend to fall to reach a given value and above this point prices tend to rise to reach another given value. Both these given values are called mean-reverting values. So if the exchange rate approaches this resistance level from below, it will tend to fall down, while if it approaches this support level from above, it will tend to rise up.

The resistance level needs to be at a psychological level, at an easily-revealing value, and must indicate precisely this value. In addition the level price should be at a round figure (Osler, 2003). Osler explains predictions of technical analysis by order flows that cluster at round figures. He examines two predictions of technical analysis using stop-loss and take-profit orders: reversals in down-trends (up-trends) at predictable support (resistance) levels, and rapid trends when support (resistance) levels are crossed. Park and Irwin (2007, p. 812) write: “According to Osler, clustering of order flows at round numbers is possible because (1) the use of round numbers reduces the time and errors incurred in the transaction process, (2) round numbers may be easier to remember and to manipulate mentally and (3) people may simply prefer round numbers without any reasoning.” In this paper the critical threshold is taken to be 2.00 for the GBP, 200 for the JPY, and 2.00 for the CHF. The reasoning is as follows. Natural thresholds for the GBP are 1.00, 2.00 and 3.00. Unfortunately the GBP did not witness any value above 3.00 in the sample nor below 1.00. Hence the level of 2.00 was chosen. Threshold candidates for the JPY are 100, 200, and 300. Unfortunately the JPY has 14 observations below 100 in the sample and 10 observations above 300. This is not enough to define a regime change and the level of 200 was selected as a threshold. Threshold candidates for the CHF are 1.00, 2.00, and 3.00. Unfortunately the CHF has only 5 observations in the sample above 3.00 and none below 1.00. Hence the threshold was taken to be 2.00. The data frequency is monthly for two reasons: (1) more than one support (resistance) level may exist with daily data, and (2) mean reversion is essentially a long run concept. If *real* exchange rates take years to mean revert this indicates that mean reversion of nominal exchange rates cannot be evident with daily data. The data is end-monthly, is retrieved from EconStats, and spans the period from 1974:1 to 2007:10, i.e. the floating exchange rate period.

Theory

The threshold auto-regressive model can be summarized in the following regression, which assumes one threshold only:

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \beta_0 D_t + \beta_1 D_{t-1} y_{t-1} + \varepsilon_t \qquad (1)$$

where D_t is a dummy variable taking the value 1 if $y_t < \lambda$, and 0 if $y_t \geq \lambda$. The threshold value λ is assumed in this paper to be constant and exogenous. A test of a regime change is a test on whether the coefficients on the shift dummy D_t and on the interactive dummy, $D_{t-1}y_{t-1}$, are jointly statistically significant. If they are, then there is evidence of two regimes. A further test of stationarity is to find out whether the t-statistics of α_1 and β_1, which follow a Dickey-Fuller t-distribution, are statistically significant or not. If they are, then in both regimes the statistical process is stationary, i.e. is not a random walk. If the random walk is rejected then weak-form efficiency is also rejected and mean reversion is a possible explanation. Mean reversion occurs when prices are autocorrelated with a partial autocorrelation coefficient less than one. A coefficient equal to one is a property of a random walk. Hence, if α_1 and β_1 are statistically significantly negative one can infer that the statistical process of the series studied is not the random walk that weak-form efficiency would predict.

The literature on non-linear mean reversion, or threshold estimates, assumes that the threshold is unknown and must be estimated by minimizing the squared residuals of the non-linear regression, i.e. equation (1). Applications of such a methodology are diverse. Barnes and Olivei (2003) test a non-linear asymmetric model on the US Phillips curve. A non-linear model means that there are at least two regimes for the data generation process. An asymmetric model means that there are two different thresholds, an upper and a lower one, within which the data follows different statistical behaviors. In an asymmetric model there are at most three regimes: in between the threshold, above the upper threshold, and below the lower threshold.

Alba and Park (2005) test a non-linear regression on the Turkish real exchange rate with an endogenous threshold. Christopoulos (2006) applies the endogenous threshold model to real GDP for seven OECD countries. Self and Mathur (2006) test G7 stock indices with an asymmetric momentum threshold autoregression. Wu and Chen (2006) test Purchasing Power Parity with a two-band symmetric threshold auto-regressive model with an endogenous threshold. Strauss and Wohar (2007) test threshold effects in the interest rate differential between domestic and foreign rates, with the use of a symmetric two-band model. In each case the empirical evidence finds in favor of thresholds. However, with an endogenous threshold model the test-statistics follow a non-standard distribution that needs to be approximated by bootstrap techniques. The reference to such an approach is in Caner and Hansen (2001). This is not the case in this paper where the threshold is selected in advance to be a round, psychological, distinct and precise figure, which is not obtainable with an endogenous threshold.

Another way to write the model is to define two dummy variables. The first dummy DD_t takes the value 1 above the threshold and 0 below it. The second dummy D_t, which equals $1\text{-}DD_t$, has already been defined, and takes the value 1 below the threshold and 0 above it. The two-regime threshold model is then as follows:

$$\Delta y_t = \gamma_0 D_t + \gamma_1 D_{t-1} y_{t-1} + \delta_0 DD_t + \delta_1 DD_{t-1} y_{t-1} + \xi_t \qquad (2)$$

Sufficient conditions for the stationarity of y_t are (Petrucelli and Woolford, 1984):

(1) $\gamma_1 < 0$ (3a)
(2) $\delta_1 < 0$ (3b)
(3) $(1+\gamma_1)(1+\delta_1) < 1$ (3c)

Conditions (3a) and (3b), if they stand, mean that the series in that given regime does not follow a random walk, is probably mean-reverting and supports weak-form inefficiency. The three conditions (3a), (3b), and (3c) will be tested separately and jointly. The separate tests for the first and second conditions will use Dickey-Fuller t-statistics, while the third test will use a Wald test and the joint test will also use a Wald test. Moreover the mean-reverting levels will be tested by t-statistics. It can be shown that these mean-reverting levels are respectively the following for each regime:

$\gamma_0/(-\gamma_1)$ for the regime below the threshold and (4a)
$\delta_0/(-\delta_1)$ for the regime above the threshold (4b)

Empirical Analysis

For the GBP, and for a threshold level of 2.00, 62 observations out of 406 lie in the upper band, and 344 observations lie in the lower band. The same statistics for the JPY, with a threshold value of 200.00, are respectively 138 and 268. For the CHF the threshold value of 2.00 divides the observations into 97 in the upper band and 309 in the lower band.

Carrying out unit root tests with a trend, as in Phillips and Perron (1988), on the three foreign exchange rates and their first-differences give evidence that the levels of the exchange rates are non-stationary, and that their first-differences are not (see Table 1). The exception is the CHF, for which the actual probability under H_0, the non-stationary hypothesis, is 0.08762, rejecting non-stationarity at the 10% level but not at the 5% level or lower. These results show that the three series follow a random walk, and that the three markets are weak-form efficient. But this is a too quick conclusion because with the presence of a regime change stationarity is more likely to be rejected.

Table 1: Phillips & Perron (1988) unit root tests with a trend.

Variable	Test statistic (probability) [# of optimal lags]
GBP	-8.9535 (0.5103) [3]
JPY	-6.7281 (0.6867) [3]
CHF	-18.9108 (0.08762) [3]
ΔGBP	-374.01 (0.00000) [2]
ΔJPY	-370.73 (0.00000) [2]
ΔCHF	-502.03 (0.00000) [2]

The results of estimating equation (1) are presented in Table 2. For the three foreign exchange rates the null of the absence of a regime change is rejected at high confidence levels. The highest actual probability is 0.00202. Therefore all three exchange rates have indeed a break around the threshold point.

Table 2: Tests of a two-regime data generation process. The model is:

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \beta_0 D_t + \beta_1 D_{t-1} y_{t-1} + \varepsilon_t$$

Where Δ is the first-difference operator, D_t is the dummy of the threshold value λ, whereby $D_t = 1$ if $y_t < \lambda$, and 0 if $y_t \geq \lambda$

y	GBP	JPY	CHF
λ	2.00	200.00	2.00
α_0	0.16844 (5.0960)	11.1846 (3.6960)	0.4057 (9.9533)
α_1	-0.07711 (-5.2362)	-0.04701 (-3.9585)	-0.17089 (-10.2555)
β_0	-0.09221 (-5.4390)	-7.9809 (-2.9205)	-0.35765 (-12.0899)
β_1	0.03075 (3.8980)	0.01857 (1.3006)	0.13570 (9.3074)
Δy_{t-1}	0.12128 (2.5035)	-	-0.18255 (-4.4243)
Adjusted R-Square	0.07968	0.03104	0.32777
Log likelihood	643.898	-1262.70	461.01
Wald test for the joint null hypothesis H_0 (probability): $\beta_0=0$ $\beta_1=0$	$\chi^2(2) = 29.811$ (0.00000)	$\chi^2(2) = 12.410$ (0.00202)	$\chi^2(2) = 146.736$ (0.00000)

Note: t-statistics in parentheses below the coefficient estimates unless otherwise noted.

Table 3 presents the results of estimating equation (2). For the GBP the behavior of the data above and below the threshold is both stationary, contradicting weak-form efficiency. Below the threshold, the condition (3a) of stationarity fails to be rejected with a probability under the Dickey-Fuller distribution of 0.03215, while, above the threshold, the similar hypothesis (3b) fails to be rejected with a probability under the same distribution of 0.00001. The third condition (3c) fails to be rejected with a Wald test and with a probability under the null of no-difference from one of 0.00001. The three conditions, (3a), (3b), and (3c) fail to be rejected with a probability of 0.00000. All these tests provide evidence that the data generating process of the GBP is stationary in both regimes and is definitely not a random walk. The half-life of mean reversion is 14.6 months below the threshold and 8.6 months above the threshold. These half-lives point to relatively fast adjustments. Table 3 also provides the mean-reverting levels. Below the threshold of 2 the data seem to revert to a value of 1.6443, and above the threshold of 2 the data seem to revert to a value of 2.1844. These mean-reverting levels are highly significant statistically and their difference is also highly significant statistically.

Table 3: Regime tests around the thresholds. The model is:

$$\Delta y_t = \gamma_0 D_t + \gamma_1 D_{t-1} y_{t-1} + \delta_0 DD_t + \delta_1 DD_{t-1} y_{t-1} + \xi_t$$

where Δ is the first-difference operator, D_t takes the value 1 if $y_t < \lambda$, and 0 if $y_t \geq \lambda$, DD_t takes the value 1 if $y_t \geq \lambda$, and 0 if $y_t < \lambda$.

y	GBP	JPY	CHF
λ	2.00	200.00	2.00
γ_0	0.07622 (3.0182)	3.20379 (1.6983)	0.04801 (1.6363)
γ_1	-0.04636 (-3.0304)	-0.02844 (-1.8858)	-0.03518 (-1.7941)
δ_0	0.16844 (5.0960)	11.1846 (3.6960)	0.40566 (9.9533)
δ_1	-0.07711 (-5.2362)	-0.04701 (-3.9585)	-0.17089 (-10.2555)
Δy_t	0.12128 (2.5035)	-	-0.18255 (-4.4243)
$\gamma_0/(-\gamma_1)$	1.6443 (28.4800)	112.638 (8.6340)	1.3645 (9.6447)
$\delta_0/(-\delta_1)$	2.1844 (25.8475)	237.911 (22.4763)	2.3738 (50.5094)
$\delta_0/(-\delta_1) - \gamma_0/(-\gamma_1)$	0.5401 (5.2424)	125.273 (7.8102)	1.0093 (6.8642)
Wald test for H_0: $(1+\gamma_1)(1+\delta_1) = 1$	$\chi^2(1) = 19.462$ probability: 0.00001	$\chi^2(1) = 11.160$ probability: 0.00084	$\chi^2(1) = 45.352$ probability: 0.00000
Wald test for the joint null hypothesis H_0: $\gamma_1 = 0$ $\delta_1 = 0$ $(1+\gamma_1)(1+\delta_1) = 1$	$\chi^2(3) = 36.049$ probability: 0.00000	$\chi^2(3) = 15.675$ probability: 0.00132	$\chi^2(3) = 157.748$ probability: 0.00000
Adjusted R-Square	0.07968	0.03104	0.32777
Log likelihood	643.898	-1262.70	461.01
Skewness t-statistic on the residuals	-2.159	-5.255	7.325
Kurtosis t-statistic on the residuals	4.368	12.129	73.005
Probability of the Ljung-Box Q-statistic on the residuals: Q(6) Q(12) Q(24)	0.5541 0.2881 0.1174	0.1126 0.1534 0.0029	0.8076 0.9487 0.9970

Probability of the Ljung-Box Q-statistic on the squared residuals: $Q^2(6)$ $Q^2(12)$ $Q^2(24)$	 0.00001 0.00005 0.00003	 0.00003 0.00000 0.00000	 0.00000 0.00000 0.00000

Note: t-statistics in parentheses next to the coefficient estimates unless otherwise noted.

Profitable trading rules can be devised. If the GBP is higher than 2.1844 the rule is to sell the GBP because it will depreciate to 2.1844. If the GBP is between 2 and 2.1844 the rule is to buy the GBP because it will appreciate to 2.1844. If the GBP is less than 1.6443 the rule is to buy the GBP because it will appreciate to 1.6443. Finally if the GBP is between 1.6443 and 2 the rule is to sell the GBP because it will depreciate to 1.6443.

In order to test whether the model is well-specified, the regression residuals are evaluated with the help of econometric diagnostics. The residuals of the regression do not suffer from serial correlation. However both heteroscedasticity and non-normality fail to be rejected. Heteroscedasticity is measured by the Ljung-Box Q-statistic on the squared residuals for lags 6, 12, and 24. Normality is evaluated by the skewness and kurtosis t-statistics. In any case, one can invoke the Central Limit Theorem for asymptotic normality because the sample size is large.

Regarding the second exchange rate, the JPY, the following results can be derived. The condition (3a) is rejected, denoting a non-stationary, random-walk-like, behavior below the threshold of 200. The probability under the null of non-stationarity, or random walk, is 0.3388. The condition (3b) fails to be rejected, denoting a stationary statistical process above the threshold. The probability under the null of non-stationarity, or random walk, is 0.00417. The condition (3c) fails to be rejected with a Wald test that has a probability of 0.00084 under the null of no-difference from one. The failure of condition (3a) means that the variable is not stationary in both regimes, but only in one of them. However the mean-reverting levels are highly statistically significant. The data seem to revert to a level of 112.638 below the threshold of 200, and to revert to a level of 237.911 above the threshold of 200. The difference between the two levels is also highly significant statistically. The fact that there is a statistically significant mean-reverting level below the threshold allows the inference that the unit root test is misleading, especially since such tests are known to have low power, and hence the data process can be considered stationary even below the threshold. This is ascertained by the result of testing jointly the following three conditions: (3a), (3b), and (3c) (see Table 3).[1] The half-life of mean reversion is 24.0 months below the threshold, and 14.4 months above the threshold.

Here again profitable trading rules can be devised. If the JPY is higher than 237.911 the rule is to buy the JPY because it will appreciate to 237.911. If the JPY is between 200 and 237.911 the rule is to sell the JPY because it will depreciate to 237.911. If the JPY is below 112.638 the rule is to sell the JPY because it will depreciate to 112.638. Finally if the JPY is between 112.638 and 200 the rule is to buy the JPY because it will appreciate to 112.638.

As for the GBP, there is evidence of heteroscedasticity and non-normality in the regression residuals. But serial correlation is rejected. In any case, one can invoke the Central Limit Theorem for asymptotic normality because the sample size is large.

For the last foreign exchange rate, the CHF, the results are quite similar to those for the JPY, except for a very high adjusted R-Square of around 33%. The condition (3a) is rejected, denoting a non-stationary process below the threshold. The probability under the null of non-stationarity, or random walk, is 0.3834. The condition (3b) holds with a probability under the null

[1] The Wald test has an actual probability of 0.00132. Hence conditions (3a), (3b), and (3c) fail to be jointly rejected.

of non-stationarity, or random walk, of 0.00000, denoting a stationary process above the threshold. The condition (3c) holds too with a Wald test that has a probability under the null of no-difference from one of 0.00000. The data generating process cannot be considered as stationary because of evidence of non-stationarity below the threshold. However, the mean-reverting levels are highly significant statistically. The process seems to revert to a value of 1.3645 under the threshold of 2, and to a value of 2.3738 above the threshold of 2. The difference between these two levels is also highly significant statistically. The existence of a statistically significant mean-reverting level below the threshold points in the direction that the data process is stationary even below this threshold and that the stationarity test is misleading. This is ascertained by the result of testing jointly the three conditions: (3a), (3b), and (3c) (see Table 3).[2] The half-life of mean reversion is 19.4 months below the threshold and only 3.4 months above the threshold. Hence adjustment is relatively fast, especially above the threshold.

Again profitable trading rules can be devised. If the CHF is higher than 2.378 the rule is to buy the CHF because it will appreciate to 2.378. If the CHF is between 2 and 2.378 the rule is to sell the CHF because it will depreciate to 2.378. If the CHF is below 1.3645 the rule is to sell the CHF because it will depreciate to 1.3645. Finally if the CHF is between 1.3645 and 2 the rule is to buy the CHF because it will appreciate to 1.3645.

As for the other two exchange rates, there is evidence of heteroscedasticity and non-normality but not of serial correlation in the regression residuals. In any case, one can invoke the Central Limit Theorem for asymptotic normality because the sample size is large.

Conclusion

This paper tested for the existence of resistance levels in three foreign exchange rates. These levels define two bands, one above and one below the threshold. The behavior of the exchange rates above the threshold is essentially a stationary process, while the behavior below the threshold is more confused. In any case the hypothesis of one regime is rejected in favor of the alternative of two regimes around the threshold. The evidence on mean reversion contradicts the unit root tests, which are known to have notoriously a low power. The GBP reverts to a mean of 1.6443 below the resistance level of 2, and to 2.1844 above that level. The JPY reverts to a mean of 112.638 below the resistance level of 200, and to 237.911 above that level. Finally, the CHF reverts to a mean of 1.3645 below the resistance level of 2, and to 2.3738 above that level. All these mean-reverting levels are highly significant statistically. The half-life of mean reversion lies between a minimum of 3.4 months, and a maximum of 24.0 months. Profitable trading rules can be devised for all three exchange rates (*Vide Supra* in the text).

These results show that one strand of technical analysis finds empirical support, which is the strand that specifies a psychological resistance level for each exchange rate. Trading around these resistance levels is likely to be critical. Since this is a kind of market inefficiency, future research will tell whether there can be another interpretation for this apparent inefficiency, an interpretation that is more in line with rationality. If there is no other interpretation then the investor can use the results in this paper to speculate. As an example, the speculator should sell the GBP as it reaches the level of 2.00 from below, and should buy the GBP as it reaches the level of 2.00 from above. If the GBP is higher than the mean-reverting level of the upper band of 2.3738, then the speculator should sell the GBP. If the GBP is between 2.00 and 2.378 then he/she should buy the GBP. If the GBP is below the mean-reverting level of the lower band of 1.6443 then he/she should buy the GBP. If the GBP is between 1.6443 and 2.00 then he/she should sell the GBP. Similar positions can be held in the other two currencies, granted however that the exchange rates are quoted in the market differently relative to the GBP.

Mean reversion, in itself, contradicts weak-form efficiency. However if the fundamentals that are driving the exchange rates are mean-reverting, then these exchange rates need not

[2] The Wald test has an actual probability of 0.00000. Hence conditions (3a), (3b), and (3c) fail to be jointly rejected.

follow a random walk. In any case the presence of mean reversion can initiate profitable trading if it persists.

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