Combining mean reversion and momentum trading strategies in foreign exchange markets

Alina F. Serban [*]

West Virginia University, College of Business and Economics, Morgantown, WV 26506, United States
Lynchburg College, School of Business and Economics, Lynchburg, VA 24501, United States

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ABSTRACT

The literature on equity markets documents the existence of mean reversion and momentum phenomena. Researchers in foreign exchange markets find that foreign exchange rates also display behaviors akin to momentum and mean reversion. This paper implements a trading strategy combining mean reversion and momentum in foreign exchange markets. The strategy was originally designed for equity markets, but it also generates abnormal returns when applied to uncovered interest parity deviations for five countries. I find that the pattern for the positions thus created in the foreign exchange markets is qualitatively similar to that found in the equity markets. Quantitatively, this strategy performs better in foreign exchange markets than in equity markets. Also, it outperforms traditional foreign exchange trading strategies, such as carry trades and moving average rules.

1. Introduction

Foreign exchange market trading strategies have attracted much attention, especially since Fama (1984) introduced the "forward puzzle," which argues that forward exchange rates are biased predictors of spot exchange rates. This paper sets forth a new strategy in the foreign exchange (FX) markets that combines mean reversion and momentum. Even though the strategy was originally designed for equity markets, I find that it produces higher Sharpe ratios than traditional FX strategies.

The starting point of this paper, the "forward puzzle," results from the rejection of the uncovered interest parity (UIP) theory. UIP states that the change in the exchange rate should incorporate any interest rate differentials between the two currencies. A large literature exists examining if and when UIP holds.[1] This paper tries to find a pattern in the deviations from UIP and to explore the similarity between this pattern and that of stock returns. The literature reveals what looks like mean reversion and momentum in both markets. A long-run mean reverting pattern in currency values has been uncovered by Engel and Hamilton (1990); a short-term momentum

effect generates profitability in FX market trading (Okunev and White, 2003).[2] Chiang and Jiang (1995) notice that foreign exchange returns show strong positive correlations in the short-run (momentum behavior) and negative correlations in the long-run (mean reverting behavior). This paper generates abnormal returns by employing a strategy that combines the long-run and short-run patterns of the deviations from UIP.

The success of the combined momentum-mean reversion strategy brings about another interesting issue: the puzzling relationship between stock and FX markets. The similarities between the stock and FX markets are perplexing because macroeconomic fundamentals explain stock returns, but not exchange rates (Meese and Rogoff, 1983). Traditional theory dictates that two markets not relying on the same fundamental variables cannot behave similarly. Yet, I find the two markets comparable. This result is in line with early studies that depict similar empirical regularities in FX and stock markets (Mussa, 1979). One possible explanation springs from Engel and West (2005), who find that exchange rates explain macroeconomic fundamentals, not the reverse. This finding, corroborated with the finding that fundamentals explain stock

* Address: West Virginia University, College of Business and Economics, Morgantown, WV 26506, United States. Tel.: +1 304 292 2460.
  E-mail address: alina.serban@mail.wvu.edu

[1] For more details on UIP, see for instance Froot and Frankel (1989).

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[2] Okunev and White actually use a moving average rule to create profits for the speculators on the FX market, but they name this "a simple momentum strategy." The strategy in my paper is different from theirs.

returns, provides one possible channel for the relation between the two analyzed markets. Another fascinating explanation is that the risk factors affecting both stock and FX returns remain unknown but are somehow connected. An additional explanation is that similar behavioral biases operate in both markets, leading to similar inefficiencies.

To explore the similarities between the stock and FX markets, I first consider the non-parametric approach that Jegadeesh and Titman (1993) exploit. These papers construct portfolio deciles based on previous months' returns and choose a winner and a loser decile. By buying the winner and selling the loser a zero-investment portfolio is constructed and this portfolio is held for less than a year. The authors find that the return on their zero-investment portfolio is always positive. If this portfolio is held for more than a year, however, the return becomes zero or negative. The aforementioned non-parametric strategy is used in the FX market by identifying a winner and a loser currency based on previous deviations from UIP. I find that the winner continues to have high returns and the loser low returns for the subsequent 9–12 months, but, in the subsequent 4–5 years, the winner and loser portfolios switch positions. However, one cannot combine mean reversion and momentum strategies with this approach.

Balvers and Wu (2006) use an alternative approach to generate trading profits in the stock market: a parametric strategy. They consider the effect of momentum and mean reversion jointly and conclude that the resulting strategy can lead to significant profits when applied to the stock markets of 18 developed countries. A contrarian strategy or a momentum strategy by itself leads to lower abnormal returns than the combination strategy. I find that the parameters obtained for the FX market are quantitatively similar to those for the stock market; hence we expect similar trading strategy returns for the zero-investment portfolios. The FX market returns have lower volatility than equity market returns. Consequently, I consider the Sharpe ratios, which allow me to compare risk-to-reward profiles of the same strategy, but in the two different markets. The Sharpe ratios obtained in the FX market are significantly larger than those obtained in the stock market.

The paper is organized as follows. The second section describes the data and presents preliminary results showing that deviations from UIP exhibit momentum initially and subsequent mean reverting behavior. The third section describes the model and the fourth examines the model empirically and compares the results to the existing literature. The final section concludes.

2. Data description and preliminary statistics

2.1. Data description

The data set consists of the 1-month forward and spot exchange rates from the Bank of International Settlements and Datastream. Due to availability, the data come from two sources: for the period December 1978–December 2001 from the BIS dataset, and for January 2002–February 2008 from Datastream. I obtain monthly data for the Canadian Dollar, German Mark/Euro, UK Pound and Japanese Yen. I focus on well-developed currencies with liquid markets, in which currency speculation can be easily implemented. Due to data availability, the literature on the FX market usually only covers these currencies. I work with December 1978 through February 2008 as the time period.[3] The US Dollar serves as the home currency.

The monthly equity market returns are obtained from the Morgan Stanley Capital International (MSCI) Barra equity market price indexes for the same set of four developed countries plus the US. The sample period is December 1978 through February 2008. The risk free rate is the one-month Treasury bill rate (from Ibbotson Associates), obtained from Kenneth French's website.

2.2. Interest parity conditions

UIP states that the currencies at a forward premium should appreciate. The "forward puzzle" suggests that the exact opposite happens: these currencies actually tend to depreciate. An investor who borrows money in their home country (with an interest rate of r_t) and lends it in another country with a higher interest rate (r_t^i) should expect a zero return due to the changes in exchange rate (denoted at time t by S_t^i, in units of home country currency per foreign country currency) . In other words:

$$1 + r_t = (1 + r_t^i)\frac{E(S_{t+1}^i)}{S_t^i}, \tag{1}$$

With this strategy, investors leave their position uncovered from t to $t + 1$ and only make arrangements to change the foreign currency into domestic currency at time $t + 1$. The UIP states that the markets equilibrate the return on the domestic currency asset with the expected yield of the uncovered position in the foreign currency. If the investors leave nothing to chance and make arrangements to convert foreign to domestic at $t + 1$ by using a forward exchange rate F_t, absence of riskless arbitrage profits implies that:

$$1 + r_t = (1 + r_t^i)\frac{F_t^i}{S_t^i}, \tag{2}$$

Eq. (2) is known as Covered Interest Parity (CIP). Taking logs of (1) and (2) and ignoring expectations, we obtain:

$$r_t - r_t^i = s_{t+1}^i - s_t^i, \quad \text{with } s_t^i \equiv \ln S_t^i, \tag{3}$$
$$r_t - r_t^i = f_t^i - s_t^i, \quad \text{with } f_t^i \equiv \ln F_t^i, \tag{4}$$

If both conditions hold, it follows that:

$$s_{t+1}^i - s_t^i = f_t^i - s_t^i, \tag{5}$$

Eq. (5) accounts for the interest rate differential implied by the CIP condition.[4]

This paper is concerned with the deviations from UIP, denoted by y_t^i and defined as follows:

$$y_{t+1}^i = (s_{t+1}^i - s_t^i) - (f_t^i - s_t^i) = s_{t+1}^i - f_t^i. \tag{6}$$

Table 1 presents summary descriptive statistics of the returns for UIP positions in the four currencies and for various similar positions in the stock market: annualized mean returns, standard deviations and Sharpe ratios. Given the low mean returns in the FX market (relative to the stock market), leverage is widely used in practice to provide the desired mean returns. The Sharpe ratios provide the proper comparison between the FX and equity markets since they remain invariant to the degree of leverage.

Panel A displays summary statistics for UIP positions in the FX market, Panel B describes stock market excess returns computed from the MSCI Barra price indexes, and Panel C shows descriptive statistics for a strategy of buying US index and short selling a foreign index, the stock market counterpart of the UIP positions in the FX market. The mean returns for the UIP positions in Panel A range

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[3] Most of the literature only considers data on the FX market starting in the 1970's, after the collapse of the Bretton Woods System. Due to data availability, the sample in this paper starts in December 1978. The choice of currencies was limited to avoid multicollinearity problems in the parameters' estimation (i.e., this paper considers currencies that are not highly correlated with each other).

[4] The CIP is the condition used by large banks for determining the exchange rates and interest rates at which trading is actually conducted. See for instance Taylor (1987) and Baba and Packer (2009).

Table 1
Summary statistics.

	Mean	Standard deviation	Sharpe ratio
Panel A. FX market			
Canada	1.37	4.68	0.29
UK	1.81	9.06	0.20
Japan	−1.66	10.19	−0.16
Germany	−0.49	9.42	−0.05
Panel B. Stock market (buy and hold excess returns)			
US	11.37	14.76	0.77
Canada	11.45	19.58	0.59
UK	12.00	18.14	0.66
Japan	7.08	22.03	0.32
Germany	10.28	21.82	0.47
Panel C. Stock market (returns of holding the US and shorting the specific country)			
Canada	−0.08	13.51	−0.01
UK	−0.63	14.69	−0.04
Japan	4.29	22.32	0.19
Germany	1.09	18.55	0.06

This table reports summary statistics (annualized mean, standard deviation and Sharpe ratio) for deviations from UIP (Panel A), stock excess returns (Panel B) and stock returns for a strategy of buying US stock and short selling foreign country stock (Panel C). The mean and standard deviations are multiplied by 100 (so 1.37 should be read as 1.37%). The deviations from UIP for the Canadian Dollar, German Mark/Euro, UK Pound and Japanese Yen relative to the US Dollar are computed as: $y_t^i = s_{t+1}^i - f_t^i$. The data are taken from Bank of International Settlements and Datastream. The stock returns are computed for the same four countries plus the US from the MSCI Barra indices. The sample period is December 1978–February 2008. Panel B reports statistics for the excess returns, obtained by subtracting the one-month US Treasury (taken from Kenneth French's website). For the Sharpe ratios in Panels A and C, US is considered the benchmark country, so there is no need to subtract the average risk free rate.

from −1.66% to 1.81% and the standard deviations from 4.68% to 10.19%. In Panel B, the mean returns for the stock market indexes range from 7.08% to 12.00% and standard deviations from 14.76% to 22.03%. Evidently, more dispersion exists in the data for the stock market returns than for the FX market, as expected from the literature (Burnside et al., 2008; Fong, 2010). By taking the US stock market as the benchmark country (by analogy to the FX positions), the strategy that Panel C proposes gives very low mean returns (ranging from −0.08% to 4.29%), and very high standard deviations (from 13.51% to 22.32%); this again shows a much higher dispersion in the equity market than in the FX market. The Sharpe ratios are relatively low in Panels A and C and relatively high in Panel B.

2.3. Confirming mean reversion and momentum

To check for mean reversion and momentum, one can use the Jegadeesh and Titman (1993) strategy easily and effectively by applying this strategy to the deviations from UIP. The strategy considers the cumulative deviations from UIP for every currency over the previous *J* months (where *J* takes the values of 6, 9, or 12). Each month I rank the currencies on the basis of past deviations from UIP and the currency with the highest cumulative return classifies as the "winner," while the currency with the lowest return becomes the "loser." For these currencies I compute the cumulative deviations from UIP over the subsequent *K* months (where *K* is 6, 9, 12, 24, 36, 48, and 60). I assign the winner and loser for every month; consequently, the holding periods overlap. Fig. 1 summarizes the results for all permutations of this strategy.

From the graph, one can ascertain effortlessly that the winner's mean return starts out positive and continues to be positive until the momentum effect disappears (after about one year). The loser's return appears to be a mirror image of the winner's return. Starting around year four, the results are reversed and the losers outperform the winners. These results do not differ from the results on the stock market (De Bondt and Thaler, 1985; Jegadeesh and Tit-

man, 1993; Balvers et al., 2000; Friesen et al., 2009). I am the first to implement a strategy of combining mean reversion and momentum in the FX market. This strategy generates significant abnormal returns in this market, as shown in the following sections.

3. Model and parameter estimation

3.1. Model

Fama and French (1988) and Summers (1986) consider a simple model for stock prices (their natural log is represented by *x*) that is the sum of a random walk and a stationary component. The stationary component classifies as a first-order autoregressive process that represents the long temporary swings in stock prices (characterized by coefficient δ). The parameter μ captures the random walk drift component. Similarly, but adding a coefficient for the momentum effect ρ, Balvers and Wu (2006) construct the log of stock prices (with dividends added and reinvested) as:

$$x_t^i = (1 - \delta^i)\mu^i + \delta^i x_{t-1}^i + \sum_{j=1}^{J} \rho_j^i (x_{t-j}^i - x_{t-j-1}^i) + \varepsilon_t^i. \tag{7}$$

They note that the log of the price with dividends reinvested implies that the return is $y_t^i = x_t^i - x_{t-1}^i$ and that the log of the price equals the cumulative return after correction for market risk:

$$x_t^i = \sum_{s=1}^{t} y_s^i. \tag{8}$$

I use Eq. (7) to find abnormal returns in the FX market. The δ^i represent the speed of mean reversion and can differ by country, while the ρ_j^i represent the momentum strength and can vary by country and by lag. The parameter μ^i also varies by country.

From Eq. (7), the return of my strategy is:

$$y_t^i = -(1 - \delta^i)(x_{t-1}^i - \mu^i) + \sum_{j=1}^{J} \rho_j^i (x_{t-j}^i - x_{t-j-1}^i) + \varepsilon_t^i, \tag{9}$$

The models proposed by Fama and French (1988) and Summers (1986) consider only mean reversion, hence all the ρ_j^i in their models equal zero. In Eq. (9) it is theoretically possible for ρ_j^i and δ^i to be outside the interval [0, 1], but empirically I expect them to fall inside the interval [0, 1]. The first part of Eq. (9) represents the mean reversion component, while the second part represents the momentum effect. Therefore, one can write my model as:

$$y_t^i = MRV_t^i + MOM_t^i + \varepsilon_t^i. \tag{10}$$

If the ρ_j^i and $1 - \delta^i$ diverge from zero, then the mean reversion and momentum effects should be correlated. In order to check for that correlation, I consider the simple model in which ρ_j^i only varies by country (as does δ^i):

$$y_t^i = -(1 - \delta^i)(x_{t-1}^i - \mu^i) + \rho^i (x_{t-1}^i - x_{t-J-1}^i) + \varepsilon_t^i. \tag{11}$$

Taking into consideration the definitions of *MOM* and *MRV*, Eq. (9) and stationarity imply[5]:

$$cov(MRV_t^i, MOM_t^i) = -(1 - \delta^i)\rho^i[1 - corr(x_t^i, x_{t-j}^i)]var(x_t^i) < 0.$$

Since δ^i and ρ^i both lie between 0 and 1, the covariance between the two effects has a negative sign. Intuitively, a positive momentum effect pushes the return upward, while the mean reversion effect tends to bring the cumulative return back to its mean, so downward. Therefore, one can anticipate a negative correlation between the two effects. Omitting one of the two effects leads to biased esti-

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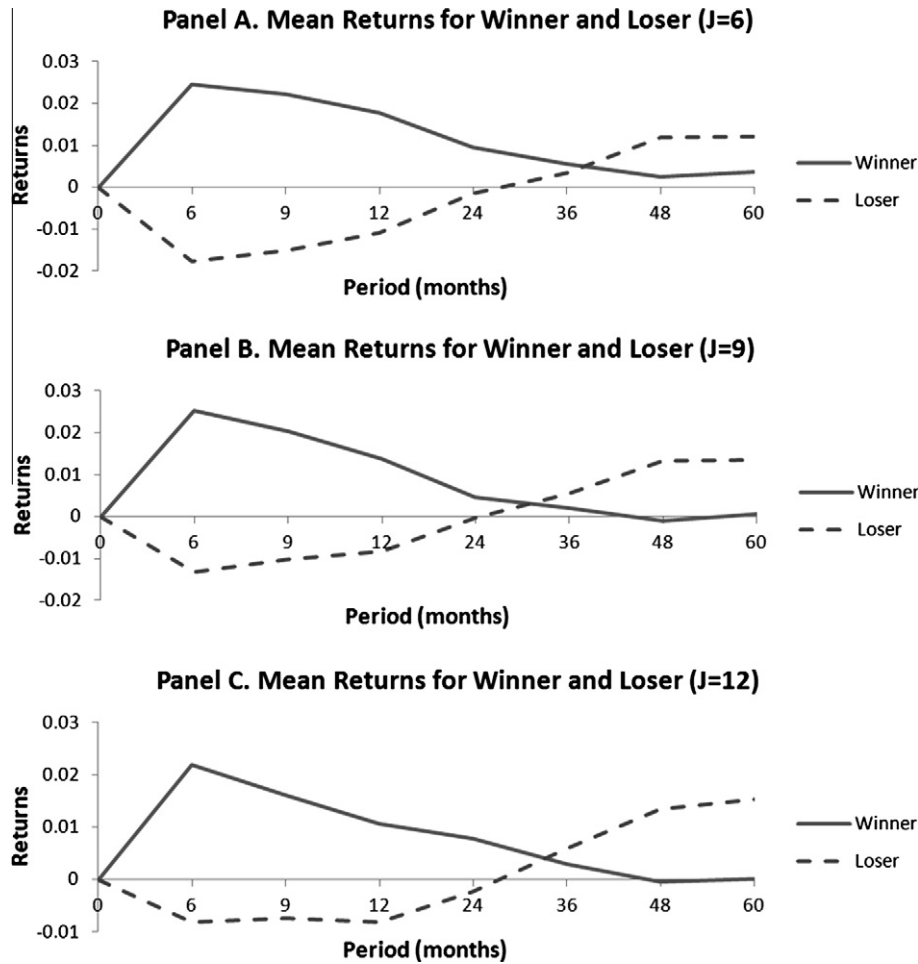[5] For a complete derivation, check Balvers and Wu (2006).

Fig. 1. Average annualized returns for the Jegadeesh and Titman (1993) strategy: over a period of J months, I compute the deviations from UIP and find a loser and a winner currency. These two currencies are held for K months. The mean returns of the winner and loser currencies are illustrated bellow for $J = 6$ (Panel A), $J = 9$ (Panel B) and $J = 12$ (Panel C).

mation of the parameters. Omitting mean reversion requires $\delta^i = 1$ in Eq. (11):

$$y_t^i = \alpha_{MOM}^i + \beta_{MOM}^i(x_{t-1}^i - x_{t-J-1}^i) + \varepsilon_{t,MOM}^i.$$

Consequently, $plim\,\beta_{MOM}^i = \rho^i - (1 - \delta^i)\,\frac{[1 - corr(X_{t-1}^i, X_{t-1}^i - X_{t-J-1}^i)]var(X_{t-1}^i)}{var(X_{t-1}^i - X_{t-J-1}^i)} <$ ρ^i. Hence, the measured impact of momentum is smaller if mean reversion is omitted. By the same logic, if one runs the following equation assuming no momentum, $\rho^i = 0$ in Eq. (11):

$$y_t^i = \alpha_{MRV}^i + \beta_{MRV}^i x_{t-1}^i + \varepsilon_{t,MRV}^i.$$

Then: $\qquad plim\,\beta_{MRV}^i = -(1 - \delta^i) + \rho^i\,\frac{[1 - corr(X_{t-1}^i, X_{t-1}^i - X_{t-J-1}^i)]var(X_{t-1}^i)}{var(X_{t-1}^i - X_{t-J-1}^i)} >$ $-(1 - \delta^i)$.

So the mean reversion coefficient estimation is inconsistent and implies a biased upward half-life, leading to a possible spurious rejection of mean reversion.[6]

3.2. Parameter estimation

The model in Eq. (9) considers a total number of parameters equal to $9(J + 2)$ ($9\delta^i$, $9\mu^i$ and $9J\rho_j^i$). That is a very large number of parameters to estimate. Consequently, in order to avoid multicollinearity problems and to improve efficiency, I only allow μ^i to dif-

fer by country (which accounts for possible "mispricing" at the beginning of the period), while:

$$\delta^i = \delta,$$
$$\rho_j^i = \rho, \quad \text{for all } i \text{ and } j.$$

I use the full range of my sample and obtain the parameter estimates using a pooled model and $J = 12$. Table 2 presents the results.

The first column reports the parameter estimates when allowing both mean reversion and momentum. Both coefficients are statistically significant. The mean reversion coefficient δ pooled across countries equals 0.9859, implying a half-life of 45 months. The speed of mean reversion $1 - \delta$ is significantly positive and equals 0.0141. The momentum parameter ρ pooled across countries is a statistically significant and positive 0.0428. These results lie very close to those obtained for the stock market by Balvers and Wu (2006): the half-life for the combination strategy remains the same for the two markets, and the momentum effect is stronger in the FX market ($\rho = 0.043$ compared to 0.023 in the stock market).

The second and third columns show the parameter estimates for each of the two pure strategies. The mean reversion coefficient increases in the pure mean reversion strategy (0.9944) leading to a very long half-life of 124 months. The theoretical asymptotic bias in the mean reversion coefficient when omitting momentum is $\rho\,\frac{cov(x_{t-1}, x_t - x_{t-J-1})}{var(x_{t-1})} = 0.009$. Empirically, the difference stays positive and very close to the theoretical value (0.0085). In the pure momentum strategy, the strength of momentum is indeed smaller

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[6] Half-life is the expected time for the analyzed stochastic variable to return half of the way toward the equilibrium level, μ. It is computed as $\ln(0.5)/\ln(1 - \delta)$.

Table 2
Model parameters and variance decomposition.

Moment	MRV and MOM		MRV only		MOM only	
δ	0.9859	(0.0035)	0.9944	(0.0033)	–	
ρ	0.0428	(0.0059)	–		0.0345	(0.0056)
$var(y_t)$	5.93E−04		5.89E−04		5.93E−04	
σ_ε^2	5.70E−04		5.88E−04		5.77E−04	
$var(MRV_t)$	7.68E−06		1.19E−06		–	
$var(MOM_t)$	2.53E−05		–		1.65E−05	
$corr(MRV_t, MOM_t)$	−0.35		–		–	
$\sigma_\varepsilon^2/var(y_t)$ (%)	96.10		99.80		97.23	
$var(MRV_t)/var(y_t)$ (%)	1.29		0.20		–	
$var(MOM_t)/var(y_t)$ (%)	4.26		–		2.78	
R^2 (%)	3.89		0.18		2.75	

This table reports the results of the following regression: $y_t^i = -(1-\delta)(x_{t-1}^i - \mu^i) + \sum_{j=1}^{J} \rho(x_{t-j}^i - x_{t-j-1}^i) + \varepsilon_t^i$. The data are pooled across currencies. I use the full sample 1979:01–2008:02. The first column presents the results for the above regression. The second column considers $\rho = 0$, while the third column assumes $\delta = 1$. The standard errors are presented in brackets.

(still positive and statistically significant) and equal to 0.0345 (the momentum effect is stronger in the FX market than in the stock market even in this case). The theoretical asymptotic bias of the momentum coefficient ρ is $-(1-\delta)\frac{cov(x_{t-1}, x_{t-1}-x_{t-J-1})}{var(x_{t-1}-x_{t-J-1})} = -0.0083$ and again it lies very close to the empirical bias (−0.0083).

If we compare columns 1 and 2 of Table 2, the half-life for the combination strategy diminishes. Intuitively, this is expected due to two effects of momentum: the first initial effect of momentum is positive and causes the downturn to come later and the second momentum effect starts after the downturn and shortens the half-life.

The remainder of Table 2 reports the variance decomposition. From Eq. (10) we observe that:

$$var(y_t^i) = var(MRV_t^i) + var(MOM_t^i) + 2cov(MRV_t^i, MOM_t^i) + \sigma_\varepsilon^2. \tag{12}$$

The variance of the returns is determined in large part by the errors (hence the small R^2 of 3.89%) and the rest by the variance of mean reversion, momentum and their covariance. The small coefficient of determination is actually higher than that obtained for the stock market.[7]

The variance of momentum explains 4.26% of the variation in the returns from UIP, while the variance of mean reversion explains only about one-third as much of the variation in returns (1.29%). For the stock market, the two effects hold similar importance in explaining the returns. Mean reversion remains a very important component and should not be disregarded as follows for instance from the bias in the momentum coefficient when mean reversion is omitted.

The correlation between the two effects is theoretically and empirically negative and the same size as that obtained for the stock market (−0.35 in both markets).

4. Trading strategies

I employ a mean reversion–momentum combination strategy, currently developed only for the stock market, for the FX market. I use the following variation of Eq. (9) by only allowing μ to change by country, while ρ and δ stay fixed by country and lags:

$$y_t^i = -(1-\delta)(x_{t-1}^i - \mu^i) + \sum_{j=1}^{J} \rho(x_{t-j}^i - x_{t-j-1}^i) + \varepsilon_t^i, \tag{13}$$

Based on the first 1/3 of the sample, using OLS, I estimate the return y_t^i for each currency. Max denotes the currency with the highest expected return and Min denotes the currency with the lowest expected return. I form a portfolio by taking a long position on Max and a short position on Min (denoted by Max–Min) and I hold these positions for the next K months (where K can be 1, 3, 6, 9, and 12). In each subsequent period, I apply the same procedure, updating the sample period by one month each time.[8] There are two exceptions to this strategy: if all expected returns are positive, I take a long position on Max only and hold it for K months; if all returns are negative, I take a short position on Min and hold it for K months. This way, the USD is effectively incorporated into the strategy. For easier representation, the tables report "Max–Min" for the portfolio return. Again, due to a very large number of parameters to estimate, I only allow μ^i to change by country.

Due to overlapping periods, when finding the returns of the strategy, I employ the same procedure as Jegadeesh and Titman (1993). If $K = 3$ for instance, at each moment t, the strategy gives weights of 1/3 to each of the portfolios decided at times $t - 2$, $t - 1$ and t (the positions chosen at $t - 3$ are closed). Hence, I revise the weights (of 1/K) each month, carrying positions for the remaining months, cancelling old positions and deciding on new ones.

For the results of the pure momentum and pure mean reversion strategies, one takes the decisions in the exact same way and using the same Eq. (13), but ρ is assumed to equal zero for the pure mean reversion strategy and δ is assumed to equal one for the pure momentum strategy.

Due to overlapping data when $K > 1$, the standard errors might be biased downward. Hence, the standard errors are corrected for autocorrelation and heteroskedasticity using Newey and West (1987) adjustment (with $K - 1$ lags).

4.1. The pure mean reversion strategy

Table 3 reports averages and standard errors for the annualized returns of Max and Max–Min portfolios for different holding periods K. Panel A presents the results for the pure mean reversion strategy. The mean return for the zero-investment portfolio ranges from around 1.6% for $K = 12$ to 3.1% for $K = 1$.

A similar mean reversion strategy has not been implemented in the FX markets. However, Rogoff (1996) finds that the PPP does revert to a long-run mean and typically the literature reports a half-life of three to five years. A study prepared by Deutsche Bank (2007) notices that PPP is one of the best fundamentals that can forecast the exchange rates and constructs a contrarian strategy. Depending on the time period considered, they obtain mean excess returns ranging from 3.8% to 4.3%. The pure mean reversion strategy this paper constructs leads to lower average returns. However,

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[7] Balvers and Wu (2006) obtain 2.12%.

[8] So I use as a first sorting period months 1 to 1/3 of the sample, then months 1 to 1/3 of the sample +1 month and so on, rolling the sample forward.

Table 3
Performance of the pure mean reversion strategy and the pure momentum strategy.

		$K = 1$		$K = 3$		$K = 6$		$K = 9$		$K = 12$	
		Ave	St error	Ave	St error	Ave	St error	Ave	St error	Ave	St error
Panel A. The pure mean reversion strategy											
Max		0.024	0.006	0.019	0.005	0.027	0.005	0.024	0.005	0.030	0.005
Max–Min		0.031	0.006	0.025	0.006	0.025	0.006	0.022	0.006	0.016	0.006
		$K = 1$		$K = 3$		$K = 6$		$K = 9$		$K = 12$	
		Ave	St error	Ave	St error	Ave	St error	Ave	St error	Ave	St error
Panel B. The pure momentum strategy											
$J = 3$	Max	0.009	0.005	0.094	0.004	0.056	0.004	0.036	0.004	0.030	0.004
	Max–Min	−0.008	0.006	0.143	0.005	0.076	0.004	0.048	0.003	0.040	0.003
$J = 6$	Max	−0.028	0.005	−0.001	0.004	0.044	0.004	0.035	0.004	0.024	0.004
	Max–Min	−0.067	0.007	−0.014	0.004	0.054	0.003	0.038	0.003	0.022	0.003
$J = 9$	Max	0.050	0.005	0.019	0.004	0.013	0.004	0.037	0.004	0.030	0.004
	Max–Min	0.107	0.006	0.044	0.005	0.030	0.004	0.068	0.003	0.055	0.003
$J = 12$	Max	0.027	0.005	0.039	0.004	0.032	0.004	0.023	0.004	0.036	0.004
	Max–Min	0.081	0.006	0.086	0.004	0.064	0.003	0.045	0.003	0.069	0.002
$J = 15$	Max	−0.002	0.005	0.012	0.004	0.031	0.004	0.029	0.004	0.022	0.004
	Max–Min	−0.013	0.006	0.012	0.005	0.041	0.004	0.035	0.004	0.023	0.004
$J = 18$	Max	0.006	0.005	−0.008	0.004	0.003	0.004	0.018	0.004	0.016	0.004
	Max–Min	−0.018	0.007	−0.032	0.005	−0.010	0.004	0.016	0.004	0.015	0.004

This table uses the following regression: $y_t^i = -(1 - \delta)(x_{t-1}^i - \mu^i) + \sum_{j=1}^{J} \rho(x_{t-j}^i - x_{t-j-1}^i) + \varepsilon_t^i$. I use the full sample 1979:01–2008:02. Based on the first 1/3 of the sample, using OLS, I estimate the return y_t^i for each currency. The currency with the highest expected return is denoted Max and that with the lowest expected return is denoted Min. The portfolio Max–Min is held for K months. The same procedure is applied in each subsequent period, each time updating the sample period by one month. The table presents annualized average returns (Ave) and Newey–West adjusted standard errors (St error) for the Max and Max–Min portfolios. The averages for the Max–Min portfolios are provided in the shaded areas. For Panel A, $\rho = 0$ (the pure mean reversion strategy). For Panel B, $\delta = 1$ (the pure momentum strategy).

the two strategies are different in that the former presents a contrarian strategy based on reversion to the PPP.

4.2. The pure momentum strategy

Panel B presents the annualized mean returns and standard errors for Max and Max–Min portfolios for different combinations of K and J when $\delta = 1$. The trend of the mean returns is very similar to that obtained for the stock market by Balvers and Wu (2006),[9] but the annualized average Max–Min portfolio is usually smaller for the FX market (as expected). Some of the average returns for the zero-investment portfolio are negative.

Since the trend is similar for different J, I only present the case of $J = 12$. The Max–Min mean portfolio return ranges from a statistically significant 5% for $K = 9$ to 9% for $K = 3$. These returns are similar to the 5–7% per year obtained by Okunev and White (2003) for their simple momentum-like strategy. However, in some cases, the mean returns here outperform the Okunev and White (2003) strategy. This result is fascinating considering the fact that they employ a strategy designed for the FX market, while I use a strategy originally designed for the stock market.

4.3. The combination strategy

Table 4 presents the annualized mean returns, standard errors and Sharpe ratios for the combination strategy. For comparison, the table also reports the results using the same strategy in the stock market for each combination (J, K) as obtained by Balvers and Wu (2006). The table also shows the outcomes of the strategy after transaction costs. Including the no-transaction costs rows of the table allows a more direct comparison between the stock and FX markets. Also, the transaction costs this paper employs are only

estimated, not actual. FX market transaction costs are not very large. According to Szakmary and Mathur (1997) they range from 0.05% to 0.2% for developed countries. I consider the maximum of a 0.2% transaction cost, which is subtracted from the return each time a purchase or short sell of a new currency occurs.

The no-transaction costs strategy for $J = 12$ generates a mean return for the zero-investment portfolio of around 10–12%.[10] Transaction costs do not significantly alter the results.

The comparison between these results and the results obtained through the pure mean reversion strategy is not straightforward, since the latter strategy assumes $J = 0$. One can study this comparison by computing an overall average for the combination strategy for each K and finding the difference between that average and the mean zero-investment portfolios in Table 4. For all K's, the mean returns increase with the use of the combination strategy. Comparing the average returns between the combination strategy and the momentum strategy is much easier. There are 25 pairs (J, K) for each of the two strategies and for all the combination strategy generates higher mean returns.

The comparison between the FX market and the stock market is one of the main objectives of this paper. As discussed previously, the Sharpe ratio is the best metric for comparing the two different markets. In all cases, the Sharpe ratio for the FX market is larger than that for the stock market. On average, standard errors for the FX combination strategy are 33% of the standard errors for the stock combination strategy, while the mean returns for FX

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[9] Note that for the strategy developed in this paper, I make a comparison with the results obtained by Balvers and Wu (2006). They conduct their research on a sample of equity market indexes from 18 countries from 1969 through 1999. The reader should bear these differences in sample selection in mind for the following discussions regarding the comparison between the FX and equity markets when using the aforementioned strategy.

[10] Following Cochrane (2005, p. 447), I check how the mean returns compare to the theoretical returns. For the combination strategy, using different μ^i and the same δ and ρ (across countries and momentum lags), I obtain the theoretical return. I use the results from Table 2. The procedure proposed by Cochrane multiplies the standard deviation of the return, $\sqrt{0.000593}$, by the standardized expected return of the currency in the top 4th of the standard normal distribution (0.3178, obtained from the expected return of the standard normal variable over the interval 0.6745 to infinity), and then by the square root of R^2 ($\sqrt{0.0389}$). I obtain an expected annualized return for the top currency of 14.08%. After following the same procedure for the bottom currency, I obtain the annualized theoretical return of the Max–Min portfolio to be 28.16%. This theoretical return is larger than the 9.9% annualized return obtained in Table 4, for the combination $J = 12$ and $K = 1$. In this light the returns obtained in this paper are not too high.

Table 4
Performance of the combination strategy.

		K = 1			K = 3			K = 6			K = 9			K = 12		
		Ave	St error	Sharpe	Ave	St error	Sharpe	Ave	St error	Sharpe	Ave	St error	Sharpe	Ave	St error	Sharpe
J = 3	FX (no trans costs)	0.315	0.006	3.744	0.244	0.005	3.116	0.165	0.004	2.475	0.129	0.004	1.914	0.117	0.005	1.700
	FX (trans costs)	0.275	0.006	3.267	0.205	0.005	2.598	0.126	0.004	1.860	0.089	0.005	1.301	0.078	0.005	1.099
	Stock	0.098	0.019	0.327	0.128	0.017	0.503	0.145	0.015	0.622	0.140	0.014	0.642	0.125	0.014	0.600
J = 6	FX (no trans costs)	0.192	0.006	2.140	0.199	0.006	2.140	0.176	0.006	2.011	0.124	0.006	1.466	0.096	0.006	1.112
	FX (trans costs)	0.152	0.006	1.689	0.159	0.006	1.699	0.136	0.006	1.535	0.084	0.006	0.970	0.056	0.006	0.629
	Stock	0.170	0.018	0.625	0.174	0.016	0.690	0.174	0.015	0.733	0.164	0.015	0.740	0.126	0.014	0.598
J = 9	FX (no trans costs)	0.129	0.007	1.269	0.151	0.007	1.407	0.154	0.006	1.581	0.130	0.006	1.411	0.100	0.006	1.121
	FX (trans costs)	0.089	0.007	0.871	0.111	0.007	1.029	0.114	0.006	1.155	0.090	0.006	0.956	0.059	0.006	0.651
	Stock	0.140	0.018	0.511	0.161	0.017	0.633	0.163	0.015	0.687	0.117	0.014	0.533	0.084	0.014	0.402
J = 12	FX (no trans costs)	0.099	0.007	0.998	0.115	0.007	1.066	0.119	0.007	1.140	0.114	0.006	1.173	0.105	0.006	1.115
	FX (trans costs)	0.060	0.007	0.601	0.075	0.007	0.694	0.080	0.007	0.753	0.075	0.007	0.752	0.065	0.006	0.679
	Stock	0.194	0.019	0.672	0.189	0.017	0.730	0.158	0.015	0.662	0.133	0.015	0.579	0.110	0.014	0.513
J = 15	FX (no trans costs)	0.113	0.007	1.135	0.113	0.007	1.000	0.109	0.007	0.999	0.102	0.007	0.989	0.098	0.007	0.964
	FX (trans costs)	0.073	0.007	0.732	0.073	0.008	0.644	0.069	0.007	0.625	0.062	0.007	0.589	0.059	0.007	0.560
	Stock	0.062	0.018	0.223	0.068	0.018	0.251	0.082	0.017	0.315	0.087	0.017	0.340	0.095	0.017	0.379
J = 18	FX (no trans costs)	0.068	0.007	0.669	0.074	0.008	0.643	0.074	0.007	0.689	0.068	0.007	0.660	0.061	0.007	0.615
	FX (trans costs)	0.028	0.007	0.275	0.034	0.008	0.295	0.034	0.007	0.315	0.028	0.007	0.269	0.021	0.007	0.208
	Stock	0.074	0.018	0.261	0.112	0.018	0.406	0.127	0.018	0.463	0.130	0.017	0.485	0.124	0.017	0.475

This table uses the following regression: $y_t^i = -(1-\delta)(x_{t-1}^i - \mu^i) + \sum_{j=1}^{J} \rho(x_{t-j}^i - x_{t-j-1}^i) + \varepsilon_t^i$. I use the full sample 1979:01–2008:02. Based on the first 1/3 of the sample, using OLS, I estimate the return y_t^i for each currency. The currency with the highest expected return is classified as the Max, and the one with the lowest expected return is the Min. The portfolio Max–Min is held for K months. The same procedure is applied in each subsequent period, updating the sample period by one month each time. For each combination (J, K), I report annualized average returns (Ave), Newey–West adjusted standard errors (St error) and annualized Sharpe ratios (Sharpe) of Max–Min portfolios for: FX market without transaction costs, FX market with transaction costs, and stock market (as obtained from Balvers and Wu, 2006).

are around 80% of the mean return for stocks. This gives Sharpe ratios around 2.5 times higher for the FX than for the stock market.[11]

Different strategies have been employed in the equity market literature. For a buy-and-hold strategy, the Sharpe ratio for the world market is 0.447 and that for the US is 0.644, according to Balvers et al. (2000). So the results that derive from using this combination strategy for the stock market are not unusual. Balvers et al. (2000) also apply two mean reversion strategies in the stock market: their own strategy, and DeBondt and Thaler's (1985) contrarian strategy. The Sharpe ratios obtained are 0.425 and 0.230, respectively. In Table 4, for 18 out of 25 (J, K) combinations the stock market has higher Sharpe ratios than the Balvers et al. (2000) strategy and, for 24 out of 25, higher Sharpe ratios than the De Bondt and Thaler (1985) strategy. Hence the combination strategy produces much higher Sharpe ratios than other strategies employed in the stock market. Moreover, usually it produces Sharpe ratios 2 or 3 times larger than the De Bondt and Thaler (1985) strategy. I next compare the Sharpe ratios for the combination strategy in the FX market to Sharpe ratios for other strategies in the FX market.

In the FX market, perhaps the most common strategy is carry trade. Burnside et al. (2008) obtain an average annual return of 4.80% and a Sharpe ratio of 1.060. When considering transaction costs, the mean returns in Burnside et al. (2008) only decrease to 4.44%, while the Sharpe ratio falls to 0.866. These results confirm that taking transaction costs into consideration in the FX market does not substantially modify the abnormal returns obtained, or the Sharpe ratios. Other strategies implemented in the FX market

are technical trading rules. LeBaron (1999) finds annualized Sharpe ratios ranging from 0.67 to 0.96 for a dynamic trading rule strategy.[12] The results obtained by implementing the combination strategy usually outperform other strategies in the FX market. When creating the strategy that combines mean reversion and momentum, the average of annualized mean returns obtained for $J < 18$ is 14.03% for no-transaction costs and 10.06% when transaction costs are included. The average Sharpe ratio is 1.57 and 1.12, respectively. When $J = 18$, the momentum effect has already passed, so the mean returns and Sharpe ratios of the strategy are noticeably lower.

The stock market Sharpe ratios are not unusual, but significantly higher when one uses the combination strategy instead of other strategies. Similarly, the FX market results for the combination strategy outperform other strategies employed in the FX market, and also provide significantly higher Sharpe ratios than those found for the stock market.[13]

5. Conclusions

This paper employs a trading strategy, previously applied only to the stock market that creates abnormal returns in the FX market. By running a simple parametric test, I find that UIP deviations follow mean reversion and momentum. In the FX market the half-life of mean reversion is very close to that obtained for the stock market, while the momentum effect is stronger than in the stock market. The combination strategy creates significant abnormal mean returns (slightly underperforming those of the stock market) and Sharpe ratios usually much higher than in the stock market. The

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[11] These differences between the two markets are typical. For instance, Okunev and White (2003) report annualized mean returns of 5–6% and standard errors of 0.006–0.008 for a momentum strategy in the FX market. Chan et al. (2000) report an annualized mean return for a momentum strategy implemented on international stock market indices of 13% and standard error of 0.039 for a holding period of 4 weeks.

[12] Neely (2002) and Harris and Yilmaz (2009) obtain similar returns when further investigating the trading rules' profitability.

[13] Results of robustness checks (different time periods, parameters allowed to vary by country and/or lag) do not significantly change the results and are available upon request.

results are also strong in comparison to strategies developed specifically for FX markets. Transaction costs do not alter the results significantly. I consider developed countries only. The portfolio I construct should be even more profitable if the currency choices are more numerous.

This paper contributes to the literature not only by applying a new strategy in the FX market, but by applying one originally designed for the stock market. The FX literature considers mean reverting behavior toward PPP values and momentum trading strategies based on moving average rules. I bring a fresh perspective to understanding FX market dynamics by considering risky asset returns, instead of macroeconomic fundamentals. This allows for the creation of a strategy based on returns (computed in this case from deviations from UIP) and a direct comparison of the exploitability of the return patterns between the FX and the stock market. Up to now strategies employed in one market have not been successfully implemented in the other market, likely due to fundamental differences between the two markets. For instance, technical trading rules were found to be completely useless in the stock market since the publication of Fama and Blume (1966), but profitable in the FX market (Sweeney, 1986; Szakmary and Mathur, 1997; and LeBaron, 1999), suggesting major differences between the markets. The striking results here, on the other hand, raise the question of why the two markets behave so similarly.

Many papers challenge the efficiency of the two markets. Neely (2002) examines the possibility that the FX market is inefficient due to Central Bank intervention. He reviews the literature regarding the abnormal returns obtained in the FX market through technical rules, but not existing in the stock market. Presumably, they are due to Central Bank interventions. Neely (2002) challenges that finding. This paper finds further evidence supporting Neely's claim since the FX and stock market inefficiencies have similar patterns.

One is left to wonder whether the two markets are indeed inefficient, or whether, in fact, there exists an unobserved risk factor that explains these returns. A possible theory is the overreaction hypothesis proposed from a behavioral perspective (e.g. De Bondt and Thaler, 1985) for the stock market: individuals tend to "overreact" to recent information, creating momentum. After some time, extreme movements in prices will be followed by a return to fundamentals, leading to movements in the opposite direction, creating mean reversion. In foreign exchange markets, Dornbusch (1976) shows that exchange rates tend to "overshoot" in their response to monetary policies, but then revert to a long-run equilibrium. The correspondence between overreaction in the stock market and overshooting in the foreign exchange market may be responsible for the similarity in results in these two markets when the combined momentum and mean reversion strategy is applied. Examining this correspondence presents a promising direction for future research.

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