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Validation of trading strategies in the foreign exchange

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Declaration

I, Lucio Idone, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Signature ____________

Date ____________

Abstract

The aftermath of the recent financial crisis has caused the narrowing of investment opportunities for foreign exchange (FX) traders and investors. A debate about the profitability of trading strategies in FX has started among practitioners and academic researchers who have wondered whether is still possible to obtain positive excess returns (alpha). In this research I validate a set of trading strategies for FX. Seven experiments are carried out on macroeconomic market factors like trend-following, carry and value, separately. The outcome holds that the dissolution of synchronous monetary policies increases the probability of observing trends and carry opportunities in the FX. The failure of the uncovered interest rate parity by the so-called forward rate puzzle and that of the purchase parity power open opportunities for strategies like momentum, carry and value. Carry is not only applicable to spot rates as can also be used to trade FX options. Two experiments are performed to study the consistency of FX option premia and the performance of carry trade for options. For short-dated options, like the weekly ones, carry cannot produce material profits as the error implied by the forward rate is not large enough. Conversely, the premium earned from trading FX call options is a consistent source. A second line of research is dedicated to the analysis of trading strategies for FX high-frequency data. This study consists of implementing machine learning algorithms, like the exponentially-smoothing recurrent neural networks (RNN), to forecast future prices and derive a trading strategy from it. The training of these models appear to be computationally intensive but simpler than that of other neural networks like the long-short-term memory ones (LSTM). The accuracy of the forecast is adequate with no signs of over-fitting. The performance appears to be highly influenced by the presence of intra-day seasonality and jumps. A range of solutions are explored to address such a limitation.

Impact Statement

Quantitative trading is a topic composed by several heterogeneous study fields: data science, computer science, finance and economics. Mastering each of these components and linking them together into a coherent model is a challenge for academics as well as for practitioners. The primary impact of this research is being part of the ideal debate between traders, academics, analysts and fund managers around methods and tools to be used to accurately design and validate trading strategies. The objective is to explore some of the most used approaches adopted by practitioners and to validate them through the rigorous scientific approach that is typical of the academic research. Similar approach is used to design new trading strategies that are presented to the readers to open new discussions around automated and algorithmic trading. Elements of this research were presented to academics and practitioners during workshops and discussed with professional traders and fund managers who provided positive feedback and helped shaping new ideas and directions of the investigation.

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Chapter 1

Is there any alpha left in foreign exchange?

In the context of trading, making money can be defined through the famous capital asset model (CAPM) developed by Fama(2004) [1][1]. An asset class or a trading strategy make money if they produce positive alpha. Foreign exchange (FX) is a young market compared to the equity and debt ones. The big-bang for FX is a relative recent event: the collapse of the Bretton-Woods agreement, which determined the start of the free-floating exchange rates. FX is a different market compared to the equity and debt ones. It has not typical range like the interest rates. It has no expectation of growth or decline like the equities. With time, FX became a specific asset class, which does not change much in response to the costs of similar goods in different countries, and to change according to relative interest rates in the different countries. Instead, it changes due to the speculation of investors as much as other asset classes. Quantitative-based trading for FX became popular from the later 1990s, when hedge funds began to launch with heavy currency components and commodity trading advisors (CTAs) specialised in offering FX-based products to their clients. The financial markets have been hit in the recent past by a financial crisis; FX market too. Among practitioners, the view is that some of the trading strategies which were previously successful for FX had their alpha largely reduced or completely wiped away by the crisis. The scope of this work is a broad recognition of the presence of alpha in FX. Not only the traditional trading strategies are tested on recent data; a more generic question is posed: is it still possible to extract alpha from FX? If the traditonal investing approaches are less succesful now, is it possible adding new methodologies for extracting it from the market? Does the FX investment still make sense from a profitability standpoint?

[1]This model measures the risk-adjusted performance of a security or portfolio with regard to the expected market returns. Such a performance is called by the model as Jensen's alpha, or just alpha, introduced by Jensen(1968) [2] to differentiate this component from beta. Alpha is the excess returns from the strategy.

1.1 Scientific soundness and objective

This works aims at validating trading strategies that use different approaches: rule-based schemes, which emerge from evidence-based knowledge or from macroeconomic theories; and statistical models. The validation of statistical models is defined by the assessment of statistical methods like the hypothesis testing and the error measurement. The validation of rule-based strategies should obey scientific criteria too. An excellent reference for this topic is Aronson 2007 ([3]) who divides rule-based strategies between subjective and objective. Only the latter being repeatable and measurable can be scientifically tested. Such testing must be carried out through probabilistic methods like bootstrapping and statistical inference. Those are widely adopted in this work. Subjective strategies are immune to empirical challenge being untestable. The primary objective of this work is to facilitate the work of future researchers and practitioners in terms of selection of trading methodologies, their validation and implementation. In particular, great attention is given to the assessment of the trade-off between performance and complexity for a wide range of investment styles and methods from the simplest approach to deep learning algorithms.

Chapter 2

Methodology and models

2.1 Moving averages

Trend-following strategies are purely price-based algorithmic trading rules. They assume that market prices, in some circumstances, move according to long-term predictable trending patterns which can be anticipated without financial or economic considerations. The strategy uses past returns to predict future price developments. A trend is a series of prices that move in one direction over a certain period of time. Positive trends are identified by a series of increasing local maxima and increasing local minima ("higher highs and higher lows"); negative trends by a series of decreasing local minima and decreasing local maxima ("lower lows and lower highs"). A quantitative approach to trading uses moving averages. Let t_n be a grid of integer indices $n = 0, 1, 2, ..., N$ with $t_0 = 0$ and $t_N = T$; then $S_n = S(t_n)$ and $w_n = w(t_n)$ are discrete functions. A moving average is a form of convolution, i.e. a composition of the functions w and S, which for discrete variables is expressed as

$$w_n * S_n = \sum_{n'=0}^{N-1} w_{n'} S_{n-n'}. \tag{2.1}$$

Usually the moving average is not calculated for the entire number of points. Instead a certain look-back window (or lag) is used such that $n_{\max} \leq N$. The moving average is a low-pass filter. This type of filter does not stop all the signals that have a frequency lower than a selected cut-off, while attenuates those with higher frequency. Correspondingly, moving averages flatten data and eliminate data spikes.

A generic weighted moving average for a discrete variable is defined as

$$\mu_{\mathrm{w},n} = \frac{1}{\sum_{n'=0}^{N-1} w_{n'}} \sum_{n'=0}^{N-1} w_{n'} S_{n-n'}, \tag{2.2}$$

in which w specifies the weight and n the value at which is calculated. Equation (2.2) corresponds to Equation (2.1) if the weights w'_n add up to one, i.e. $\sum_{n'=0}^{N-1} w'_n = 1$. The simple moving average adopts the same weight for each observation. That is for each n', $w_{n'} = 1/N$,

$$\mu_{s,n} = \frac{1}{N} \sum_{n'=0}^{N-1} S_{n-n'}. \tag{2.3}$$

Once a new observation is available a moving average can be updated with a fast recursive formula

$$\mu_{s,n+1} = \mu_{s,n} + \frac{S_{n+1} - S_{n-N}}{N}. \tag{2.4}$$

Equation (2.4) shows that as a new value comes into the sum, an old value drops out.

The exponential average gives more weight to the most recent observation S_n which has weight 1, whereas the earlier observations have smaller weight. For example, $S_n - 1$ has weight ψ with $0 < \psi < 1$, $S_n - 2$ has ψ^2, $S_n - 3$ has ψ^3 and so on. Following Equation (2.1), we sum all these terms and we divide it by the sum of the weights, obtaining

$$\mu_{e,n} = \frac{S_n + \psi S_{n-1} + \psi^2 S_{n-2} + \psi^3 S_{n-3} + \cdots + \psi^{N-1} S_{N-1}}{1 + \psi + \psi^2 + \psi^3 + \ldots \psi^{N-1}}. \tag{2.5}$$

The geometric series $1 + \psi + \psi^2 + \psi^3 + \ldots \psi^{N-1}$ is equal to $\frac{1-\psi^N}{1-\psi}$, which for large N can be approximated by $\frac{1}{1-\psi}$. From this we have

$$\mu_{e,n} = (1-\psi)(S_n + \psi S_{n-1} + \psi^2 S_{n-2} + \psi^3 S_{n-3} + \cdots + \psi^{N-1} S_{N-1}) = (1-\psi)S_n + \psi \mu_{e,n-1}. \tag{2.6}$$

By taking take $\lambda = 1 - \psi$ so that $0 < \lambda < 1$ the equation becomes

$$\mu_{e,n} = \lambda S_n + (1 - \lambda)\mu_{e,n-1}, \tag{2.7}$$

or also

$$\mu_{e,n} = \lambda \sum_{n'=0}^{N-1} (1 - \lambda)^{n'} S_{n-n'}. \tag{2.8}$$

We calculate the exponential moving average through the Equation (2.7) with the commonly used value $\lambda = 2/(N + 1)$, which means that the expected values of the exponential, $(1 - \lambda)/\lambda$, and of the simple moving average, $(N - 1)/2$, are equal[1].

Following [4], Equation (2.8) can be written as

$$\mu_{e,n} = \frac{1}{\tau} \sum_{n'=0}^{N-1} e^{-\frac{t_n - t_{n'}}{\tau}} S_{n-n'}. \tag{2.9}$$

For continuous variables Equation (2.9) is based on a certain trailing interval $[t-T, t]$. By letting $N = T/\Delta t$ and $t_n = n\Delta t$, $S_n = S(t_n) = S(n\Delta t)$ so that $S_{n-n'} =$

[1]The formulae displayed in this section do not change if the lag of the moving average is equal to $n_{\max}$. We just replace N with $n_{\max}$.

$S(t_n - t'_n) = S(t - n'\Delta t)$. With these changes Equation (2.8) becomes

$$\mu_{\mathrm{e}}(t) = \frac{1}{\tau} \sum_{j=0}^{T/\Delta t - 1} e^{-\frac{t - j\Delta t}{\tau}} S(t - j\Delta t), \tag{2.10}$$

where $\Delta t = \frac{T}{N}$. Moreover, τ is the lifetime or the average duration of the moving average[2]. An exponential distribution can be parameterised through a rate or activity parameter λ or through a scale parameter $\tau = 1/\lambda$, where τ corresponds to the mean of the distribution for which the average duration is the inverse of the decay rate.

2.2 Option profile

Trend-following stands out from other trading strategies not only for its persistent historical success; another relevant aspect is the convexity of its payoff. Fung 2011 [5] shows that trend-following invests in proportion to the past performance of a specific market, whether it is positive or negative. It is similar to a type of options strategy where the investor simultaneously buys put and call options on the underlying assets to profit from price trending in both directions. Such an option is called a straddle [3].

Option traders buy a call option on a certain currency pair and sell the currency pair so that they can keep a delta neutral strategy at time t_0. If the currency appreciates then they need to sell more of it to keep the strategy delta neutral. So, the strategy sells the currency pair at the time t_N or around that time. This is identical to the long position assumed by the trend-followers. Trend-followers buy a certain currency pair if at time t_0 they expect that the pair will appreciate between times t_0 and time t_N based on the positive trend. This is equivalent to having $\mu_0 < \mu_N$. If the expectation is verified, the strategy sells the currency at the time t_N or around that time.

Option traders buy a put option on a certain currency pair and buy the currency pair so that they can keep a delta neutral strategy at time t_0 . If the currency depreciates then they need to buy more of it to keep the strategy delta neutral. So, the strategy buys the currency pair at the time t_N or around that time. This is identical to the short position assumed by the trend-followers. Trend-followers sell at time t_0 a certain currency pair if they expect that the pair will depreciate between times t_0 and time t_N based on the negative trend such that $\mu_0 > \mu_N$. If the expectation is verified, the strategy buys the currency at the time t_N or around that time. Figure 2.1 shows an example of the payoff of a straddle option strategy.

Bruder 2011 [6] defines a framework which represents the payoff of the trend-

[2]For example, if $\lambda = 0.02$ then $\tau = 50$ which means that after 50 data points the variable has a decay of approximately 30%.

[3]A long straddle is a non-directional long volatility strategy. It consists of either the purchase of a call and a put option with the same strike price and expiration period. Buying a straddle implies making a bet on the future volatility of the underlying rather than on its future price direction.

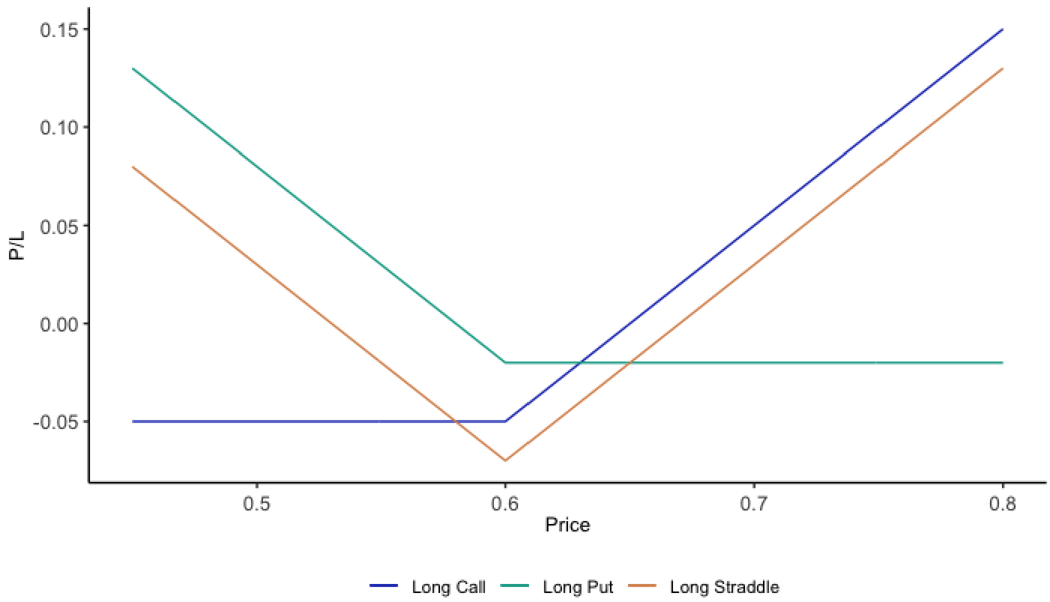


FIG. 2.1: Payoff of a long straddle for which the currency pair at expiration ranges from 0.45 to 0.80 and the strike price is set to 0.60. The call and put options have a premium of 0.05 and 0.02 respectively. The payoff of the long straddle strategy is calculated from the payoffs of the call and the put options.

following strategy as an option. We illustrate their approach in the remaining part of this section. Equation (2.10) calculated for daily returns becomes

$$\mu_{\mathrm{e}}(t) = \frac{1}{\tau} \sum_{j=0}^{N-1} e^{-\frac{t-j\Delta t}{\tau}} \frac{S(t-j\Delta t) - S(t-(j+1)\Delta t)}{S(t-(j+1)\Delta t)}. \tag{2.11}$$

In line with Equation (2.7), the dynamics of the exponential moving average is

$$\mu_{\mathrm{e}}(t+\Delta t) = \left(1 - \frac{\Delta t}{\tau}\right) \mu_{\mathrm{e}}(t) + \frac{1}{\tau} \frac{S(t+1) - S(t)}{S(t)} = \left(1 - \frac{\Delta t}{\tau}\right) \mu_{\mathrm{e}}(t) + \frac{1}{\tau} \frac{\Delta S(t)}{S(t)}, \tag{2.12}$$

which is equal to

$$\Delta \mu_{\mathrm{e}}(t) = -\frac{1}{\tau} \mu_{\mathrm{e}}(t) \Delta t + \frac{1}{\tau} \frac{\Delta S(t)}{S(t)}. \tag{2.13}$$

As Δt goes to zero, Equation (2.13) becomes

$$d\mu_{\mathrm{e}}(t) = -\frac{1}{\tau} \mu_{\mathrm{e}}(t)\, dt + \frac{1}{\tau} \frac{dS(t)}{S(t)}. \tag{2.14}$$

The model is introduced for continuous assets that can be traded at each date t at price $S(t)$ and is modelled with geometric Brownian motion:

$$dS(t) = \mu_{\mathrm{e}} S(t) dt + \sigma(t) S(t) dW(t). \tag{2.15}$$

A certain strategy $f(S(t))$ results into the P/L:

$$dG(t) = f(S(t))dS(t). \tag{2.16}$$

By Ito's lemma the P/L at time t is

$$G(t) - G(0) = F(S(t)) - F(S(0)) - \frac{1}{2}\int_0^t f'(S(t'))S^2(t')\sigma^2(t')dt'. \tag{2.17}$$

So the P/L is provided by the difference of the option profile and the trading impact. The option profile (in this case European) is $F(S(t)) - F(S(0))$ and the trading impact is equal to $-\frac{1}{2}\int_0^t f'(S(t'))S^2(t')\sigma^2(t')dt'$. The trading impact increases with the holdings $S(t)$, which are defined by the strategy $f(S(t))$, and with the volatility. If the strategy buys when the prices rise — buying high and selling low — $f'(S(t')) > 0$ and conversely the P/L deteriorates. Instead, if the strategy buys low and sells high then $f'(S(t')) < 0$ so that the P/L increases.

Trend followers buy or sell a certain amount $e(t)$ of a currency pair between times t and $t + dt$[4] based on the estimated trend μ_e and their risk appetite. Let the risk appetite be a function of a parameter m and the annualised volatility σ^2.

$$f(S(t)) = e(t) = m\frac{\mu_\mathrm{e}(t)}{\sigma^2}. \tag{2.18}$$

Equation (2.16) becomes

$$\frac{dG(t)}{G(t)} = m\frac{\mu_\mathrm{e}(t)}{\sigma^2}\frac{dS(t)}{S(t)}, \tag{2.19}$$

and Equation (2.17) can be written as

$$\log\frac{G(t)}{G(0)} = \frac{m\tau}{2\sigma^2}(\mu_\mathrm{e}(t)^2 - \mu_\mathrm{e}(0)^2) + m\int_0^t\left(\frac{\mu_\mathrm{e}(t')^2}{\sigma^2}\left(1 - \frac{m}{2}\right) - \frac{1}{2\tau}\right)dt'. \tag{2.20}$$

The option profile of the trend-following is similar to the intrinsic value of a straddle option in which the strike is equal to the trend of the underlying asset. The intrinsic value is the difference between the underlying asset's price and the strike price. The payoff depends on the position of the trend at the end $\mu_\mathrm{e}(t)$ compared to the initial trend $\mu_\mathrm{e}(0)$ i.e. on the length of the trend from time 0 to time t independently on the direction of the trend given that the strategy is long/short. If the final trend is larger than the initial one or if the initial trend is zero then the payoff is positive. Vice versa the option payoff is negative if the trend fades away i.e. $\mu_\mathrm{e}(t) < \mu_\mathrm{e}(0)$ like in the scenario of a price reversal[5]. The trading impact is defined in detail in the next section.

The performance of the strategy depends on the risk tolerance m, the initial estimate $\mu_\mathrm{e}(0)$, and the average duration of the moving average τ. The losses are bounded by the value $\frac{m\tau}{2}\frac{\mu_\mathrm{e}^2}{\sigma^2}$, which is obtained if the trend at t disappears completely

[4] In the discrete case between n and $n + 1$.

[5] The price reversal is the change of the direction of a trend from up to down or vice versa.

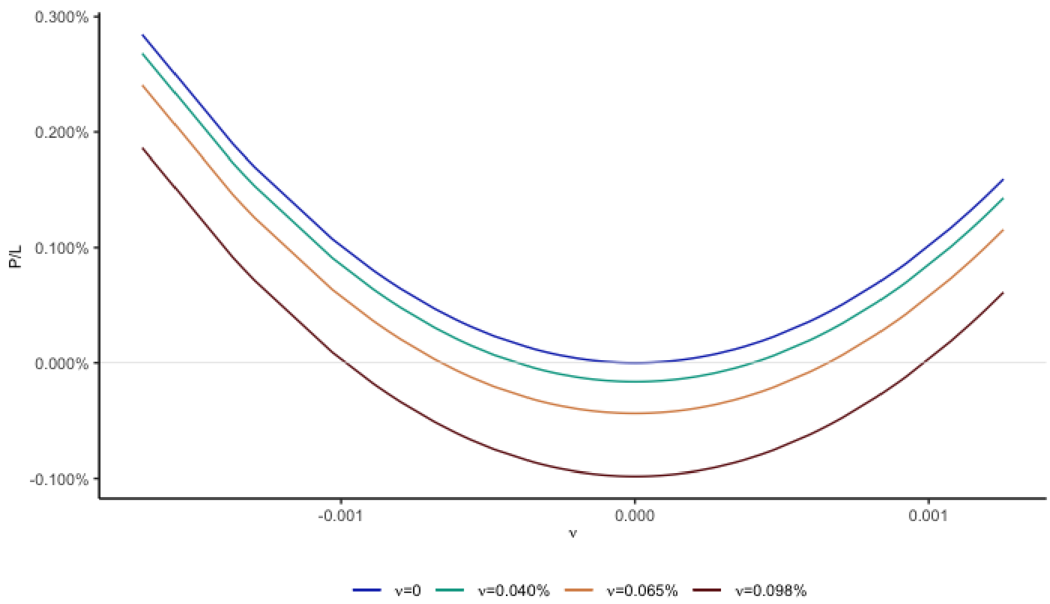


FIG. 2.2: Option profile of a trend-following strategy applied on EUR/USD from Q3 1989 to Q2 2017 with different estimates of the initial trend μ_e. Given that the higher the trend and the larger is the position of the strategy, the greater the initial estimate and the higher the losses.

i.e. $\mu_e(t) = 0$.

The reason is that price reversals are more frequent in the long-term period and that the size of the position depends on the quantity $m\frac{\mu_e(0)}{\sigma^2}$ so the strategy has higher exposure at risk when the trend is high.

The payoff is a function of the value of the underlying currency pair. The payoff is convex if compensation from movements of the currency is asymmetric: the profits are proportional to large changes in the currency, whilst the losses are less proportional to small changes. The payoff is concave if the profits are larger for small for small changes in the currency and smaller for large changes.

Jusselin 2017 [7] used the Bruder and Gaussel model with a small variation of its parameters. They use the length of the look-back window used to calculate the exponential moving average μ_e instead of the duration τ. So the P/L is expressed as

$$\log \frac{G(t)}{G(0)} = \frac{\alpha}{2\lambda}(\mu_e(t)^2 - \mu_e(0)^2) + \alpha\sigma^2 \int_0^t \left(\frac{\mu_e(t')^2}{\sigma^2} \left(1 - \frac{\alpha\sigma^2}{2}\right) - \frac{\lambda}{2}\right) dt'. \quad (2.21)$$

Given that $\tau = \frac{1}{\lambda}$, if we take $\alpha = \frac{m}{\sigma^2}$, Equations (2.20) and (2.21) are identical.

Figure 2.2 shows the option profile of the trend-following strategy applied on EUR/USD from Q3 1989 to Q2 2017. We use different values of the initial estimate of the trend. The higher the value and the larger the losses implied by the strategy. When the initial trend is equal to 0, the option profile is always positive.

2.3 Trading impact

The trading impact is the second component of the Bruder and Gaussel model from Equation (2.20). Following [7], we can define the trading impact as the time value of an option: the difference between option value and intrinsic value. Just like the time value of an option, the trading impact of trend-following is influenced by the realised volatility.

It depends on the square of the Sharpe ratio $\xi(t)$ calculated at each instant $\frac{\mu_e(t)^2}{\sigma^2}$ and on the length of the trend estimator τ. The trading impact is positive if the Sharpe ratio is greater than the quantity $\frac{1}{\sqrt{2\tau}}$. So a necessary condition to obtain a positive return is that the absolute value of the Sharpe ratio is greater than the inverse of the moving average duration. Similar to the option profile, the trading impact causes losses if $\mu_e(0)$. Hamdan 2016 [8] calculated the volatility and the kurtosis of the trading impact, which are a decreasing function of the moving-average duration. This means that a short-term trend-following strategy is more risky than a long-term strategy.

Trading impact depends on the variation in the number of holdings in relation to market fluctuations. Based on Equation (2.18), trend followers buy a certain currency pair based on the estimated trend, the volatility and their risk appetite. Thus, the strategy has the characteristic feature of adaptive position sizing. This means that the longer the trend, the larger the exposure. The adaptive position sizing causes positive skewness of the P/L (i.e. distribution skewed to the left) and convexity. Positive skewness is implied when a strategy combines frequent small losses with infrequent large gains when it anticipates trends[6]. Negative skewness corresponds to the opposite scenario.

Jusselin 2017 [7] show that the trading impact is explained by the gamma gain $\alpha\sigma^2\xi(t)^2$ and the gamma cost, which depends on the variance of the Sharpe ratio $v_\xi(t)$. The trading impact is equal to $\frac{1}{2}\alpha\sigma^2 v_\xi(t)$ as

$$\alpha\sigma^2 \int_0^t \left(\frac{\mu_e(t)^2}{\sigma^2} \left(1 - \frac{\alpha\sigma^2}{2}\right) - \frac{\lambda}{2} \right) dt' \approx \alpha\sigma^2\xi(t)^2 - \frac{1}{2}\alpha\sigma^2 v_\xi(t). \tag{2.22}$$

2.4 Volatility

Frequent market reversals may imply losses for trend-following strategies as they need time to benefit from the reversal and produce positions that do not conflict with the new market conditions. Because trend-following strategies lead to investment positions, which are coherent with the preceding period, it is reasonable to assume that they may generate losses during conditions of high volatility. [9] prove that across numerous asset classes, momentum strategies historically generated high Sharpe ratios and strong positive returns. However, the P/L of momentum strategies

[6]To use some finance jargon, this means that the strategy has lower volatility when loses money and higher volatility when makes money.

is positively skewed as includes infrequent but large negative returns. These momentum crashes occur in “panic" states when market declines and market volatility is high.

The correlation between the profitability of the strategy and volatility is less intuitive. [10] show that trend-following can perform well in both high and low volatility environments. Their research is not quite focused on the FX market; it rather takes into consideration equity and the index S&P500. The outcome, which is a well known concept [11], is known as the “CTA smile". The comparison between the P/L of an equity index with a CTA index[7] results in a smile. The returns of the CTA Index have a non-linear relationship with equity as trend-following performs well when equity returns are very high and very low. The authors note that low volatility does not imply absence of trend and that in particular in equity the indices have up trended strongly between 2006–2017 when the equity volatility was near all-time lows.

The years of the recent financial crisis exhibit a peak in the volatility; but this rarely helped trend-followers. The crisis of market liquidity and the increased volatility convinced traders to lower their risk appetite and trade liquid safe-haven currencies such as the US dollar and Japanese yen. The performance of trend-following strategies declined during a period of scarce liquidity in the FX market. The liquidity crisis exacerbated the crisis and increased the magnitude of volatile swings in currency rates, which increased the trading risk even further. Low price volatility can on the other hand lead to trend-less markets. For example, [12] states that negative alpha in recent periods (i.e. 2007–2015 and 2010–2015) was caused by low volatility: “while we can only speculate at this point, there are at least two possible explanations for this shift. [..] The increasing number of momentum-based mutual funds and ETFs being marketed may bear evidence to this fact. Second, the reduced efficacy of momentum in the most recent period may be due to the unusually low volatility that has persisted for the last few years. Without volatility, it is possible that momentum is unable to shine".

Dao 2017 [13] derive a model which well describes the impact of volatility on trend-following. This model shares much of the assumptions of the Bruder and Gaussel model and links trend-following with the term structure of realized volatility. The P/L of the strategy does not depend on the values of high or low volatility regimes; instead it is influenced by the relationship between the long-term and the short-term volatility.

The trend-following strategy takes position Π_n for a certain currency pair S_n based on a risk parameter m, the exposure e_n and the difference $D_{n'} = S_{n-n'} - S_{n-(n'+1)}$ of prices between times $t_{n-n'}$ and $t_{n-(n'+1)}$. Given that S_n can be written as

$$S_n = S_0 + \sum_{n'=0}^{n-1} (S_{n-n'} - S_{n-(n'+1)}) = S_0 + \sum_{n'=0}^{n-1} D_{n'}, \tag{2.23}$$

[7] As an example one could use the BarclayHedge CTA, the SG CTA Index, or the Morgan Stanley World Equity Index.

we have that

$$\Pi_n = e_n m(S_n - S_{n-1}). \tag{2.24}$$

From Equation (2.24), the P/L at time t_n is equal to

$$G_n = \Pi_{n-1} D_n = m D_n \sum_{n'=0}^{n-1} D_{n'}. \tag{2.25}$$

The total P/L at time N is equal to

$$G_N = \sum_{n=0}^{N} G_n = m \sum_{n=1}^{N} D_n \sum_{n'=2}^{n-1} D_{n'} = \frac{m}{2}\left(\sum_{n=1}^{N} D_n\right)^2 - \frac{m}{2}\sum_{n=1}^{N} D_n^2 = \frac{m}{2}(S_N - S_0)^2 - \frac{m}{2}\sum_{n=1}^{N} D_n^2. \tag{2.26}$$

Equation (2.26) expresses the aggregate P/L of a trend-following strategy as the difference between the realised variance $(S_N - S_0)^2$ between times 0 to N, and the variance implied by the t_n-day returns $\sum_{n=1}^{N} D_n^2$, which are the square of the long-term and the short-term volatility, σ_L and σ_S, respectively. The model does not change if we replace the price differences D_n with the normalised returns $R_n = D_n/\sigma_{n-1}$. By doing so we derive

$$G_N = \frac{m}{2}\left(\sum_{n=1}^{N} R_n\right)^2 - \frac{m}{2}\sum_{n=1}^{N} R_n^2. \tag{2.27}$$

By estimating the trend with the exponential moving average[8], Equation (2.27) becomes

$$G_N = \frac{m\tau}{2}\left(\Big(\sum_{n=1}^{N} R_n\Big)^2 - 1\right). \tag{2.28}$$

Equation (2.28) states that the P/L of the trend-following is positive when the long-term volatility σ_L is larger than the short-term volatility σ_S. This is consistent with the assumption that trend-following shares the same payoff of a straddle which are options that benefit from high volatility. Trend-following can also be profitable during low volatility scenarios if the long-term volatility is greater than the short-term one.

2.5 Interest rate parity

In an open economy investor returns generated by investing in domestic and foreign securities (i.e. bonds) are influenced by two components: the difference of the domestic with the foreign interest rate and the expectation around future value of the exchange rate. Let assume that an investor can purchase a domestic bond or a foreign bond. Let also assume the interest rate in the domestic is 5% and in the foreign is 2%. This means that by holding domestic rather than foreign bonds, the investor gets an additional interest return of 3%. In the context of highly integrated

[8]As before its duration is indicated by τ.

international capital markets, investors can switch from foreign to domestic bonds. In order to buy domestic bonds, domestic currency is required and there is therefore be a surge in the demand for it. This will lead to an immediate appreciation of the domestic currency. Investors will do so until this investment is not profitable anymore; that is when the expected capital loss from holding the domestic bonds for one year because of a depreciation of the exchange rate is equal to the interest rate gain (i.e. carry). In the example if the domestic currency depreciate by 3% over the period for which the interest differential is expected to persist, then the profits gained by holding the domestic bond would be wiped away. This is the uncovered interest parity condition (UIP). In the uncovered interest parity model ([14]; [15]; [16]; [17]; [18]; [19]), under the assumption of perfect capital mobility, the interest rate differential can be offset by the exchange rate depreciation or appreciation. The condition that the interest rate differential in favour of bonds denominated in a certain currency must be equal to the expected exchange rate depreciation of the currency over the period for which the interest differential is expected to persist is called the uncovered interest parity condition. This happens through adjustments of the spot exchange rate or are incorporated by the value of the correspondent forward rate. In practice when an interest rate differential is opens up, there is a jump in the exchange rate that is sufficient to eliminate the interest rate gains. Then over the period for which the interest differential is expected to remain, the exchange rate appreciation gradually unwinds and the exchange rate returns to its expected long run value. The UIP can be represented as

$$(1 + r_d) = \frac{E[S(T)|S(t)]}{S(t)}(1 + r_f). \tag{2.29}$$

From this equation we derive the approximation

$$i_d \approx i_f + E[s(T)|s(t)] - s(t), \tag{2.30}$$

where $s(t)$ is the logarithm of $S(t)$.

where r_d is the domestic, r_f the foreign interest rate, S is exchange rate, and $E[S]$ is the expected exchange rate.

If the domestic interest rate is greater than the foreign interest rate, then the domestic currency is expected to depreciate by the same magnitude. If the domestic interest rate is less than the foreign interest rate, then the domestic currency is expected to appreciate by the same magnitude. Interest rate parity is justified by arbitrage arguments: if it holds then the expected return from foreign investing will be the same as the domestic return. It is worth noting that the actual rate of return may differ between countries if the actual depreciation differs from the expected depreciation. However, as long as expected returns are the same, there will be no major movements affecting the current exchange rate. Another way to express the UIP is using the forward exchange rate.

The forward rate is based on the difference between the interest rates of the two currencies and the time until the maturity of the option T.

$$F(t,T) = S(t)e^{(r_d - r_f)(T-t)}. \tag{2.31}$$

When the no-arbitrage condition defined by equation 2.29 is satisfied with the use of a forward contract, the interest rate parity is said to be covered.

$$(1 + r_d) = \frac{F(t,T)}{S(t)}(1 + r_f). \tag{2.32}$$

From equation 2.29 we can derive the formula of the forward rate implied by the covered interest rate parity.

$$F(t,T) = S(t)\frac{1 + r_f}{1 + r_f}. \tag{2.33}$$

2.6 Purchasing power parity

The purchasing power parity (PPP) is a theory concerning the long-term equilibrium exchange rates based on relative price levels of two countries. The concept is founded on the law of one price - the idea that in absence of transaction costs, identical goods in different markets would be priced the same. The demand for foreign goods and services is influenced by their relative value i.e. the relationship between price of foreign goods and services expressed in the domestic currency and the price of domestic good and services. This concept defines what is called the real exchange rate: $\theta = \frac{P^* \times S}{P}$ where P^* is the foreign price, P is the domestic price and S is the nominal exchange rate (i.e. number of domestic currency per unit of foreign currency which is the ratio of base or foreign currency and the quote or domestic currency). Under the MF model the concept of real exchange rate is linked to that of purchase power. The purchase power is defined by the relationship between domestic and foreign goods. They can be compared when foreign goods are expressed in the common currency price of the trade and based on the real exchange rate this is done by multiplying the foreign price with the nominal exchange rate. In formula for each good or service k this is defined by: $P_k = P_k^* \times S$. This condition is called the law of the one price (LOOP). This law holds that there can be only one price for a given product at any given time.The law of one price need not apply exactly due to the following reasons transportation costs; ease of access. When the equality holds for each traded good and service k and between various countries then θ is equal to 1.

$$P = P^* \times S. \tag{2.34}$$

The latter equation is called the absolute purchasing power parity.

2.7 Multi-risk premia

The multi risk premia FX is a notional rule-based and volatility targeting index built as combination of different systematic macro trading strategies. The risk premium is the difference between the expected return on a security or portfolio and the riskless rate of interest (the certain return on a riskless security). Underlying the terminology is the notion that there should be a premium (higher expected return) for bearing risk. So the concept of premium is linked to that of the outperformance of a benchmark and therefore to the generation of alpha (strategy returns above the market) even when the market is in a downtrend. The index is rule based as its trading positions are determined by trading models (that define rules); moreover, also the weight of the constituents within the aggregation of the multi premia index constituents is determined through rules (e.g. how much of the notional is invested by the G10 momentum or by the G10 carry models). The index is updated every day using closing prices. Each month the index identifies a unique portfolio based on its constituents. The index tracks the performance of a hypothetical portfolio which invests in G10 and EM currency pairs. The value model only invests in G10 currencies. The momentum and the carry model can trade G10 and EM currencies. The five indices e.g. G10 momentum, EM momentum, G10 value, G10 carry and EM carry are the constituents of the multi risk FX index. The index is a volatility-target one as it tracks the performance of a notional long position based on the estimation of the realised volatility of the portfolio. The volatility targeting mechanism adjusts the exposure to each index constituent based on a predefined level of expected risk. The mechanism cannot override trading signals but can reduce the exposure triggered by a constituent if the risk is not adequately compensated by the returns of that trade. The exposure of the index to its constituents is adjusted potentially on a daily basis through a formula that links the recent volatility of the index constituents with the annualised volatility level of 10% as reference. The choice of the target volatility is determined by the risk appetite of the investors. Alternatively we could have used a more conservative level of 5%. A volatility targeting approach is a way to dynamically manage portfolio asset allocation to keep the overall volatility of the strategy stable at a targeted level. At the core of the approach there is the relationship between volatility and returns and in particular a negative correlation between the two. Li(2005) [20] found evidence that stock market returns and stock market volatility are negatively correlated, lending support to claims by Bekaert(2000) [21] as well as Whitelaw(2000) [22].

The autocorrelation of the returns implies volatility clustering i.e. persistent and long periods of high and low volatility. Similar results can be found in Cont(2001) [23], who notes the persistence of volatility in the equity markets. By design the volatility targeting implies the deleveraging of the risky asset in periods of high volatility and leveraging in periods of low volatility. A volatility target index sells more while the risk- adjusted expected return is falling and the index volatility is rising. The allocation is continuously reduced until the price exhibits a reversal and a new up trending rally. A volatility target index buys more while their risk-adjusted expected return is rising and the index volatility is falling. The allocation increases until there is a significant decline in the price. Ribeiro and Di Pietro (2008) [24], and Khuzwayo and Mare [25] showed that the volatility targeting approach should increase the risk-adjusted returns and decreased tail-risks relative to a static asset allocation. The volatility targeting approach is not able to avoid large drawdowns. This is because the allocation is generally at its highest just before a huge shift in the price is observed (e.g. huge downturn after a positive rally or huge upturn after a long sell off) and the adjustment to the exposure is done once the shift is observed. So as an example the mechanism cannot reduce the exposure before a crash and cannot increase the exposure when a new rally emerges as for both cases it firstly needs to observe the reversal of the price. The constituents of the multi-premia index $I_{G10,Mom,n}$, $I_{EM,Mom,n}$, $I_{G10,Value,n}$, $I_{G10,Carry,n}$, $I_{EM,Carry,n}$ are weighted in accordance with their performance over a certain look back period (e.g. 21 days). Each of the five index constituents are calculated by the following equations. The index is rebalanced every quarter on the first business day of January, April, July and October. Extraordinary rebalancing aiming at reducing the index decline in correspondence to severe market corrections is not implemented. One could in theory adjust every time the portfolio incurs in losses exceeding a certain threshold (e.g. 5%, 8% or 10%); but as we said this kind of adjustment is not included to allow a more transparent assessment of the performance of the index and its underlying constituents. For the sake of clarity the index starts at a predefined value of 100 at the index start date. The index level I_t as of each index business day t following the index start date is an amount determined by the following formula:

$$I_n = I_{n-1} + \left(\frac{I_{\$,n}}{I_{\$,n-1}} - f\frac{d_{n,n-1}}{365}\right), \tag{2.35}$$

where I_n is index level on the business day n; I_{n-1} is index level on the business day immediately preceding the business day n; f is the index fee; and $d_{n,n-1}$ is the number of calendar days between the business day n and the immediately preceding business day. $I_{\$,n}$ is the gross index level and is defined below. The index level on each business day is a function of the exposure E_n of the index and the core index. The gross index level $I_{\$,n}$ is determined on each business day n in accordance with the following formula 2.36:

$$I_{\$,n} = I_{\$,n-1} + \left[1 + E_{n-1}\left[\frac{I_{Strat,n}}{I_{Strat,n-1}} - 1\right]\right] - |E_{n-1} - E_{n-2}| * I_{\$,n-1}, \tag{2.36}$$

where $I_{\$,n}$ is the gross index level on the business day n; E_{n-1} is the exposure of the index to the core index as of the the business day immediately to the day n; $I_{Strat,n}$ is the core index level on index business day $I_{Strat,n-1}$ is the core index level on index business day immediately preceding index business day n; and $|E_{n-1} - E_{n-2}| * I_{\$,n-1}$ is the notional cost in respect of any change in the exposure of the index to the core index at the business day n. The core index level and the exposure are calculated on each index business day in accordance with the formula 2.41 and 2.37: The exposure in respect of each index business day n is an amount (expressed as a percentage) determined in accordance with the formula 2.37:

$$E_n = \min\left(V_{n-2}\frac{V_N}{R_{V,n-2}}, \gamma_1\right), \tag{2.37}$$

where V_{n-2} is the volatility adjustment factor in respect of the index business day which falls two index business days immediately preceding index business day t; $R_{V,n-2}$ is the realised volatility of the core index on the index business day which falls two index business days immediately preceding index business day n. The value of γ_1 can be defined in base of the risk appetite. As an example it could be equal to 200% or 300%. The realized volatility of the core index $R_{V,n}$ in respect of each index business day t is an amount (expressed as a percentage) determined by the following formula

$$R_{V,n} = \sqrt{\sum_{i=t-19}^{t}\left(\frac{1}{20}\left(\ln\left(\frac{I_{Strat,i}}{I_{Strat,i-1}}\right)\sqrt{\frac{365}{d_{i,i-1}}}\right)^2\right)}, \tag{2.38}$$

where $I_{Strat,n}$ is the core index level on the index business day n and $d_{n,n-1}$ is the number of calendar days in the period from the business day n and and the business day n-1. The volatility adjustment factor V_n is calculated by the equation

$$V_n = \max\left(\gamma_2, \min\left(\gamma_3\sqrt{\frac{1}{d_{n'+1,n}}\left(0, d_{n'+1,n'} - d_{n,n'}\frac{R_{V,n}}{V_N}\right)^2}\right)\right), \tag{2.39}$$

where $R_{V,n}$ is the realised volatility of the index in respect of index business day n; $d_{n'+1,n'}$ is the number of the business days in the period between two consecutive observation dates; $d_{n,n'}$ is the number of business days in the period from the preceding observation date and the business day n; and $d_{n'+1,n}$ is the number of business days in the period from the business day n and the following observation. The value of γ_2 and γ_3 are defined in base of the risk appetite. As an example they could range from 0.5 and 1 and from 1 and 1.5, respectively. The realised volatility is obtained in accordance with the following formula

$$R_{V,t} = \sqrt{\left(d_{n-1,n'}R^2_{V,n-1} + ln\left(\frac{I_{\$,n}}{I_{\$,n-1}}\right)^2\frac{365}{d_{n,n-1}}\right)\frac{1}{d_{n,n'}}}, \tag{2.40}$$

where $R_{V,n-1}$ is the realised volatility of the index on the index business day immediately preceding index business day n. The core index level as of each index business day t following the core index start date shall be an amount determined by the following formula 2.41:

$$I_{Strat,n} = I_{Strat,n*} + \left[1 + \sum_{p=1}^{P}\left(\frac{S_{CL,p,n}}{S_{CL,p,n*}} - 1\right)W_{p,n*}\right], \tag{2.41}$$

where $I_{Strat,n*}$ is the core index level on the rebalancing date n* immediately preceding index business day n; $S_{CL,p,n}$ is the strategy closing level of constituent p on the business day n; $S_{CL,p,n*}$ is the strategy closing level of constituent p on the rebalancing date $n*$ immediately preceding the business day n; and $W_{p,n*}$ is the percentage weight of constituent p on the rebalancing date n*. The strategy closing level of each such constituent p is determined in accordance with the following formula

$$S_{CL,p,n} = S_{CL,p,n-1} + \left[1 + \Psi_{n-1}\left(\frac{S_{p,n}}{S_{p,n-1}} - 1\right)\right], \tag{2.42}$$

where $S_{p,n}$ is the the spot rate for the constituent p as of index business day n; Ψn is the unadjusted strategy signal of the constituent p on business day n.

The multi-risk index combines the indexes obtained through the 3 strategies momentum, value and carry applied to the G10 and EM currency groups. It is constructed by the formula (2.43)

$$I_n = I_{n-1} + \left[1 + \sum_{k=1}^{5}\left[\chi_{k,n-1} \times \frac{I_{k,n}}{I_{k,n-1}}\right]\right] \tag{2.43}$$

where $\chi_{k,n}$ is the weight relative to the specific index kth index[9] at time n. In this exercise we give equal weight to each strategy. Therefore $\forall$ k and n: $\chi_{k,n} = 20\%$.

The formula (2.43) combines five FX indexes I_k, which are determined by the following approach. Let Ψ_p be the signal obtained by the k-th strategy for the correspondent p-th FX currency pair S_p; and let W_p be the weight of S_p in relation to the index I_k. Then, I_k is obtained as

$$I_{k,n} = I_{n-1} + \left[1 + \sum_{p=1}^{P}\left[\psi_{p,n-1} W_{p,n-1} \times \frac{S_{p,n}}{S_{p,n-1}}\right]\right] \tag{2.44}$$

The weights and $W_{p,n}$ for the value strategy applied to the G10 currency group are defined by the following algorithm 2.7.1, which compares the purchase parity index of the currency p ($I_{PPP,p,n}$) with its spot price (S_p) at each time n.

The weights and $W_{p,n}$ for the carry strategy applied to the G10 and EM currency groups are defined by the following algorithm 2.7.2, which compares the foreign interest rate ($r_{f,n}$) and domestic one ($r_{d,n}$) at each time n. They are defined by the algorithm 2.7.2.

2.8 Option pricing

A foreign exchange option is a derivative product that gives the owner the right but not the obligation to exchange money denominated in one currency into another currency at a predefined exchange rate on a specific future date. The price of the option is called premium and the date at which the contract can be exercised is called expiry date or maturity. Call options give the investor the right to buy the

[9]In this context k varies from 1 to 5.

Algorithm 2.7.1. Ranking methodology to determine the weights of the constituents of the G10 Value Index.

Set a value for the threshold $\rho*$.
for $N = 1, 2, \ldots, N$ **do**
  for $p = 1, 2, \ldots, 9$ **do**
    Let $\eta_{p,n}$ be the difference $I_{PPP,p,n} - S_{p,n}$.
    Let $\rho_{p,n}$ be the rank of the p-th $\eta_{p,n}$:
    if $\rho_{p,n} \leq \rho*$ **then**
      $k_{p,n} = 1$.
    end
    if $\rho_{i,t} > \rho*$ **then**
      $k_{p,n} = 0$.
    end
    $W_{p,n} = \frac{100 \times k_{p,n}}{9}$
  end
end

Algorithm 2.7.2. Ranking methodology to determine the weights of the constituents of the G10 Carry Index.

Set a value for the threshold $\rho*$.
for $N = 1, 2, \ldots, N$ **do**
  for $p = 1, 2, \ldots, 9$ **do**
    Let $\eta_{p,n}$ be the difference $r_{f,n} - r_{d,n}$.
    Let $\rho_{p,n}$ be the rank of the p-th $\eta_{p,n}$:
    if $\rho_{p,n} \leq \rho*$ **then**
      $k_{p,n} = 1$.
    end
    if $\rho_{i,t} > \rho*$ **then**
      $k_{p,n} = 0$.
    end
    $W_{p,n} = \frac{100 \times k_{p,n}}{9}$
  end
end

asset at a fixed price (the strike price), while put options give the right to sell at the strike price. The amount of currency that the option allows to buy or sell is called notional. The price of an option depends on the probability that the contract will retain a value on the date when it can be exercised. In option jargon this is achieved if the option expires in the money. Such a possibility depends on the evolution of the underlying, here the exchange rate, during the life of the option.

Options can be priced by different models and this generally depends on the type of the contract: there are e.g. European, barrier, look-back, digital and touch options. Here we consider only European options and in particular call, put and straddle options. European calls and puts identify a type of option contract; a straddle is derived from calls and puts i.e. buying a call and put with same strike price and expiration date. The price of European options is calculated with the

Garman-Kohlhagen model ([26]), an extension of the Black-Scholes-Merton model. Excellent references on FX option pricing are [27] and [28]. Let $S(t)$ be the FX rate at time t, K the option strike price, r_d the domestic interest rate, r_f the foreign interest rate, T the maturity or expiry of the option, σ the implied volatility of the option and $\Phi()$ the standard normal cumulative distribution function. The prices $c(t)$ and $p(t)$ of a FX European call and put option are

$$c(t) = S(t)e^{-r_f T}\Phi(d_1) - Ke^{-r_d T}\Phi(d_2) \tag{2.45}$$

$$p(t) = Ke^{-r_d T}\Phi(-d_2) - S(t)e^{-r_f T}\Phi(-d_1), \tag{2.46}$$

where

$$d_1 = \frac{\log \frac{S(t)}{K} + \left(r_d - r_f + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}, \quad d_2 = d_1 - \sigma\sqrt{T}. \tag{2.47}$$

Similarly to equity options, also for FX options a trader must take into account the evolution of the price and its comparison with the strike price at maturity. With FX options there is another important component that defines the lifetime of a trade and that is the forward rate. This is defined by equation(2.31). At the money forward (ATMF) options define the strike price based on the value of the forward price at the time in which the contract is agreed by the option buyer and seller. The profitability for the trader clearly depends on the relationship between the spot rate at maturity and the forward rate that was observed at the inception of the contract. Out of the money options (OTM) are those with unfavourable strike compared to the forward rate. In the money (ITM) options have strike price favourable compared to the forward rate. In detail FX options can be systematically miss priced when the forward rate is not on average an accurate estimator of the future value of the spot rate i.e. the premium does not reflect the relationship between spot at maturity $S(T)$ and the strike price $F(t,T)$ of an ATMF contract.

2.9 Block-bootstrapping

Bootstraps are non-parametric algorithms that form hypothetical price scenarios from actual data. The most common bootstrap algorithm, which we call the standard bootstrap, samples randomly individual observations from the original time series, thus assuming that the underlying data comes from an independently and identically distributed (i.i.d.) process. This procedure generates samples that have the same return distributions as the original data, but cannot preserve the dependent structures observed within the original time series. The block-boostrap is a method to improve the accuracy of bootstrap for time series data. The idea is to divide the time series into blocks of data so to replicate the time series dependency structure within the samples and blocks; the block bootstrapped series retain some of the original dependencies, such as volatility clustering and chart patterns, but lose them between the blocks. The block bootstrap was developed separately by Hall(1985)

[29], Carlstein(1986) [30] and Kunsch(1989) [31]. Non-overlapping block bootstrap follows the so-called Carlestein's rule; whereas the overlapping one is based on the Künsch's rule. The stationary bootstrap is another variant of block-boostrap and was developed by Politis(1994) [32]. It is based on a scheme of creating new stationary samples from the original time series. The feature of time series stationarity is retained in the samples through a re-sampling approach that uses different length of the blocks. The length of each block follows the geometric distribution. Let the original sample $X_1, X_2, ..., X_n$ be a strictly stationary and weakly dependent time series. Let $B_{il} = (X_1, X_2, ..., X_{i+l-1}$ be the block which contains l repeatedly observations starting from X_i. Independently of l , let $L_1, L_2, ...$ be the series of independent and identically distributed random variables with geometric distribution: $P(L_i = m) = (1-p)^{m-1}p$, where $p = \frac{1}{q}$ is the smoothing parameter and q is the average length of the blocks, which is generally unknown and needs to be determined empirically. Independently of X_i and L_i, let $I_1, I_2, ...$ be the sequence of independent and identically distributed variables with discrete uniform distribution from the set 1,...,n. Hence, pseudo time series $Y_1, Y_2, ..., Y_n$ are generated by the sequence of random length blocks $B_{I_1,L_1}, B_{I_2,L_2}, ...$ First L_1 observations are determined using the first block B_{I_1,L_1} of observation series $X_{I_1},, ..., X_{I_1+L_1-1}$that are followed by the second L_2 number of observations in the block B_{I_2,L_2} of series $X_{I_2},, ..., X_{I_2+L_2-1}$. The defined process continues until it reaches n observations within the pseudo-sample, although it is clear that mentioned process leaves space to expand the pseudo-sample for an arbitrary number of observations. Once q is specified, the stationary bootstrap algorithm is implemented. The algorithm is illustrated in details in James(2010) [33]. In this exercise we determine the optimal block length by studying the autocorrelation function of the returns. In particular we look for the lag τ of the autocorrelation function after which the autocorrelation coefficients are not significant anymore. The bootstrap algorithm is shown within 2.9.1 By doing so we assume that the dependency structure embedded in the original time

Algorithm 2.9.1. Politis-Romano block bootstrap algorithm.

1. Let X_1^*, i=1,2, . . . , N be the bootstrapped series and X_i^* be the bootstrapped series.
2. Let X_n be randomly extracted from X_i^*.
3. Take X_2^* equal as: 1) X_m which is randomly selected form X with probability p and 2) X_{n+1} which is the next observation after X_n with probability (1-p).
4. If $X_i^* = X_N$ then $X_{i+1}^* = X_1$ with probability (1-p).
5. Repeat until we form a sample X^* made of N observations.

series is measured by the autocorrelation structure of the returns.

Once the bootstrap samples are assembled together we can validate our trading strategies using those samples as input for the trading strategies. The validation is thus composed by two elements: a) the generation of samples and b) the trading strategy. These two steps can be combined together in two different ways. We tested both and we achieved almost identical results from them. The first approach is described by the algorithm 2.9.2. This approach bootstrap the original prices and then test the trading strategy on the bootstrap samples. Therefore the bootstrap is a distinct step compared to the application of the trading strategy.

ALGORITHM 2.9.2. Validation of trading strategy with the block bootstrap samples from the historical prices.

Step1: Creation of block boostrap samples:
Let X_1^*, i=1,2, ..., N be the bootstrapped series and X_i^* be the bootstrapped series.
Let X_n be randomly extracted from X_i^*.
Take X_2^* equal as: 1) X_m which is randomly selected form X with probability p and 2) X_{n+1} which is the next observation after X_n with probability (1-p).
If $X_i^* = X_N$ then $X_{i+1}^* = X_1$ with probability (1-p).
Repeat until we form a sample X^* made of N observations.
Step2: Testing the trading strategy on the M bootstrap samples:
Let T be the trading strategy that we want to validate and let B_m the m-th sample obtained with the bootstrap.
Back-test the strategy on each of the M B_m samples.
Derive performance metrics of the trading strategy e.g. the distribution of the Sharpe ratio by combining together the K results relative to the Sharpe ratios calculated on the K independent samples.
Build the distribution of the performance metric and study it in terms of shape and dispersion.

The second approach, which is described by the algorithm 2.9.3, combines the bootstrap step and the application of the trading strategy together. Firstly trading strategy is back-tested on the historical data; then the returns of the model are bootstrapped to form K samples of returns.

2.10 Calculation of the Sharpe ratio for high-frequency data

The Sharpe ratio is a generally used metric to measure the performance of an investment strategy. [34] applied Markowitz' mean variance approach to determine the performance of financial investments ([35]). Let r_n be the excess returns of a certain strategy i.i.d. and normally distributed with mean μ and standard deviation σ. The Sharpe ratio is calculated as

$$S_R = \frac{\mu}{\sigma^2}. \tag{2.48}$$

The Sharpe ratio is based on the first two moments and ignores skewness (s_3) and kurtosis (s_4) . Thus, it can fail to distinguish good investments (i.e. $s_3 > 0$ and $s_4 < 0$) and bad investments (i.e. $s_3 < 0$ and $s_4 > 0$). [36] proved that we do not need to observe the normality distribution of the returns to calculate the Sharpe ratio: the indicator follows normal distribution even if returns do not. [36] in the proof assumed that the returns are i.i.d., while [37] showed that is possible creating a

ALGORITHM 2.9.3. Validation of trading strategy with the block bootstrap samples from the strategy price changes.

1 **Step1**: Testing the trading strategy on the historical prices:
2 Let T be the trading strategy that we want to validate.
3 Backtest the strategy on the historical data and create a vector of price changes C_T implied by the strategy.
4 **Step2**: Creation of block boostrap samples:
5 Let C_1^*, i=1,2, ..., N be the bootstrapped series and C_i^* be the bootstrapped series.
6 Let C_n be randomly extracted from C_i^*.
7 Take C_2^* equal as: 1) C_m which is randomly selected form C with probability p or 2) C_{n+1} which is the next observation after C_n with probability $1-p$.
8 If $C_i^* = C_N$ then $C_{i+1}^* = C_1$ with probability (1-p).
9 Repeat until we form a sample C^* made of N observations.
10 Derive performance metrics of the trading strategy e.g. the distribution of the Sharpe ratio by combining together the K results relative to the Sharpe ratios calculated on the K independent samples.
11 Build the distribution of the performance metric and study it in terms of shape and dispersion.

limiting distribution based on stationary and ergodic returns (i.e. non i.i.d. returns) to calculate the Sharpe ratio. [38] proved that the index defined by [36] and by [37] are equivalent i.e. we do not need i.i.d. returns to build the Sharpe ratio. A key feature of the calculation of the Sharpe ratio is including the longest possible track record (e.g. a long set of historical returns determines a smaller Sharpe ratio) and adding (s_3) (s_4) in the calculation of the index. High-frequency returns are generally affected by non-zero skewness and positive kurtosis. A possible solution consists of replacing the equation 2.48 with the adjusted Sharpe ratio S_{Ra} or with the modified Sharpe ratio S_{Rm}. The adjusted Sharpe ratio SR_a was proposed by [39]. It is defined by

$$S_{Ra} = S_R\left(1 + \frac{s_3}{6}SR - \frac{(s_4-2)}{24}S_R^2\right). \tag{2.49}$$

The modified Value-at-Risk Sharpe ratio adjusts the Sharpe ratio by the modified Value at Risk (VaR) which is equivalent to standard VaR but is modified in terms of skewness and kurtosis. The concept of VaR describes the expected maximum loss over a target horizon within a given confidence level α. For example, a 10-day VaR of 10% at a α=0.05 confidence level means that the maximum loss in the next 10 days will not exceed 10% of an asset value in 95% (e.g. (1-α)%) of all cases. If returns are normally distributed returns, the VaR of a long-position is calculated as a quantile z_α of the standard normal distribution at a given confidence level α ([40])) as

$$VaR_n = -r_n + z_\alpha \sigma_n. \tag{2.50}$$

The excess return on VaR (VaR_e) was developed by [41] and compares the excess return of an asset to the VaR of the asset as follows

$$VaR_e = \frac{r_n}{VaR}. \tag{2.51}$$

The modified VaR (VaR_m) is estimated via quantile of the standard normal distribution using a Cornish-Fisher-Expansion ([42]) as

$$VaR_m = z_\alpha + \frac{1}{6}(z_\alpha^2 - 1)s_3 + \frac{1}{24}(z_\alpha^3 - 3z_\alpha)s_4 - \frac{1}{36}(2z_\alpha^3 - 5z_\alpha)s_3^2. \tag{2.52}$$

The modified Sharpe ratio is obtained as

$$S_{Rm} = \frac{r_n}{VaR_m}. \tag{2.53}$$

In this work we use the adjusted Sharpe ratio S_{Ra} from daily returns. The daily Sharpe ratio is annualised accordingly as shown in [43].

2.11 Recurrent neural networks (RNN)

Recurrent neural networks (RNN) are a class of neural networks designed to make computations on sequential data. Let x_t be the data sequence with the tie step t ranging from 1 to τ. At the core of the RNN there is the equation of the hidden state h. The forward propagation of a RNN is defined as follows:

$$\begin{aligned} a_t &= b + Wh_{t-1} + Ux_t \\ h_t &= tanh(a_t) \\ o_t &= c + Vh_t \\ y_t &= softmax(o_t)), \end{aligned} \tag{2.54}$$

where the parameters are the bias b and c with the weight matrices u,v and w, respectively, for input-to-hidden, hidden-to-output and hidden-to-hidden connections.

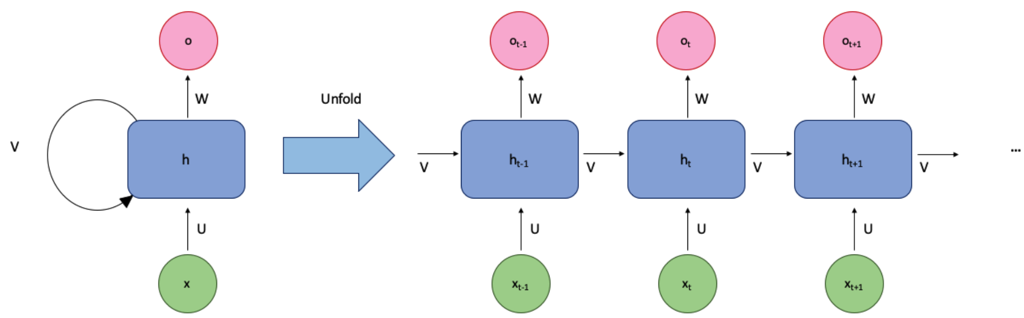
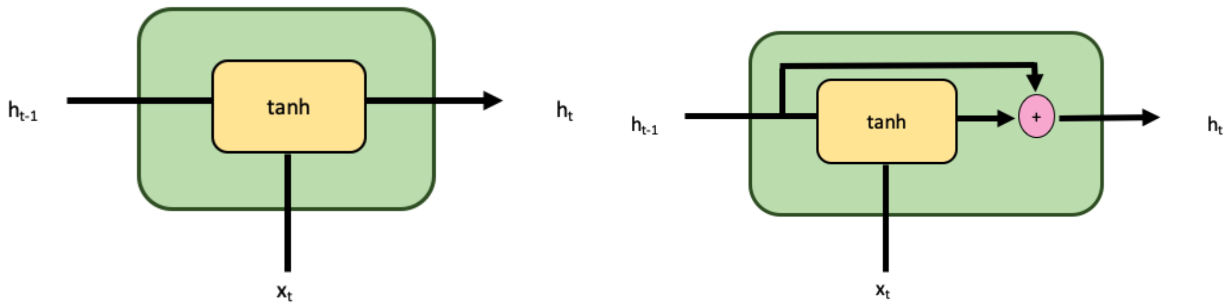


FIG. 2.3: Unfolding the RNN structure in terms of hidden layers h as function of the weights V, U, and W.



(a) RNN learning cell

(b) α-RNN learning cell

FIG. 2.4: Learning cells of the RNN and α-RNN algorithms. Arithmetic operations are applied element wise.

The RNN and α-RNN cells is displayed in Figure 2.4a and 2.4b.

Given auto-correlated observations of covariates or predictors, x_t, and continuous responses y_t at times t=1,...,N, it is possible to estimate an m-step prediction $\hat{y_{t+m}} = F(\underline{x}_t)$ for the target y_{t+m} from a vector of p elements $\underline{x}_t = x_{t-p+1}, \ldots, x_t$ through the equation $y_{t+m} = F(\underline{x}_t) + \epsilon_t$. Dixon 2020 ([44]) introduces the α-RNN model using the smoothing function

$$\hat{y}_{t+m} = F_{W,b,\alpha}(\underline{x}_t), \tag{2.55}$$

where $F_{W,b,\alpha}(\underline{x}_t)$ is a α smoothed RNN with weights $W = (W_h, U_h, W_y)$. For each time step forward passes update the hidden state $\hat{h}_s$ though the recurrence functions:

$$\begin{aligned} \hat{h}_s &= g(W_h x_s + U_h \tilde{h}_{s-1} + b_h, \\ \tilde{h}_s &= \alpha \hat{h}_s + (1-\alpha)\tilde{h}_{s-1}, \end{aligned} \tag{2.56}$$

where $g(.)$ is the non-linear activation function tanh and $\tilde{h}_s$ is the exponentially smoothed hidden state for $\alpha \in [0, 1]$. The output from the final hidden state is obtained by:

$$\hat{y}_{t+m} = W_y \hat{h}_t + b_y, \tag{2.57}$$

where $\hat{h}_{t-p+1} = g(W_h x_{t-p+1})$. The memory in the model can be measured through the partial autocorrelation function (PACF) ρ_h, which measures the correlation between the variable y_t and y_{t-h}. RNN models exhibit a vanishing gradient problem ([45]). Dixon 2020 ([44]) shows that the α-RNN reduces the vanishing gradient problem and adds a guaranteed stability if the tanh activation function is adopted. The RNN and the α-RNN models can be compared with the more complex Long-Short-Term-Memory (LSTM) model. LSTMs are explicitly designed to avoid the long-term dependency problem. They process information through gates: the input gate, the forget gate and the output gate.

The forget gate looks at h_{t-1} and x_t and outputs a number between 0 and 1 for each number in the cell state C_{t-1} completely keep or drop.

$$h_t = f(h_{t-1}, x_{t-1}, \theta) \tag{2.58}$$

The first step in our LSTM is to decide what information must be thrown away from the cell state. This decision is made by a sigmoid layer called the forget gate layer. Let i_t be the input gate, f_t the forget gate, o_t the forget gate, σ the sigmoid function, w_x the weight for the gate(x), h_{t-1} the output of the previous block of the network at time t-1, x_t is the input at time t, b_x is the bias for the gate(x).

The forget gate looks at h_{t-1} and x_t and outputs a number between 0 and 1 for each number in the cell state C_{t-1} completely keep or drop.

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i). \tag{2.59}$$

The next step is to decide what new information to store in the cell state. This has two parts. First, a sigmoid layer called the input gate layer decides which values are updated. Next, a hyperbolic tangent (tanh) layer creates a vector of new candidate values, $\tilde{C_t}$ that could be added to the state. In the next step, they are combined to create an update to the state.

$$\begin{aligned} i_t &= \sigma(w_i[h_{t-1}, x_t] + b_i), \\ \tilde{C_t} &= tanh(w_C[h_{t-1}, x_t] + b_C) \end{aligned} \tag{2.60}$$

Then, the new cell state C_t is updated using The forget gate looks at h_{t-1} and x_t and outputs a number between 0 and 1 for each number in the cell state C_{t-1} completely keep or drop.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C_t} \tag{2.61}$$

Finally, the information is filtered version and prepared for being outputted. Then, we put the cell state through tanh and multiply it by the output of the sigmoid gate, so that we only output the parts we decided to.

$$\begin{aligned} o_t &= \sigma(w_o[h_{t-1}, x_t] + b_o), \\ h_t &= o_t * tanh(C_t) \end{aligned} \tag{2.62}$$

The LSTM cell is displayed in Figure 2.5.

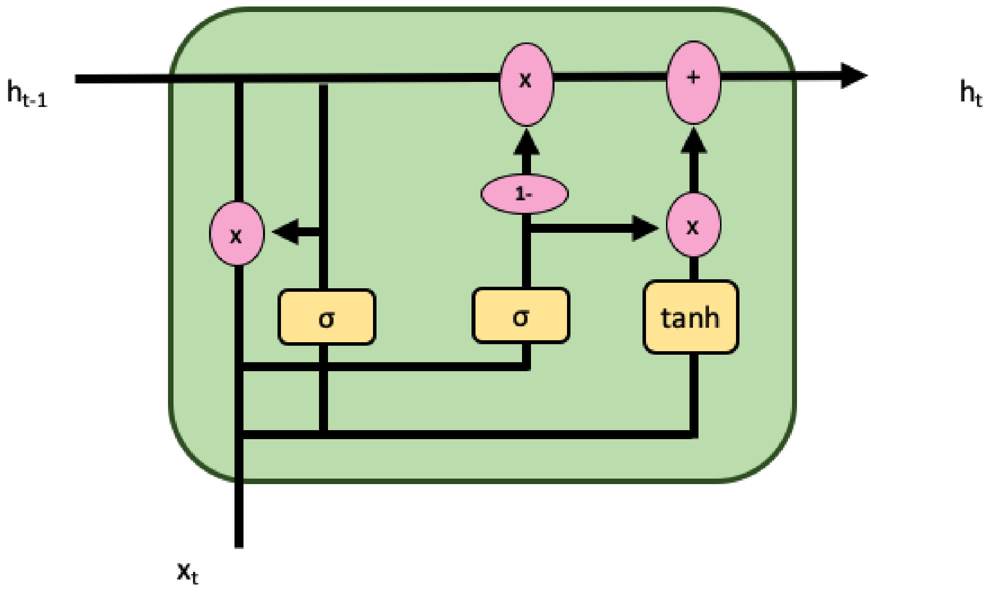


Fig. 2.5: LSTM learning cell. Arithmetic operations are applied element wise and "1-" denotes one minus the input.

Chapter 3

Trading strategies

3.1 Trend-following and momentum

The strategy buys a currency pair if a short-term moving average calculated on that currency pair crosses from below a long-term moving average as this is assumed to be a signal for a bullish sentiment about that currency pair on the horizon. The strategy sells if a short-term moving average crosses from above a long-term moving average as a bear sentiment is considered to be likely. In the literature these crossings are sometimes called golden and death cross, respectively.

The difference between a short-term and a long-term moving average of the asset price is positive when past returns are mostly positive during the last period. The long-term moving average determines a delayed time series which is used to assess the trend of the non-lagged curve or the less lagged curve. As an example, when the price curve crosses from below (above) the lagged price curve that means that the price is presenting an ascending (descending) trend as the prices are moving towards a new direction compared to the past prices. In real life situations, investors tend to combine such indicators in more complex ways. As an example the choice of different look-back periods can help finding trends and improving the profitability of the strategy.

The strategy can use simple moving averages, exponential or other weighted moving averages. We use the simple and exponential moving averages and we simplify the notation to facilitate the interpretation of the strategy. In this context we indicate with $\mu_{N_1,n}$ and $\mu_{N_2,n}$ the short-term and the long-term moving averages calculated at time t_n.

Following previous section, N_1 and N_2 are the lag of the moving average such that $N_1 < N_2$. Using simple moving averages[1], we

1. buy if $\mu_{N_1,n-1} < \mu_{N_2,n-1}$ and $\mu_{N_1,n} > \mu_{N_2,n}$ or
2. sell if $\mu_{N_1,n-1} > \mu_{N_2,n-1}$ and $\mu_{N_1,n} < \mu_{N_2,n}$.

Recently Zakamulin (2014) [46] produced one of the most exhaustive study about the computation of trading indicators based on moving averages of prices. In par-

[1]If we use exponential moving averages we replace $\mu = \mu_{\mathrm{s},n}$ with $\mu_{\mathrm{e},n}$.

ticular along with the most common simple moving average and exponential moving average, he analyzed the performance of trading rules based on the linear (or linearly weighted) moving average, and the less commonly used type of moving average as the reverse exponential moving average. Other researchers have proposed to use directional changes in the moving average as the signal. An example of the latter application can be found in [47]. The link between past returns and simple moving averages is clearly described by [48] and is explained by Equation (2.4).

ALGORITHM 3.1.1. Trend-following strategy.

Let N be the number of n trading days in each calendar month.
Given a fast (e.g. short-term) and a slow (e.g. long-term) moving averages, $\mu_{N_1,n}$ and $\mu_{N_2,n}$;
given Ψ the indicator for the trading signal being 1 if we buy and -1 if we sell
if $\mu_{N_1,n-1} < \mu_{N_2,n-1}$ *and* $\mu_{N_1,n} > \mu_{N_2,n}$ **then**
    $\Psi_n = 1$,
end
if $\mu_{N_1,n-1} > \mu_{N_2,n-1}$ *and* $\mu_{N_1,n} < \mu_{N_2,n}$ **then**
    $\Psi_n = -1$,
end

Indicators like the stochastic oscillator shows the strength of momentum and can anticipate future price reversal identifying overbought and oversold levels. The rate of change C is a ratio which moves up or down only if the price is accelerating or decelerating.

$$C_{n,n'} = \frac{S_n}{S_{n-n'}} - 1. \tag{3.1}$$

A simple momentum strategy can be implemented using rate of changes. Having chose an opportune look-back window, we compare current price S_n with the price observed n periods before $S_{n-n'}$.

ALGORITHM 3.1.2. Momentum strategy.

Let N be the number of n trading days in each calendar month.
Given the rate of change $\frac{S_n}{S_{n-n'}} - 1$;
given Ψ the indicator for the trading signal being 1 if we buy and -1 if we sell
if $\frac{S_n}{S_{n-n'}} - 1 > 0$ **then**
    $\Psi_n = 1$,
end
if $\frac{S_n}{S_{n-n'}} - 1 < 0$ **then**
    $\Psi_n = -1$.
end

The algorithm 3.1.2 buys a currency pair if $\Psi_n = 1$; it sells if $\Psi_n = -1$. For example if $\Psi_n = 1$ for the EUR/USD then the algorithm will buy *U.S.* dollar and sell Euros. Another approach to implement momentum strategy is based on the technical analysis. With that trends are identified through line graphs like channels and trend lines, analysis of high and lows and indicators like the average directional index (ADX). The ADX is built from the positive directional indicator (DI^+) and negative directional indicator (DI^-). Algorithm 3.1.3 shows the key steps:

Algorithm 3.1.3. A_{DX}.

Let H_t be the high price of day t and L_t be the low price of day t.
Calculate the move up M^+ as:
$M^+ = H_t - H_{t-1}$.
Calculate the move down M^- as:
$Move^- = L_t - L_{t-1}$.
if $M^+ > M^-$ *and* $M^+ > 0$ **then**
    $D_M^+ = M^+$.
end
else
    $D_M^+ = 0$
end
if $M^+ < M^-$ *and* $M^- > 0$ **then**
    $D_M^- = M^-$.
end
else
    $D_M^- = 0$
end
Calculate $D_I^+ = 100$ times the smoothed moving average of D_M^+ divided by average true range.
Calculate $D_I^- = 100$ times the smoothed moving average of D_M^- divided by average true range.
Calculate $D_X = \frac{D_I^+ - D_I^-}{D_I^+ + D_I^-}$.
Calculate A_{DX} as the smoothed moving average of the absolute value of D_X.

3.2 Carry trade

The UIP holds that the profit of this strategy is zero on average. This is because the interest rate premium (i.e. the gain provided by the interest rate differential) must be perfectly offset by the exchange rate depreciation that is generated by the very same interest rate differential. The fact that carry trade strategies can generate positive average returns is a manifestation of the failure of UIP assumption. This violation of the UIP often referred to as the forward premium puzzle is precisely what makes the carry trade profitable on average and makes the monitoring of the UIP as a fundamental source to find inspiration for designing trading strategies on spot and forward rates. Previously we introduced the forward rate and the UIP at continuous time; below we present the carry trade strategy in discrete time as the strategy is in fact implemented at a discrete frequency[2].

[2]The two notations are identical if T=N and t=n.

ALGORITHM 3.2.1. Carry trade strategy.

Let N be the number of n trading days in each calendar month.
Let r_f be the base or foreign interest rate and r_d be the numeraire or domestic interest rate.
Let m_n be the month number at each time n.
Given Ψ the indicator for the trading signal being 1 if we buy and -1 if we sell;
for $n = 1, 2, \ldots, N$ **do**
  if $m_n \neq m_{n-1}$ **then**
    $\Psi_n = 1$ if $r_{d,n} > r_{f,n}$.
    $\Psi_n = -1$ if $r_{d,n} \leq r_{f,n}$.
  end
  if $m_n = m_{n-1}$ **then**
    $\Psi_n = \Psi_{n-1}$.
  end
end

3.3 Value trade

This strategy is built from the following economic assumption: in the long run, currencies tend to move towards their fair value. Consequently, systematically buying undervalued currencies and selling overvalued currencies is profitable in the medium term.

ALGORITHM 3.3.1. Value trading strategy.

Let $\mathcal{N}$ be the number of n trading days in each calendar month.
Let S_n a given spot currency observed at time t.
Let $I_{PPP,S}$ be the Purchase Power Parity for a given currency pair S.
Let $R_n = \frac{I_{PPP,S,n} - S_n}{S_n}$.
Let z equal to zero for the first n.
Given Ψ the indicator for the trading signal being 1 if we buy and -1 if we sell;
foreach $n \in \mathcal{N}$ **do**
  if $R_n - R_{n-k} \geq 0$ **then**
    $z_n = 0$.
  end
  if $R_n - R_{n-k} < 0$ **then**
    $z_n = 1$.
  end
  if $S_n < I_{PPP,S,n}$ ***and*** $z_n = 1$ **then**
    $\Psi_n = 1$.
  end
  if $S_n > I_{PPP,S,n}$ ***and*** $z_n = 1$ **then**
    $\Psi_n = -1$.
  end
end

3.4 Options trading strategies

The systematic mismatch between forward rate and spot defines the core of the carry trade strategy. If the yield of international assets is systematically different from that of domestic assets while the risk is similar then an arbitrage opportunity would occur. For example, the condition that the interest rate differential in favour of bonds denominated in a certain currency must be equal to the expected exchange rate depreciation of the currency over the period for which the interest differential is expected to persist is called the uncovered interest parity condition. This happens through adjustments of the spot exchange rate or are incorporated by the value of the correspondent forward rate. In practice when an interest rate differential is opens up, there is a jump in the exchange rate that is sufficient to eliminate the interest rate gains. Then over the period for which the interest differential is expected to remain, the exchange rate appreciation gradually unwinds and the exchange rate returns to its expected long run value.

Thus, substantial differences in interest rates across different countries, should be compensated by changes into the exchange rate. In the uncovered interest parity (UIP) model ([49]; [14]; [15]; [18]; [19]), under the assumption of perfect capital mobility, the interest rate differential can be offset by the exchange rate depreciation or appreciation.

The uncovered and the covered interest rate parity are illustrated by equations(2.29,2.30,2.32,2.33). Based on this relationship, the forward rate makes sure that no arbitrage profits are possible: the return on domestic deposits is equal to the return on foreign deposit as the forward rate compensates for differences between the domestic and the foreign interest rates. If investors form expectations rationally then FX rates fluctuate to track the forward rates determined by the interest rates of the corresponding countries.

We consider two strategies that try to profit from the possibility that the forward rate $F(t, T)$ is not an accurate estimator of the future rate $S(T)$ which determines the payout of the option.

The first strategy consists of buying put or selling call options irrespective of the domestic and foreign interest rates. Another possible strategy is carry trade. We buy a put if the foreign interest rate is greater than the domestic one; we buy a call if the the foreign interest rate is smaller than the domestic one. This strategy is very much similar to a carry trade strategy on the spot price through a forward contract. In there we would buy a forward contract if the foreign interest rate is smaller than the domestic one and buy it if the foreign interest rate is smaller than the domestic one.

The UIP holds that the profit of this strategy is zero on average. This is because the interest rate premium (i.e. the gain provided by the interest rate differential) must be perfectly offset by the exchange rate depreciation that is generated by the very same interest rate differential. The fact that carry trade strategies can generate positive average returns is a manifestation of the failure of UIP assumption. This violation of the UIP often referred to as the “forward premium puzzle" is precisely what makes the carry trade profitable on average and makes the monitoring of the UIP as a fundamental source to find inspiration for designing trading strategies on spot and forward rates.

As an example let us assume that the forward rate is higher than the spot rate, i.e. that the interest rate linked to the quote currency is higher than that of the base currency. Under the hypothesis that the future spot $S(T)$ will not significantly move from the spot rate at inception $S(t)$ then going short of the forward rate will provide a profit. The direction of the trade depends on the relationship between domestic and foreign interest rate i.e. the base and the quote interest rates. If the quote currency has higher interest rate the strategy buys puts, when the base currency has higher interest rate the strategy buy calls.

3.5 High-frequency directional strategies

The directional strategy assumes that the price pattern tend to follow some sort of regular behaviour which can be accurately guessed observing the historical data. Trend-following and mean reverting strategies bet on emergence of short trends and on the disappearance of the short term trend respectively. The strategy 3.5.1 is based on the directional-change (DC) event and the run in between which is also called overshoot (OS).This strategy was developed by [50].

[51] show that 12 scaling laws exist in high-frequency foreign exchange data. Of the 12 scaling laws the most important ones in the context of validating trading strategies are

- the average overshoot as a function of the directional change threshold;
- the average time of the directional change as a function of the directional change threshold;
- the average time of the overshoot as a function of the directional change threshold;
- the average directional change tick count as a function of the directional change threshold;
- the average overshoot tick count as a function of the directional change threshold.

The main idea of the strategy is that at high frequency the most important factor to guess right is the direction of the prices. The aim is on dissecting the price curve based on a parameter λ, which defines the price threshold. The direction is determined by the upward and the downward run. A downward run is a period between a downturn event and the next upturn event, while an upward run is a period between an upturn event and the next downturn event. The logic is that downturn and upturn are linked together: a downturn follows an upturn and so on.

This defines the name of the strategy as the emphasis is on the direction of the prices and on the turning points where the price direction changes.

The strategy tries to profit from guessing the right change of the direction and from the fact that the direction does not change immediately after a directional change. During a downward run, the last low price is continuously updated to the minimum of the current market price and the last low price. Similarity, during an upward run, the last high price is continuously updated to the maximum of the current market price and the last high price. In an upward run, a downturn event is an event when the absolute price change between the current market price and the last high price is lower than a given threshold λ. The starting point of a downturn event is a downturn point which is the point at which the price last peaked. The end of a downturn event is a downturn directional-change point which is the point at which the price has dropped from the last downturn point by the threshold. In a downward run, an upturn event is an event when the absolute price change between the current market price and the last low price is higher than a given threshold. This approach is described by the algorithm 3.5.1. Following [50], we set the quantity S_{ext} to the first observation of the price S and the starting trading signal to 1 or buy.

ALGORITHM 3.5.1. Directional change algorithm.

Given Ψ the indicator for the trading signal being 1 if we buy and -1 if we sell;
if Ψ_n=*-1* **then**
    if $S_n > S_{ext}$ **then**
        $S_{ext} = S_n$.
    end
    if $\frac{S_{ext}-S_n}{S_{ext}} \geq \lambda_n$ **then**
        $S_{ext} = S_n$.
        Ψ_n=1.
    end
end
if Ψ_n=*1* **then**
    if $S_n < S_{ext}$ **then**
        $S_{ext} = S_n$.
    end
    if $\frac{S_n-S_{ext}}{S_{ext}} \geq \lambda_n$ **then**
        $S_{ext} = S_n$.
        Ψ_n=-1.
    end
end

3.6 High-frequency momentum strategies

The approach is based on the assumption that prices that are observed at high frequency can exhibit short trends that can be captured by crossovers between moving averages of the observed prices. The moving average $\mu_{s,n}$ is defined by equation(2.3).

The lookback period is found by analysing the pattern of the autocorrelation function. By doing so we assume that the dependency structure embedded in the original time series is measured by the autocorrelation structure of the returns.

ALGORITHM 3.6.1. Trend-following algorithm.

Given Ψ the indicator for the trading signal being 1 if we buy and -1 if we sell;
calculate the moving average of the price: $\mu_{s,n}$ based on lookback parameter n' as
$\mu_{\mathrm{s},n} = \frac{1}{N}\sum_{n'=0}^{N-1} S_{n-n'}$.
if $S_n > \mu_{s,n}$ ***and*** $S_{n-n'} < \mu_{s,n-n'}$ **then**
    Ψ_n= 1,
end
if $S_n < \mu_{s,n}$ ***and*** $S_{n-n'} > \mu_{s,n-n'}$ **then**
    Ψ_n= -1,
end

We label this strategy “Trend-following".

We also considered three variations of the trend-following strategy based on the pattern of the observed spread and based on indicators of overbought and oversold like the Bollinger bands $\mathcal{B}$. Bollinger bands were proposed by Bollinger in the 1980s and are a registered trademark. They simply consist of a moving average $\mu_{s,n}$, an upper band equal to K times the standard deviation above the moving average $\mu_{s,n} - K\sigma$, and a lower band given by K times the standard deviation below the moving average $\mu_{s,n} - K\sigma$.

Overbought signals that the price is above its true value and therefore it should go down. Conversely oversold suggests that price is below the true value and therefore it should go up. It is worth noting that in this context the “true” price value does not refer to the concept of fair value of the asset or to an “economic” value. The true price is determined by the recent price movements. There are many ways to identify overbought and oversold. As an example traders can use indicators provided by the technical analysis like the relative strength index (RSI) developed by Wilder (1978) and the Bollinger bands.

Using these elements we construct the algorithm 3.6.2, which we label “Trend-following Bollinger".

We also test two variations of the trend-following strategy which are illustrated in the appendix **??** and we call them “Simplified trend-following" and “Simplified trend-following Bollinger".

Algorithm 3.6.2. Trend-following and Bollinger bands algorithm.

Given Ψ the indicator for the trading signal being 1 if we buy and -1 if we sell;
calculate the moving average of the price: $\mu_{s,n}$ and the moving volatility $\sigma_{s,n}$ based on lookback parameter n'.
Calculate the Bollinger bands as:
$\mathcal{B}_n^+ = \mu_{s,n} + \sigma_{s,n}$
$\mathcal{B}_n^- = \mu_{s,n}$ - $\sigma_{s,n}$
if $S_n > \mathcal{B}_n^+$ ***and*** $S_{n-n'} < \mathcal{B}_n^-$ **then**
    Ψ_n= 1.
end
if $S_n < \mathcal{B}_n^+$ ***and*** $S_{n-n'} > \mathcal{B}_n^-$ **then**
    Ψ_n= -1.
end

3.7 High-frequency mean reverting strategies

Mean reversion assumes that prices tend to revert to their average over time. Mean reverting and trend-following trading strategies are based on a opposite point of view. The intuition is that when the prices go down much less than their average this could attract investors who would wish to buy at that price. Same argument holds for prices that are above the average: investors can consider them a good price point to sell. Mean reversion implies that the price of the next period is proportional to the current price level or to the difference between the mean price and the current price. Such a behaviour is generally tested through the Augmented Dickey-Fuller test, defined by the following equation

$$\Delta S_n = \alpha + \beta n + \gamma S_{n-1} + \delta_1 \Delta S_{n-1} + \cdots + \delta_{p-1} \Delta S_{n-p+1} + \epsilon_n. \tag{3.2}$$

If the hypothesis that $\gamma = 0$ is rejected then the following price S_n is proportional to the current price and so is not a random walk. Following [52] the stability of financial time series can be investigated through the Hurst exponent. The Hurst exponent allows to study the evolution of the variance of a quantity in relation with time. In particular we are interested to assess if the variance has a linear function of time, like for the geometric random walk or not. Mathematically this is expressed as

$$\sigma_\tau = \left\langle |S_{n+\tau} - S_n|^2 \right\rangle. \tag{3.3}$$

Equation (3.3) is linked to time by the following approximation

$$\left\langle |S_{n+\tau} - S_n|^2 \right\rangle \sim \tau^{2H}, \tag{3.4}$$

where H is the Hurst exponent. As an example for $H = 0.5$ we have

$$\left\langle |S_{n+\tau} - S_n|^2 \right\rangle \sim \tau, \tag{3.5}$$

which is a characteristic of the geometric random walk. Conversely, if $H < 0.5$ the variable tends to revert to its mean, whilst it follows a trending behaviour if $H > 0.5$.

The reversion to the mean can be modelled by the Ornstein−Uhlenbeck stochastic process ([53]), which forces the process to revert to the mean through the following stochastic differential equation, defined in a continuous time

$$dS(t) = \lambda(\mu - S(t))dt + \sigma dW(t), \tag{3.6}$$

where the parameter μ is the mean value; σ is the volatility which is determined by shocks, and λ the rate by which the variable reverts towards the mean.

One application of the Ornstein−Uhlenbeck process is a trading strategy known as pairs trade. The idea behind pairs trading lies in taking an advantage of financial markets that walked away from their previous equilibrium. If two (or more) currency pairs of prices S_1 and S_2 exhibit strong similarity in the long run and if they currently deviate from this equilibrium, a trading strategy can consist of buying one currency pair and/or selling the other. The position is closed when the spread between the two currencies reverts to the long term mean. Examples can be found in [54] and [55] which used this approach to model currency exchange rates and commodity prices, respectively.

Let $\Psi_{1,n}$ and $\Psi_{2,n}$ the trading signal for S_1 and S_2 at time n. We calculate the moving average $\mu_{\mathrm{s},n}$ for S_1 and S_2 based on lookback parameter n': $\mu_{\mathrm{S}_1,n}$ and $\mu_{\mathrm{S}_2,n}$.We also compute the spread ν between two pairs. We fit the spread ν with a Ornstein−Uhlenbeck process and estimate: λ, μ, and σ for equation(3.6). We simulate the prices with the equation(3.6) and obtain the simulated spread ν'_n. Finally we calculate the variation of the spread as: $\widetilde{\nu_n} = |\frac{\nu'_n - \nu_n}{\nu_n}| * 100$. After the calculations we apply the following algorithm.

Algorithm 3.7.1. Mean reversion pair trading.

Given Ψ the indicator for the trading signal being 1 if we buy and -1 if we sell;
let c a threshold of the spread amplitude.
if $S_{1,n} > \mu_{\mathrm{S}_1,n}$ ***and*** $\widetilde{\nu_n} \geq c$ **then**
  $\Psi_{1,n} = 1$ **and** $\Psi_{2,n} = -1$,
end
if $S_{1,n} < \mu_{\mathrm{S}_1,n}$ ***and*** $\widetilde{\nu_n} \geq c$ **then**
  $\Psi_{1,n} = -1$ **and** $\Psi_{2,n} = 1$,
end

The algorithm 3.7.1 assumes to trade both currency pairs. For the sake of simplicity we assume to equally allocate the investment capital over S_1 and S_2. Another possible approach is to determine the size of the position in terms of the estimated spread. This approach is not considered in the presented research.

Another application for the mean reverting approach is to directly trade Ornstein−Uhlenbeck process. This approach, which is less common than the application for the pairs trading, consists of identifying buying and selling prices from extreme moves of the spread. We fit the FX price with a Ornstein−Uhlenbeck process and estimate the quantities λ, μ, and σ for equation(3.6). We simulate the prices with the equation(3.6) and obtain the simulated prices S'_n. The algorithm would buy the currency pair if $S_n > S'_n$ and sells if $S_n < S'_n$. We label this strategy as "Stochastic".

One final implementation of the mean reverting strategy consists of taking an opposite position with respect to the pattern of the most recent prices. For example, we can look at the three previous prices and buy the currency pair S if $S_n > S_{n-1}$ and $S_{n-1} < S_{n-2} < S_{n-3} < S_{n-4}$. We sell if $S_n < S_{n-1}$ and $S_{n-1} > S_{n-2} > S_{n-3} > S_{n-4}$. We label this strategy “Mean reverting".

Algorithm 3.7.2. Mean reverting.

Given Ψ the indicator for the trading signal being 1 if we buy and -1 if we sell;
let S_n be the price of a currency pair at time n.
if $S_n > S_{n-1}$ ***and*** $S_{n-1} < S_{n-2} < S_{n-3} < S_{n-4}$ **then**
    Ψ_n= 1.
end
if $S_n < S_{n-1}$ ***and*** $S_{n-1} > S_{n-2} > S_{n-3} > S_{n-4}$ **then**
    Ψ_n= -1.
end

Chapter 4

Overview of the literature

4.1 Systematic trading strategies

A strategy is a set of investment rules that define how an investor decide to trade a security. The two most frequently categories to define trading strategies are systematic and discretionary. With the discretionary (or fundamental) trading all the decisions about investing and the configurations of the risk management connected to the investment decisions are left to individuals operating at the firm (e.g. traders, structurers, portfolio managers and risk managers). The name is due to the fact that the strategy, its returns and its risk are determined at the trader's discretion. The terms quantitative, systematic, algorithmic and rule-based are often used interchangeably. All the algorithmic strategies are rule-based and systematic but not all the rule-based strategies are algorithmic based. And more, not all algorithmic strategies are quantitative. Systematic trading strategies have two advantages: they can be repeated many times and they are executed by software code. Given that ideas and strategies are translated into software, systematic strategies can be better tested and improved before they are used. This exercise is called validation of the strategy and is normally carried out using historical prices or simulated prices thorough back-testing and simulation exercises. More, systematic traders usually do not have just one algorithm but a range: this allows using better strategies and also facilitates the risk differentiation as the capital can be invested in multiple assets and or by multiple strategies.

FX global macro strategies can be grouped in three main themes: momentum, value and carry. Momentum strategies buy currencies that appreciated in the recent past and short those that depreciated in the recent past. Value strategies buy undervalued currencies and sell overvalued currencies. Carry trade is built on interest rate differentials between currency geographies. Momentum is based on the long-term fluctuation of the asset prices; carry is inspired by risk assessment; value is extracted from assumption relative to economic value of the securities, Asness(2013) and Koijen(2018) [56, 57] studied these three trading strategies and defined them as dynamic factors to differentiate them from the group of traditional factors (equity, credit, and fixed income) and from volatility factors (e.g. buying call and put options and holding till expiry). In particular they studied the relation between returns and two specific factors or effect. A value effect is the ratio between the long-run value of the asset and its current market value; a momentum effect is the relation between returns and the asset's historical performance.

4.2 Trend-following and momentum in the literature

In the literature, trend-following is often used interchangeably with momentum. Some papers define momentum as the investment style, which includes trend-following among others. Others consider trend-following as the investment style which consists of momentum among others. For example, [58] refers to momentum as a class composed of cross-sectional momentum and trend-following. On the other hand, [59] define trend-following as a strategy which can be implemented using either momentum or moving-average rules. In this context, we consider trend-following and momentum as synonyms, which refer to the same trading strategy. Trend-following is very different from cross-sectional momentum, range trading and market timing. Cross-sectional momentum is based on the comparison of trends of different securities. Range trading consists of selling highs and buying lows during a period of ranging prices. Traders adopt a market timing strategy when they try to predict future trends based on forecasts rather than from past data.

The term momentum is borrowed from physics. Prices exhibit momentum when they follow a direction until an event happens which changes their direction. Thus, the existence of trends implies momentum. Trend-following strategies buy high expecting that prices will go higher and sell low expecting that they will go lower. The strategies benefit from markets rising or falling substantially when they can capture the direction of moves in asset prices and profit from the persistence of those moves by taking positions opportunistically. They are more likely to be wrong and to lose money when they fail at getting the direction of the prices right or when the prices cease to follow trends e.g. in a range-bound market.

There exist two main schools of thought about time-series momentum trading. The first approach considers momentum an opportunity that can be exploited when market conditions are favourable. Behavioral finance assumes that momentum is one of the class of phenomena which are determined by the interaction of not fully rational agents in the market. The interaction between fast and automatic and slow and reflective thinking causes flaws and cognitive biases, which can influence humanity's action much more than rational economic decisions (Barberis(2000) [60]). When traders are inclined to make decisions based on how readily available information is to them and accepting the status quo, then trends can emerge or strengthen in the markets. Real-life traders appear to be conditioned by limits to gain profit from arbitrage conditions and by a psychological component which inevitably affects their behavior and their financial choices (Barberis(2000) [60]. Markets can be inefficient if prices and trades are influenced by each agent's cognition and by the mental process, which is dedicated to acquiring knowledge, understanding through thought and experience, and elaborating information available in the market. This can result in overconfidence, overreaction, representative bias, information bias and also in trends (Sewell(2010) [61]. Another point of view assumes that momentum is an anomaly of the market: volatility, arbitrage mechanisms and trading costs are forces that remove momentum conditions in the market. Thus, momentum should be an episodic market anomaly, and any strategy based on it should not bring enduring excess returns. This approach can be found as an example in the efficient market hypothesis (EMH), which states that asset prices fully reflect all existing information in the market (Fama(1970) [62]). A direct implication in fact is that it is impossible to predict future returns and outperform the market. Some other researchers have explained investment mistakes and financial losses from cognitive bias of the investors and traders. Yao(2016) [63] identifies overconfidence as a factor for that investors sell off securities during a down market placing the cash into bank accounts until the market bounces back. Loss aversion thus can bring to the disposition effect i.e. the tendency to sell winning assets too early and holding loosing assets to long. Instead of buying low and selling high one would be buying securities at high price and selling at low price. A vast academic literature proves that time-series momentum has produced exceptional returns in FX market during the last 20 years. Researchers have provided broad-based evidence of persistent excess risk-adjusted returns from momentum trading strategies — across the globe, across time, and across different asset classes ([64, 65, 66]). These findings have supported a general consensus that trading strategies based on price momentum provide a way to generate positive, risk-adjusted excess returns. The first and comprehensive work about momentum investing was published by Jegadeesh(1993) [67]. They show that buying the top 10% of stocks with the highest returns over the past months and simultaneously shorting the 10% worst performing stocks generates excess risk-adjusted returns across subsequent holding periods of similar length. This approach combines together two key ideas that have then originated two distinct trading strategies: the cross-sectional momentum and the time series momentum (also called trend following). This work determined the success of momentum research towards a wide range of asset classes. Carhart(1997) [68] finds that portfolios of mutual funds, constructed by sorting on trailing one-year returns, decrease in monthly excess return nearly monotonically, in line with momentum expectations. Rouwenhorst(1998) Rouwenhorst(1998) [69] demonstrates that stocks in international equity markets exhibit medium-term return continuations. The study covered stocks from Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom. Rouwenhorst1999 [70], in a study of 1700 firms across 20 countries, demonstrates that emerging market stocks exhibit momentum. Momentum became a robust alternative to prevalent rational pricing models across several asset classes like stocks, commodities, corporate bonds and also FX. LeBaron(1999) [71] finds that a simple momentum model creates "unusually large profits in FX series". Okunev(2003) [72] examines the performance of momentum trading strategies in FX; results show that momentum strategies applied on equities and currencies were profitable throughout the 1980s and the 1990s. In particular the long/short strategy of buying the most attractive currency and shorting the least attractive currency obtains average excess returns that are significantly positive. Of particular note, the profitability to momentum strategies in FX markets was particularly strong during the latter half of the nineties. Claude(2006) [73] shows evidence of success for momentum investing in commodity futures. Gorton(2012) [74] extends momentum research on commodities, confirming its existence in futures but also identifying its existence in spot prices. Additional evidence from stock markets in the U.S. Ammann(2010) ([75]), the U.K. Siganos(2007) ([76, 77]), and Switzerland [78] demonstrates that momentum trading profits can be attained by retail investors, even after factoring transaction costs and other pertinent market frictions, such as bid/ask spreads and short-selling constraints. All these papers show that momentum was considered as a key investment strategy before the recent financial crisis for equities, commodities and also FX. Right after the crisis we find more papers that confirm the success of adopting momentum strategies. As an example, Moskowitz(2012) [58] analyses time series momentum in equity index, currency, commodity, and bond futures for 58 liquid instruments, finding positive returns for one to 12 months. Bruder(2011) [79] studies trend filtering methods, distinguishing between linear and nonlinear models as well as univariate and multivariate filtering and testing them to the S&P 500 index. Antonacci(2011) [80] investigates time series momentum applied to stocks, bonds, and real assets, showing that absolute momentum can effectively identify regime change and add significant value. Jostova(2013) [81] shows that momentum profits are significant for non-investment grade corporate bonds. Luu(2012) [82] identifies that for liquid fixed-income assets, such as government bonds, momentum strategies may provide a good risk-return trade-off and a hedge for credit exposure. The excess returns from trading FX on momentum, i.e. buying past winners and selling past losers, can hardly be explained by traditional risk factors (Burnside(2011) [83]). Menkhoff(2012) [84] described the major approaches to explain momentum can be classified as (i) risk-based and characteristics-based explanations, (ii) explanations invoking cognitive biases or informational issues, and (iii) explanations based on transaction costs or other forms of limits to arbitrage. Menkhoff(2012) [84] provide a broad empirical investigation of momentum strategies in the FX market. They find a significant cross-sectional spread in excess returns of up to 10% p.a. between past winner and loser currencies. This spread in excess returns is not explained by traditional risk factors, it is partially explained by transaction costs and shows behaviour consistent with investor's under-and over-reaction. Asness(2013) [56] evaluate momentum in stocks, currencies, and commodities jointly across eight markets and find consistent momentum return premia across all evaluated markets. Daniel(2016) [9] prove that across numerous asset classes, momentum strategies have historically generated high Sharpe ratios and strong positive alphas relative to standard asset pricing models. However, the returns to momentum strategies are negatively skewed: they experience infrequent but strong and persistent strings of negative returns. These momentum crashes occur in "panic" states and following market declines and when market volatility is high, and are contemporaneous with market "rebounds." Baltas(2013) [85] rigorously establishes a relationship between time-series momentum strategies in futures markets and CTAs showing that CTAs follow time-series momentum strategies, by showing that such benchmark strategies have high explanatory power in the time-series of CTA index returns. Hurst(2017) [86] study the performance of trend-following investing across global markets since 1880, finding that trend following has delivered strong positive returns and realized a low correlation to traditional asset classes for more than a century. He analyses trend-following returns through various economic environments and highlight the diversification benefits the strategy has historically provided in equity bear markets. DSouza(2016) [87] studies the performance of time series momentum on stock returns over nearly 100 years. This study documents the significant profitability of momentum strategies in individual stocks in the US markets from 1927 to 2014 and in international markets since 1975. Momentum performs well following both up and down market states. Researchers, practitioners and commentators have recently pointed out that momentum investing experienced a structural break as a result of the recent global financial crisis and that sub-par results from CTAs were in large part triggered by the fact that this trading strategy has become obsolete. As an example, Moskowitz(2012) [58] found that momentum returns vanished during the financial crisis years from 2007 to 2009 and directly after it. Hutchinson(2014) [88, 89] studied the crisis of momentum across various asset classes: equity indices, bond indices, currencies, and commodities. They note that following large positive returns in 2008, the subsequent performance was below its long-term average. Their results show that in an extended period following financial crises average returns from trend-following strategies are on average less than half those earned in no-crisis periods, four years following the start of a financial crisis. They observed that the enduring intervention of governments and central banks in the recent years has helped the formation of unfavorable market conditions for momentum strategies as they caused sharp reversals and the breaking of trends. Georgopoulou(2016) [90] verified that time series momentum for equity and commodity markets is different in developed and emerging markets. Most studies examining momentum strategies halt their analyses either prior to or immediately following the most recent financial crisis. They observe that time series momentum experienced losses in the first stage of the recent financial crisis; then it delivered significant profits for a long period and finally severe losses when the market started to recover. Their view is that during normal market conditions, momentum strategies lead to positions, which are coherent with the preceding period. Market reversals generate losses for momentum strategies, which need time to benefit from the reversal and determine positions that do not conflict with the new market conditions. Boudoukh(2016) [91] also emphasises the importance of the purchase parity power (PPP) in explaining the forward premium puzzle over multiple horizons. Barroso(2015) [92] study the diversification benefit of the optimal currency portfolio that incorporates the currency characteristics into the parametric portfolio policy framework proposed by Brandt(2009) [93]. More authors have recently highlighted the effect of monetary policy on momentum investing: market intervention by central banks can be detrimental because it depresses asset price volatility and caused trendless markets. Dolvin(2016) [12] states that negative alpha on recent periods (i.e. 2007–2015 and 2010–2015) was indeed caused by low volatility: "while we can only speculate at this point, there are at least two possible explanations for this shift. [..] The increasing number of momentum-based mutual funds and ETFs being marketed may bear evidence to this fact. Second, the reduced efficacy of momentum in the most recent period may be due to the unusually low volatility that has persisted for the last few years. Without volatility, it is possible that momentum is unable to shine". On the whole, the evidence of recent data suggests that momentum strategies can fail to perform during specific periods where market and economic conditions are less favourable to momentum strategies but can deliver positive returns in the long term. The rapid succession of favourable and less favourable conditions for momentum strategies in FX after the recent financial crisis can explain the emergence of contradictory results. When periods of high volatility lead to strong market fluctuations and uncertainty around the future, the past becomes a weaker predictor for future prices. These circumstances increase the probability that market indicators may produce conflicting signals. This phenomenon could be indeed an obstacle for the emergence of trends in the market and so determine losses for momentum strategies. Dahlquist(2020) [94] propose to instead trade currencies on the momentum signals of macroeconomic fundamentals and their alternative strategy generates notable alpha after controlling for currency carry, momentum, and value risk premia. Their empirical evidence also suggests that investors' expectations on macroeconomic fundamentals, such as yield differentials, are positively related to their past trends. Moreover, Dahlquist(2017) [95] argues that it is the real exchange rate (RER), not the yield differential, that acts as the dominating predictor of currency returns at longer horizons. The missing risk premium associated with the deviations from long-run PPP implied RER helps to reconcile the puzzling empirical findings of (i) the contemporaneous positive relationship between RER and yield differential, and (ii) the reversed relationship between currency risk premia and yield differential at long horizons ([96]).They find that carry, momentum, and value all contribute to the resulting portfolio's performance in terms of largely increased Sharpe ratio and reduced crash risk.

4.3 Carry trading in the literature

Carry trading has received a great deal of attention in the academic literature as researchers struggle to explain its apparent profitability. The acknowledgment that the UIP does not necessarily hold is not a recent phenomenon in the specialised literature. The first study on the failure of the UIP was provided by Bilson(1981)[97] and Fama(1984) [98]. A number of empirical studies show that exchange rate changes do not compensate for the interest rate differential. Instead, the opposite holds true empirically: high interest rate currencies tend to appreciate while low interest rate currencies tend to depreciate. As a consequence, carry trades form a profitable investment strategy, violate UIP. Froot(1990) [99] reviewed dozens of empirical studies that tested the relationship and found the average coefficient was -0.88. Bansal(2000) [100] showed that the failure of UIP is more significant for industrialized economies, compared with developing economies. Baillie(2006) [101] argue that the existence of the relationship depends on the whether the interest rate gap is positive or negative. A deviation from the UIP relationship will appear when the US interest rate is higher than the local interest rate. Chinn(2005) [17] assessed the UIP relationship for periods of 5 and 10 years for the G7 countries, and found stronger support for the existence of the relationship for long-term interest rates than short-term interest rates of 12 and three months. In their study, they showed that the coefficient of the interest rate spread was positive and closer to 1 than to 0. Coffey(2009) [102], who refer to the 2008 financial crisis, assert that the basic assumption of UIP that the financial markets function effectively enough to prevent arbitrage was invalid in the 2008 financial crisis. Investors during this period therefore preferred to wait in currency positions until the crisis subsided. More recently several authors tried to investigate the reasons for the profitability of the strategy against the assumptions of the economic models. [103] show that carry trade risk premia line up with loadings on the *U.S.* aggregate consumption growth. Menkhoff(2012) [104] explains carry risk premia to covariances with the global stock market and foreign exchange rate volatility shocks. [105] link the empirically documented violation of the UIP to the so-called crash risk, that is, positive interest rate differentials are associated with negative conditional skewness of exchange rate movements. Carry trade losses increase the price of crash risk but lower speculator positions and the probability of a crash. An increase in global risk coincides with reductions in speculator carry positions and carries trade losses. The crash risk can convince speculators to avoid taking too large positions to enforce UIP. The failure of UIP can be determined by slow-moving capital subject to liquidity risk and by a long-run overreaction. As an example when interest rate goes up, in a frictionless and risk-neutral economy, this should attract foreign capital and lead to an immediate appreciation of the domestic currency. Felcser(2014) [106] studied the correlation between carry trade and the so-called concept of delayed overshooting (DOS). This is a feature introduced within the Dornbusch's model ([107]. Based on this model the empirical failure of the UIP could be triggered by shocks to the exchange rate to which the monetary policy reacts. After an unexpected monetary tightening the nominal exchange rate appreciates instantaneously and then gradually depreciates to its new level that is consistent with purchasing power parity. Then the UIP could hold only conditionally: the effect of the shock on the interest rate differential is equal to its effect on the expected change in exchange rate, which jumps according to Dornbusch's model. If the markets react to changes of monetary policy with a delay, the UIP should not hold and carry trade could provide enduring positive returns. Menkhoff(2012) [104] find the source of carry in the volatility risk. They studied the notion of time-varying risk premia ([98] and Engel(1996) [108]) to explain that when investment in currencies with high interest rates delivers low returns during "bad times" for investors, this requires a compensation for higher risk-exposure by investors. They showed that that in general FX volatility is a key driver of risk premia in the cross-section of carry trade returns: high interest rate currencies are negatively related to innovations in global FX volatility and thus deliver low returns in times of unexpected high volatility, when low interest rate currencies provide a hedge by yielding positive returns. Carry trades are the consequent trading strategy derived from the forward premium puzzle, that is the tendency of currencies trading at a positive forward premium (high interest rate) to appreciate rather than depreciate. Chinn(2012) [109] again supported the conclusion that the UIP relationship is valid for long-term interest rates. Gabaix(2015) [110] proposed a novel theory of exchange rate determination where financial markets are imperfect and financiers absorb the imbalances in currency demand resulting from international trade and financial flows. Financiers, however, are financially constraint and in equilibrium the currencies of countries that require capital inflows, external debtor economies, have high expected returns such that financiers are compensated for bearing currency risk. In this model, capital flows drive both the size and the composition of financiers' balance sheets and, hence, determine both the level and dynamics of exchange rates. As a result, the risk-bearing capacity of financiers weakens when the variance of future imbalances rise. This causes immediate currency depreciation and an expected future currency appreciation such that financiers have greater incentives to lend to external debtor countries. An increase in the variance of future imbalances corresponds to tighter financial constraints and, hence, positive shocks to the dispersion of current account forecasts should be associated with negative carry trade returns, and vice versa. DellaCorte(2016) [111] explained positive carry risk premia from global imbalances in terms of net foreign asset. They showed that buying (selling) the currencies of extreme net debtor (creditor) countries with the highest (lowest) propensity to issue foreign currency denominated liabilities generates excess returns that are related to but different from those arising from a strategy that purely captures the interest rate differentials.In a recent comprehensive study, Engel(2016) [96] reviews articles addressing UIP, and discusses the apparent contradiction between the UIP theory and the empirical findings. According to these studies, the exchange rate of countries with a high interest rate tends to be revalued more than according to the interest rate spreads based on the UIP model. He also found, as found in other studies, that the real exchange rate converges to the UIP relationship over time. Engel(2016) tested the UIP on six leading economies (Canada, France, Germany, Italy, Japan, and the UK), in 1979-2009 in comparison with the US. The study showed that the exchange rate risk plays an important role in explaining this contradiction. He includes liquidity of assets as a factor that can explain his findings with respect to the UIP relationship. DellaCorte(2019) [112] reveal a strong relationship between carry trade risk premia and macroeconomic uncertainty. They found strong empirical evidence that this is the case as investment currencies deliver low returns whereas funding currencies offer a hedge when current account forecast dispersion is unexpectedly high. The UIP under these assumptions would hold as the exchange rate should depreciate. However, capital only arrives slowly such that the exchange rate only appreciates gradually, occasionally disrupted by sudden depreciation as speculative capital is withdrawn. Ready(2017) [113] linked the emergence of carry trade opportunities to imbalances in commercial trades between countries. Countries that specialize in exporting basic commodities, such as Australia or New Zealand, tend to have high interest rates. Conversely, countries that import most of the basic input goods and export finished consumption goods, such as Japan or Switzerland, have low interest rates on average. These differences in interest rates do not translate into depreciation of commodity currencies on average; rather, they constitute positive average returns, giving rise to a carry trade-type strategy. Countries that specialize in exporting basic goods such as raw commodities tend to exhibit high interest rates whereas countries primarily exporting finished goods have lower interest rates on average; thus, currency risk premia could be also based on technological differences between countries. A recent paper by Fratzscher(2015) [114] study the relationship between carry trade and intervention of central banks. The hypothesis is that the interventions of central banks are driven by the same common, systematic factor underlying carry trades, which they call "systematic intervention". Central banks appear to trade against carry (and momentum) in calm market periods, whereas in bad times there is systematic intervention in support of carry, momentum, and especially the US dollar. In essence, the "leaning against the wind" nature of intervention activities curbs carry and momentum profits during good times, but helps reducing the carry losses in bad times, effectively smoothing fluctuations in carry returns. Favourable conditions for carry trade for example could emerge by the following scenario: central banks of high interest rate countries buy their currencies during bad times (when these currencies typically depreciate strongly) and central banks of low interest rate countries sell their currencies during bad times (when these currencies typically appreciate strongly). In summary the review of the academic research showed that for an large part of the literature the existence of the UIP relationship, especially for the short run, is not supported by empirical evidence. A key reasons for that could be the existence of what we call “sand in wheels”: the complexity of trading goods and services on international markets has the effect that changes of the exchange rates do not have a large impact upon net exports. On the other hand the volatility of exchange rates in the markets is a reason for exporters to not adjust their prices based on FX fluctuations unless these changes are permanent. These constraints limit the applicability of the MF model and of the UIP and the PPP and therefore can open opportunities for global macro traders.

Historically the origin of carry trading is linked to the dissolution of the Bretton Woods system of monetary management system between 1968 and 1973. In August 1971, U.S. President Richard Nixon announced the suspension of the dollar's convertibility into gold: the currencies of the world's developed countries were free to float against each other again. The collapse of the that monetary system allowed developed economies to choose any form of exchange arrangement they wish except pegging their currency to gold. As the International Monetary Fund (IMF) notes on their web section dedicated to the history of FX, the end of Bretton Woods systen reshaped the FX market allowing the currencies to float freely, pegging to other currency, adopting the currency of another country, participating in a currency bloc, or forming part of a monetary union. Free exchanges rates are an important economic variable whose fluctuations have been interpreted by various models. With regards to carry trade key models are the Mundell Fleming model ([115]) and the monetary model. Carry trade opportunities appear when fundamental assumptions of these economic models do not hold in the empirical evidence. The carry trade consists of selling low interest rate currencies (funding currencies) and investing in high interest rate currencies (investment currencies" or lending currencies). Its name descends from the fact that the strategy tries to exploit the difference between higher yielding vs. lower yielding currencies. An example of carry trade involves buying currencies with the highest short-term interest rates and selling currencies with the lowest short-term interest rates. Compared to momentum, carry trading is intrinsically cross-sectional. It is also considered as a 'slope' factor in exchange rates. High interest rate currencies load more on this slope factor than low interest rate currencies. According with economic free exchanges rates of developed countries were supposed to fluctuate based on key economic variables as the domestic and foreign country interest rate and their inflation rate. The Mundell-Fleming (MF) was built by Robert Mundell and Marcus Fleming independently in 1962 and 1963. The model is a generalisation of the IS-LM model, or Hicks–Hansen model ([116]), which studies the relationship between investment and saving (IS) with "liquidity and money in a closed economy. Within the context of FX carry trading the MF model is important as it considers the determination of the exchange rate and how the exchange rate affects imports and exports. The MF can be summarised by a set of equilibrium equations. Let y be the aggregate output and y^d the aggregate demand; the goods market equilibrium condition holds that $y^d = y$. The aggregate demand is determined by the domestic absorption and by the trade balance. Let c be the , I the planned investment, g the public spending,t the taxation regime, i the domestic interest rate, w the internal wealth, x the export of goods and services and m the import of goods and services. The equation for the expenditure is given by: $y = c(y, t, r, w) + I(i) + g + x - m$. The balance of trade is equal to $x - m$. Assuming that the level of export is exogenous i.e. $x = \overline{x}$ and that the level of import is determined by the marginal propensity to import and by the internal demand, the balance of trade is given by: $\overline{x} - m_y y$. The internal consumption can be expressed as linear combination of an intercept c_0, the marginal propensity to consume c_y and the disposable income $(y - t_y y)$ obtaining. Substituting the equation of the balance trade and that of the internal consumption in the equation of the aggregate output gives: $y = c_0 + c_y(y - t_y y) + I + g + \overline{x} - m_y y$. This equation can be modified by solving in terms of the output y and by taking the propensity to save as $1 - c_y$: $y = \frac{1}{s_y + c_y t + m_y}(c_0 + I + g + \overline{x})$. This equilibrium condition links the planned non-consumption of income and saving $(s_y + c_y t + m_y) \times y$ with the additions to investment, government spending and exports $c_0 + I + g + \overline{x}$. The equilibrium condition can also be expressed in terms of financial balances. The following condition holds at the equilibrium:the sum of the private sector financial balance and the government financial balance is equal to the trade balance, In formula this is: $(s_y y^{disp} - c_0 - I) + (t_y y - g) = (\overline{x} - m_y y)$, where $y_{disp} = (1 - t_y)y$ is the disposable income as function of the marginal taxation. The MF links monetary policies, fiscal policies, fluctuations of exchange rates with the expectations of future values of the spot rates. Central banks can modify (loose) their monetary policy by changing the interest that they set for the economy. A loose monetary policy means lower interest rate; whereas a tighter monetary policy requires higher interest rates. Lower interest rate implies cheaper money to borrow for investors and thus more borrowing i.e. this provides (or should provide) a stimulus for the domestic economy. High interest rates determines less borrowing and is often adopted to control or reduce the domestic inflation. The equations of the model can be used to assess the effects on the exchange rates when interest rates are pushed in the same direction as opposed to opposing policies. As an example the combination of loose monetary policy and expansion in the fiscal policies move the exchange rate in a clear direction. On the other hand loose monetary policy and loose fiscal policy can imply uncertain move of the FX. If monetary policy is loosened, the exchange rate tend to fall because foreign investors do not want to lend when they get a bad return on capital. When fiscal policy is loosened the effect of these economic stimuli will lead to higher interest rates. A tighter fiscal policy tends to weaken domestic demand, which reduces the demand for money, and then reducing interest rates. This would determine a capital outflow, which reduces the exchange rate. And this raises net exports and offsets the fall in domestic demand. A monetary expansion increases the downward pressure upon interest rates, thus forcing the exchange rate down further, which boosts output.

4.4 Value strategy in the literature

The assumptions of the PPP are central for the value trading factor. PPP theory states that price differences between countries should narrow over time by the exchange rate movements or by different rates of inflation which also has some implications on exchange rate movements. Moreover the evidence from several studies suggests that the parity could not hold between countries where the gross domestic product (GDP) per capita is very different. Most notable works on the PPP are Taylor(2004) [117], Abuaf(1990) [118], Fraser(1991) [119], Mark(1995) [120], Lothian(1996) [121], Taylor(2001) [122], Sarno(2004) [123];,Coakley(2005) [124],Sideris(2006) [125], Sarno(2008) [126] and Yotopoulos(200 [127]. The long-run PPP is not confirmed by empirical studies like Rogoff(1996) [128] and Sarno(2002) [129]. Menkhoff(2017) [130] showed that trading currency valuation derived from real exchange rates can provide FX excess returns. Similar to other global factors also value originates from cross-country differences in macroeconomic fundamentals; differently from momentum and carry, risk premia originated by value strategies are fairly static over time. This is because the price differences between countries fluctuate slower than other macroeconomic variables. The authors considered the real exchange rate as a key measure of currency valuation. Moreover, fluctuations of real exchange rates and the misalignment between them imply adjustments to the currency fundamental values. In their paper the authors showed that empirical evidence does not seem to support the standard PPP thesis i.e. currencies with a low valuation level appreciate in the future and thus deliver high excess returns. They found that low valuation levels actually predict a significant relative depreciation of the currency, which is just the opposite of the intuition of the PPP. They explained this deviation from the PPP model through the influence provided by the intervention of central banks and by the existence of persistent structural differences across countries: some countries feature persistently high valuation levels and strong real exchange rates; currencies of such countries exhibit low risk premia and tend to experience further nominal appreciations going forward. Aloosh(2018) [131] tested the currency-value factor using a PPP factor return in three steps relative to 28 countries from the OECD for the period from January 1973 to December 2015. These PPPs reflect annual averages of monthly values and vary over the year. The Organisation for Economic Co-operation and Development (OEC) constructs PPP for several geographies and publishes them every year.

4.5 Macroeconomic based strategies

This section investigates a particular group of systematic trading strategies that are extensively adopted by practitioners: the global macro trading strategies. Macroeconomic ("macro") strategies implement trading decisions based on the current observation or the forecast of economic events. An interesting application consists of predicting the changes of asset prices from the changes of economic variables. The academic literature showed particular interest in these strategies for almost forty years. Two distinct opinions have confronted on whether macro models can explain FX price changes. For example, Meese(1983) [132] belong to the first group. They compared the accuracy of time series and structural models with that of random walk to predict exchange rates finding that the latter could have predicted FX with the same accuracy of the predictive models. Berkowitz(2001) [133] tried to predict exchange rate with a set of fundamentals using an error correction models (ECM) finding unsatisfactory predictability from the adopted model. Faust(2003) [134] did not confirm the evidence of predictability of long-horizon exchange rate using economic fundamentals, Obstfeld(2000) [135] used a generalisation of the Mundell-Fleming-Dornbusch ([115]) approach link FX dynamics to monetary and fiscal shocks, terms of trade, differential in interest rates, government spending. Volatile expectations or departures from rationality are likely to account for the failure of exchange rate models. As an example the failure of rational expectations is often blamed for the failure of uncovered interest parity ([108]), while the positive returns obtained by the trend-following strategies violate the efficient markets hypothesis (e.g. Levich(1993) and Neely(1996) [136, 137]). They found that a list of factors including nominal exchange rate change, the deviation from a canonical monetary fundamentals model, the interest rate differential, the net foreign asset position of the US relative to the foreign country in question, the trade balance can produce forecasts that beat random walk predictions. However, the evidence is that model that optimally uses the information in the fundamentals changes often and is consistent with frequent shifts in the parameters. Thus, unstable forecast could be due to instability of FX and poor model selection criteria to predict its fluctuations. Other researchers stressed that FX cannot be accurately predicted by economic fundamentals as other forces take place to influence FX fluctuations, Abhyankar(2005) [138]studied what is considered a major puzzle in international finance: the inability of economic models based on economic and monetary fundamentals to estimate exchange rates more accurately than a simple random walk. Their research suggests that economic fundamentals in fact can explain some of the exchange rate fluctuations. In line with research from Mark(1995), Mark(2001) and Groen(2005) [120, 139, 140] studied the relationship between the nominal exchange rate and monetary fundamentals for US, Canada, Japan and the UK found that the prediction of the exchange rates using the monetary-fundamentals model can yield different results to the one obtained under a random walk model, hinting that monetary-fundamentals model have indeed predictive power in predicting the exchange rate. Bacchetta(2004) [141] argued that the relationship between exchange rate and macro fundamentals is generally unstable and that this unstable relationship develops when structural parameters in the economy are unknown. Their research tried to show such instability is implied by the fact that the relationship between the two is not really driven by quantities but rather by expectations of these quantities. The variability around these expectations can result in uncertainty and resulting in a rational "scapegoat" effects, Sweeney(2009) [142] stressed that the Group- of-Ten (G10) nominal rates are mean-reverting and that this implies some predictability of the exchange rates. In particular mean-reversion models predict exchange rates better than random walks on average. Sarno(2008) [126] considered the hypothesis that the poor forecasting performance of fundamentals with regards to may be due to the fact that the parameters in the estimated equations are unstable. This instability may be rationalized on a number of grounds, including policy regime changes; instabilities in the money demand or purchasing-power-parity equations, or also agents' heterogeneity leading to different responses to macroeconomic developments over time (Schinasi(1989) [143]). Menkhoff(2013) [144] investigated the information content of a set of fundamentals like interest rate differentials, real GDP growth, money growth, real exchange rate. Their work showed that the information contained in macro fundamentals could form basis of a profitable FX investment strategy. In particular the construction a cross-sectional portfolio approach, which selects currency pairs based on differences between corresponding countries, is key to detecting the link between fundamentals and FX excess returns. Similar results were also found by Fratzscher(2012) [145] who tested regressed changes in exchange rates on the macro fundamentals for 12 currency pairs finding evidence of a time- varying relationship between exchange rates and macro fundamentals.

Despite academics and researchers have not yet found a common opinion around the relationship between economic fundamentals and changes of the exchange rates, global macro strategies are largely adopted by hedge funds and Investment banks across various asset classes like equity, fixed income and FX. Macro traders try to profit from macroeconomic imbalances, trends and geopolitical events. Key economic variables define a landscape of interconnected macroeconomic phenomena that are believed to influence fluctuations of financial markets. Macro strategies are designed to embed the interpretation of economic events like interest rates, currency exchange rates; countries gross domestic product (GDP), unemployment rate, inflation rate, monetary policy intervention. Similar to interest rate portfolio managers also FX traders look at global interest rates (e.g. LIBOR, EURIBOR), inflation rates and at the growth of the home economy compared to that of other countries. Interest rate traders and equity traders would implement a macro strategy differently from a FX trader but the type of information that they seek is generally similar. As an example an interest rate trader could trade one debt instrument to another when she observes changes of government debt and expected or realised changes of the interest rates. An exchange rate by definition links two currency areas. Thus, a systematic trader generally does not only look at global macro of one currency. She considers those of the foreign and the domestic currency and their expected evolution. As an example three types of events could trigger an increase in the euro dollar exchange rate: conditions for a stronger euro, conditions for a weaker dollar or both. The interrelations between economies and currencies cannot be ignored. In fact currency traders try to profit from the relative strength of one currency versus another. Macro strategies for FX link the relative strength of one currency versus another in terms of relationship between macroeconomic variables.

4.6 FX trends and fundamentals

The analysis of the Mundell-Fleming model(1963) (MF) ([115, 146]) suggests that the exchange rate can be influenced by a much broader group of factors than the only domestic growth: interest rates, balance of trades, internal demand, fiscal policy and monetary policy to list a few. As an example a trade deficit (e.g. import exceeds export) by definition implies a higher relative demand of foreign currency respect to the domestic currency. If the demand of domestic goods by foreign consumers is less the demand of foreign goods by the internal consumers then the domestic currency can weaken pushed by demand and supply mechanism. A similar logic applies with regards to the investment trade deficit as foreign investors are less likely to buy the domestic currency compared to the amount of foreign currency bought by internal investors. Based on the MF model this component can be written as: $(c_0^f + c_1^f Y^f + I^f) - (c_0^d + c_1^d Y^d + I^d)$ and we can refer to it as demand and supply for the domestic currency. On the other hand the trade balance can be also influenced by the relative value of the domestic on a foreign currency: following the assumption of the MF model, if domestic and foreign goods are similar, then fluctuation of the exchange rate can modify the balance of international trade. A cheaper exchange rate can make the domestic goods more attractive whilst a more expensive exchange can ma them less desirable. Still following the model, given that the aggregate output also depends on the trade balance then a cheaper domestic currency can push the growth of the economy if this is not more than compensated by the increase of the costs of imported goods. The influence of the trade balance on the exchange rate is generally an important factor for the so called commodity-linked currencies. These are currencies of economies that are highly specialised on trading one or more specific commodities (e.g. metals, gas, oil). Commodity-linked currencies can show trends that follow the rise or the fall in commodities prices. The stronger the correlation between the price of the currency and the price of the commodity and the stronger is the effect on trends in the exchange rate implied by rallies in the commodity price.

The monetary divergence between countries can trigger inflow and outflow of investments and thus stimulate trends in FX based on changes of the demand and supply of the currency. As an example, the Norwegian krone (USD/NOK) appreciated substantially from summer 2000 to January 2003. In the same period, the interest rate differential against other countries was high and increasing. Interest rates abroad declined, whereas in Norway, they remained relatively high. This created a stronger demand for the Norwegian krone.

Following Binny in [147], "currency market do not move in a random walk and so it is possible to manage currency exposures actively". Currencies may have a fair value which is the value the market will revert to from short-term adjustments which are triggered by interest rate differentials, economic fundamentals, and government controls ([147]). Sarno (2008) [126] explores the macroeconomic factors that can predispose trends for the exchange rate. The value of a currency is measured in three ways: exchange rates, government debt instruments, and foreign exchange reserves. The exchange rate compares the value of a currency to the currencies of other countries. The exchange rates change every day because currencies are traded on the foreign exchange market. A currency's value depends on many factors like the country's debt levels, the strength of the economy and central bank interest rates. A high yield relative to the domestic treasury notes means low demand of the domestic currency. Vice versa, a low yield corresponds to high demand of the domestic currency. In detail, during the actions of Treasury notes, the demand of those securities can influence the strength of the domestic currency. As an example, if the demand is high the investors pay more than the face value of the securities accepting a lower yield. If the demand is low, the investors pay less than the face value of the notes and receive higher yield.

Excluding other external factors, low demand of the currency implies high yield which at some point triggers higher demand. Similarly, high demand of the currency implies low yield which at some point leads to lower demand. Higher interest rates can strengthen the domestic currency as foreign investors will be motivated to invest in the higher interest rates and thus increasing the demand for domestic currency. Lowering interest rates implies less appetite for investments by foreign investors and therefore less demand for the domestic currency. Increasing the money supply implies that money denominated in the domestic currency is valued less than before. A higher money supply causes higher inflation which further weakens the value of the currency.

James (2003) [64] shows that the currency pairs which historically have not trended are the exchange rates between closely linked economies like EUR/CHF, GBP/USD etc. A healthy and growing economy can appear more appealing to investors who may believe that their investment will increase in value if the currency appreciates. A slowing economy generates the opposite effect; due to a reference weakening currency, investments may lose their value. In an open economy different countries compete to attract foreign investors so that the strengthening (weakening) of foreign economies may strengthen (weaken) the investment of foreign investors and the domestic currency as they bring (move away) capital.

An industry slowdown can cause investors to become wary of the domestic currency. A persistent divergence in the domestic and the foreign aggregate demand may generate a persistent divergence in the in the demand and supply of a currency and therefore in a persistent move of the exchange rate. Persistent divergence in economic across countries may trigger the emergence of trend in the FX market. [148] and [149] study the strength of the *U.S.* dollar, the divergence of the American and the European economies, and the differential of the correspondent interest rates. The divergence of the fundamentals is clearly visible from the 2014 onward: the US dollar strengthened as result of higher domestic interest rate and also the American economy improved compared to that of the Eurozone.

Based on the MF model the monetary policy is another key factor to influence demand and supply for the domestic currency. Increasing the money supply implies that money denominated in the domestic currency is valued less than before. Moreover, a higher money supply can determine higher inflation which by definition weaken further the value of the currency. Higher interest rate can strengthen the domestic currency as foreign investor can be motivated to invest in the higher interest rates and thus increasing the demand of domestic currency. Lowering interest rates implies less appetite for investments by foreign investors and therefore less demand of the domestic currency. Therefore the monetary divergence between countries which can be determined by differential of interest rates can trigger inflow and outflow of investments and thus determine trends in the FX based on changes of the demand and supply of the currency.

Following Harvey(2015) [150] we start from the hypothesis that when the economies of two currency geographies are synchronized the forces that can push the currencies to diverge and therefore creating a trend can be subdued. As a consequence the correspondent exchange rate can follow range-bounding patterns rather than trends for a long period of time. These authors stated trends tend to occur when there is a sustained divergence between economies. As a proof Harvey(2015) [150] shows the evolution of the dollar index over the last 40 years in comparison with the GDP growth of the *U.S.* and that of the rest of the world. The dollar index exhibits stronger uptrend (downtrend) when the GDP grew more (less) than that of the rest of the world. This hypothesis surely appears sound (at least with regards to the example provided relative to the euro dollar rate). Ricci(2013) [148] and Nozaki(2010) [149] reached similar conclusions.

4.7 High-frequency trading strategies

High-frequency trading (HFT) is a style of investment that consists of buying and selling assets at extremely low latency. Latency is the time needed to receive trading instructions. The instructions are determined by algorithms which are designed to quickly process huge amount of data. HFT strategies are based on high number of orders, rapid order cancellation and do not require significant positions open at the end of the trading day. The holding periods are generally short or very short and deployed using low latency approach. Some practitioners also highlight one further characteristic of HFT: its technological complexity ([151]). HFT strategies can be grouped in two main categories: market making and opportunistic strategies ([152]). The first group consists of liquidity provision strategies: new information implies new bid and offer prices. Liquidity providers must react as fast as possible and incorporating the new information into new prices. The source of income of liquidity provision strategy is essentially the spread between bid and ask prices ([153]) and [154]). The group of the opportunistic strategies can be based on the statistical arbitrage approach which tries to exploit market inefficiencies e.g. prices or quotes of similar financial securities. The arbitrage consists on the fact that traders firstly estimate the fair price of the security and then sell the security that appears to them more expensive and buy the one that is cheaper. Another group of opportunistic strategies is composed by the so called trend-following or momentum strategies. These strategies are designed to gain profits by betting on changes of the prices as new information is available. Such a change of the price can determine a short-term movement.

4.8 Forecasting with recurrent neural networks

A recurrent neural network (RNN) is any network whose neurons send feedback signals to each other [155]. Recurrent neural networks (RNNs) are the building blocks of modern sequential learning, which permit the information processed by the network to persist. RNNs use recurrent layers to capture non-linear temporal dependencies with a relatively small number of parameters [156]. Vejendla 2013 [157] apply RNN to forecast S&P500, DJIA, NYSE and NASDAQ indexes. Shotaro 2018 [158] uses a sequential learning model for prediction of a single stock price with corporate action event information and macro-economic indices using a LTSM-RNN method. Chen 2018 [159] applies a RNN model to predict the price of the Shanghai-Shenzhen 300 Stock Index. Fischer 2018 [160] apples LSTM networks for predicting out-of-sample directional movements for the constituent stocks of the S&P500. Notable empirical studies on the application of recurrent neural networks to prediction from financial time series data such as historical limit order book and price history can be found in [161], [162], [163]. Sirignano and Cont (2019) [164] show that combining networks and technical indicators improves the performance on intra-day stock data. Long Short Term Memory networks are a special type of RNN, introduced by Hochreiter Schmidhuber (1997) [165].

Chapter 5

Data

5.1 Systematic strategies

The focus of this section is to test the performance of time-series momentum and in particular trend-following strategies over almost 30 years of daily prices. We look at the most traded currency pairs, i.e. G10, G20 and emerging countries. Particular interest is on performance of the trading strategy during the financial crisis and on the most recent years. We extracted a sample of daily prices (mid, bid and ask) for G10, G20, emerging markets (EM) currencies. The data is extracted from Thompson Reuters. We focus on the most traded currencies. The Triennial Central Bank survey of FX is a precious source to find the most liquid currencies. Figure 5.1 shows the most recent Triennial Central Bank FX survey publised by the Triennial(2016) report [166].

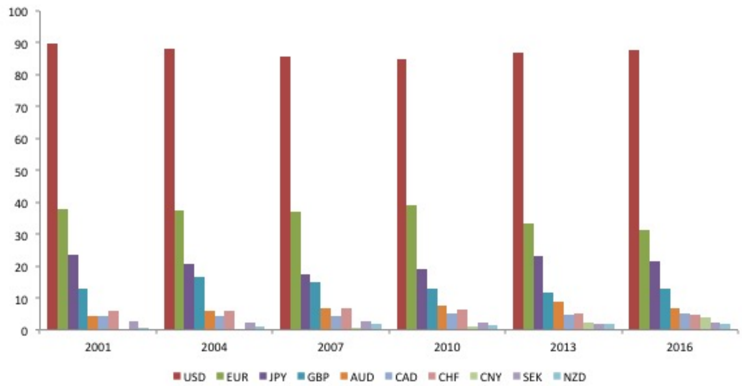


FIG. 5.1: Currency distribution of OTC foreign exchange turnover - Triennial Central Bank Survey of foreign exchange and OTC derivatives markets in 2016

We extract prices relative to the currency pairs reported in table 5.1, table 5.2, and table 5.3.

The time series are recorded up to the first week of August 2017. The length of historical data is not generally the same for the currency pairs. G10 FX rates start from 16/10/1989; G20 FX rates from 21/12/1992 with the exception of USD/CNY

TABLE 5.1: USD G10 and G20.

G10		G20	
EUR/USD	Euro vs. US Dollar	USD/ARS	US Dollar vs. Argentinian Peso
USD/JPY	US Dollar vs. Japanese Yen	USD/BRL	US Dollar vs. Brazilian Real
GBP/USD	British Pound vs. US Dollar	USD/CNY	US Dollar vs. Chinese Yuan
USD/CHF	US Dollar vs. Swiss Franc	USD/INR	US Dollar vs. Indian Rupee
AUD/USD	Australian Dollar vs. US Dollar	USD/IDR	US Dollar vs. Indonesian Rupiah
NZD/USD	New Zealand Dollar vs. US Dollar	USD/KRW	US Dollar vs. South Korean Won
USD/CAD	US Dollar vs. Canadian Dollar	USD/MXN	US Dollar vs. Mexican Peso
USD/SEK	US Dollar vs. Swedish Krona	USD/RUB	US Dollar vs. Ruble
USD/NOK	US Dollar vs. Norwegian Krone	USD/ZAR	US Dollar vs. South African Rand
USD/DKK	US Dollar vs. Danish Krone	USD/TRY	US Dollar vs. Turkish Lira

TABLE 5.2: EM and cross-currency pairs.

EM		Cross-currencies and crypto	
USD/CLP	US Dollar vs. Chilean Peso	AUD/NZD	Australian Dollar vs. New Zealand Dolla
USD/CNH	US Dollar vs. Chinese Yuan Offshore	AUD/JPY	Australian Dollar vs. Japanese Yen
USD/COP	US Dollar vs. Colombian Peso	AUD/CNY	Australian Dollar vs. Chinese Yuan
USD/CZK	US Dollar vs. Czech Koruna	AUD/CNH	Australian Dollar vs. Chinese Yuan Offshore
USD/HUF	US Dollar vs. Hungarian Forint	BTC/USD	Bitcoin vs. US Dollar
USD/ILS	US Dollar vs. Israeli Shekel	ETH/USD	Ethereum vs. US Dollar
USD/PHP	US Dollar vs. Philippine Peso		
USD/PLN	US Dollar vs. Polish Zloty		
USD/SGD	US Dollar vs. Singapore Dollar		
USD/TWD	US Dollar vs. Taiwan New Dollar		

and USD/RUB which start from 06/09/1995 and 05/01/1999, respectively. EM FX rates start from 8/10/1993 excluding USD/CNH and USD/COP which start from 01/10/2010 and 19/04/1994. G10 EUR FX rates start from 04/01/1992; G20 EUR FX rates from 13/01/1999. EM EUR FX rates start from 4/1/1999 except for EUR/CNH that starts from 17/03/2011. The first observation of G10 AUD FX is on 29/11/1996, whilst that of EM AUD FX rates is on 3/5/2013. CHF/JPY starts from 25/7/1996.

5.2 Multi-risk premia

The data used for validating the trading strategies based on macro factors are sourced from Bloomberg. The data consists of the spot rate, the one month forward outright, the one month forward implied yield and the one month currency deposit rate. The forward implied yields are annualised interest rates for the given

TABLE 5.3: EUR G10 and EM.

EUR G10		EUR EM	
EUR/CHF	Euro vs. Swiss Franc	EUR/TRY	Euro vs. Turkish Lira
EUR/GBP	Euro vs. British Pound	EUR/ZAR	Euro vs. South African Rand
EUR/JPY	Euro vs. Japanese Yen	EUR/CNY	Euro vs. Chinese Yuan
EUR/SEK	Euro vs. Swedish Krona	EUR/CNH	Euro vs. Chinese Yuan Offshore
EUR/NOK	Euro vs. Norwegian Krone	EUR/CZK	Euro vs. Czech Koruna
EUR/DKK	Euro vs. Danish Krone	EUR/HUF	Euro vs. Hungarian Forint
		EUR/RUB	Euro vs. Ruble
		EUR/PLN	Euro vs. Polish Zloty

currency and tenor, derived from the covered interest rate parity theorem. They are derived from the prevailing spot and forward rates for the currency versus the USD (or EUR, where applicable) for the corresponding time period, along with the US (or euro) interest rate for the same period' (source: Bloomberg terminal guide). The data is extracted at daily frequency and ranges from 01/10/2001 to 18 July 2018. The list of Bloomberg tickers sourced for this exercise is contained in appendix **??**. For simplicity we show the results relative to G10 and EM currency pairs[1].

5.3 Options

Following [167] we note that the pricing model introduced in previous section requires the following data: spot prices and implied volatility data along with interest rate and forward points. From these we calculate the premium of each option at the inception of the trade. The payout of the option is determined at the expiry date[2]. We extract from Thomson Reuters the underlying exchange rate, the option implied volatility, the forward rate or the forward points, the domestic deposit rate, and the foreign deposit rate. The forward points are the number of basis points that are added to (forward premium) or subtracted from (forward discount) the current spot rate to obtain the forward rate. The transaction costs are includes in terms of bid-ask spreads. We look at data from 01/10/2001 to 18/07/2018 for over 30 currency pairs belonging to the G10[3] and EM[4] groups. Given that we focus on one week ATMF options, we use one week forward exchange rate, one week deposit rates and one week at-the-money implied volatility. The list of Reuters's RICs sourced for this exercise is contained in appendix **??**.

[1]The FX pairs that are part of this group before were included within the G20 currency group. It is industry practice to rename EM as G20 when a large number of EM currency pairs is considered.

[2]For example, the payout of the European ATMF call option at expiry T is equal to $\max(S(T) - F(t,T), 0) - c(t)$.

[3]The G10 currencies are ten of the most heavily traded currencies in the world: the Australian dollar (AUD), the Canadian dollar (CAD), the Euro (EUR), the Japanese Yes (JPY), the New Zealand dollar (NZD), the Norwegian Krone (NOK), the Pound sterling (GBP), the Swedish krona (SEK), the Swiss franc (CHF), and the United States dollar (USD).

[4]These currencies of Emerging market countries.

5.4 High frequency

The data is constituted by high-frequency quoted bid and ask prices relative to a wide set of G10 and EM currency pairs charged on a single-bank platform by a large global bank, the identity of which we keep anonymous for confidentiality purposes. The term quote or indicative quote means the price is offered by the market maker to a client. when a market maker provides an indicative quote to a client, the parties are not obligated to trade the given currency pair at the price or the quantity stated in the quote. Generally counterparties ask for quotes when they do not yet want to specify the amount of currency that they intend to trade. As such the data source that was used for this research does not contain information about traded volumes. Nevertheless, it is a rich source information as: data is recorded at millisecond frequency; it looks at a huge number of currency pairs; it also registers quotes in correspondence of important economic days: the non-farm payroll days relative to year $2014-2015$ and a set of "special" trading days like the Flash Crash, the Brexit referendum, and the intervention of central banks. Non-farm payroll (NFP) is a number of statistics published the first Friday of each month by the *U.S.* Bureau of Labor Statistics within the Employment Situation Report. It contains data relative to number of job created or lost over the previous calendar month all over the *U.S.* relative to any sector except for farm work and unincorporated self-employment, employment by private households, nonprofit organizations and the military and intelligence agencies. In the context of FX trading the release of NFP numbers are a relevant piece of information as they provide an indication of the health of the economy. Traders generally trade the news by comparing the released numbers with the values relative to the previous month and with the forecast of econometric models. Any currency pair that is quoted with respect to the *U.S.* dollar is influenced by the release of the NFP numbers; such an impact on FX is often observed within a ultra short term time frame. FX jumps within seconds of the release of the statistics. Therefore it is meaningful to observe high-frequency quotes during NFP trading days. Figure 5.2 shows the historical data relative to the NFP relative to the last 18 years. The historical data reflect the economic cycle of the American economy: the statistic dropped during the recent financial crisis to the the historical minimum.

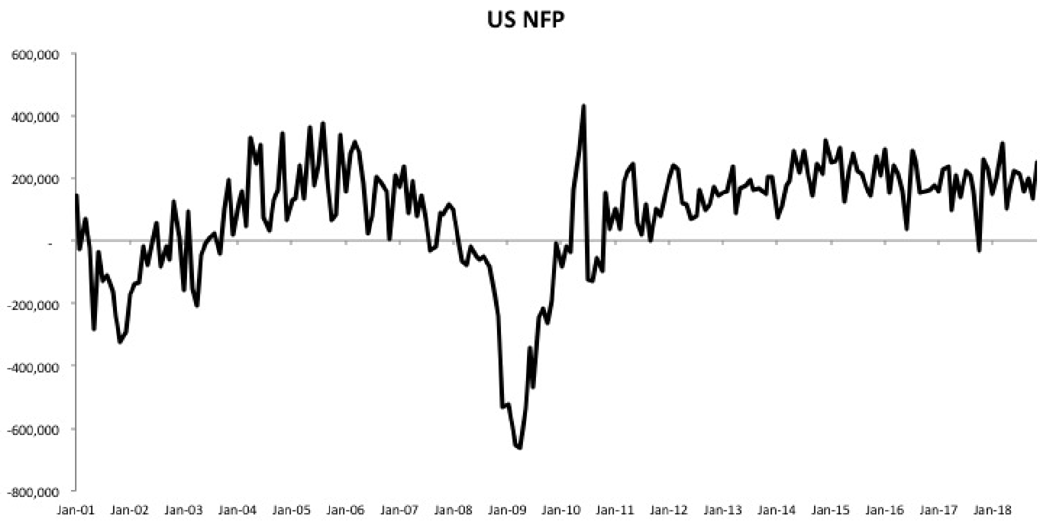


FIG. 5.2: *U.S.* Non farm payrolls historical data.

A very well known property of high-frequency data is the fact that they are irregularly spaced in time. This means that the data points are not observed and recorded based on a certain physical time (e.g. seconds, minutes, hours); instead they are recorded as soon as they are generated by the algorithm. The generation of a data point is triggered by events which do not happen based on physical time. Physical time is replaced by the concept of intrinsic time ([168]). Each tick (i.e. transaction price/quote) is formed at varying time intervals and the frequency of the ticks is determined by the algorithm that has generated them. In order to back-test HFT trading strategies the irregular data points must be reorganised and reshaped based on a defined data design. There exist two different approaches: the data interpolation and the data smoothing. Interpolation is in fact a way to smooth data; but the two approaches achieve very much different outcomes in this context. The first approach consists of homogenising the high-frequency data by means of interpolation ([169] and Engle(2010) [170]). This approach is reasonably simple and can be customised by different interpolation filters. On the other hand it has two drawbacks: the choice of the filter can lead to very much different results. Moreover, Bauwens(2009) [171] argues that some precious information can be lost when ticks are aggregated and interpolated. As an example the volatility of the price (high price volatility vs low volatility) could be excessively smoothed and the difference between high and low number of orders could be ignored. Taking into account price volatility and volume of orders could provide valuable information about the need to avoid taking a position or the opportunity of entering a trade. Both could also have discriminative power into predicting future prices. The second approach is loosely derived from the fractal theory ([172]). This approach looks for empirical patterns in market data ([173]). An empirical pattern is a certain regularity that is observed in the data at different scales: this can be mathematically modelled by scaling laws which connect data to scaling factors. The discovery of the scaling factors could be sufficient to predict future changes of the price with marginal errors. Glattfelder(2011) [51] have shown that 12 scaling laws exist in high-frequency foreign exchange data. Of the 12 scaling laws the most important ones in the context of validating trading strategies are: a) the average overshoot move as a function of the directional change threshold; b) the average time of the directional change as a function of the directional change threshold; c) the average time of the overshoot as a function of the directional change threshold; d) the average directional change tick count as a function of the directional change threshold; e) the average overshoot tick count as a function of the directional change threshold. Modelling the price change over the intrinsic time is done estimating the directional change of the price between tricks. By doing so the observed data is replaced by a coastline of price which are the input of the trading strategy. The shape of the coastline is determined by a directional change λ which determines the duration of a rally or a sell off at high frequency.

In this exercise we sample at different time interval: 15 seconds, 30 seconds, 1 minute, 5 minute. We present the results obtained by sampling the tick using a 15-second physical time interval. We focused on the available currency pairs for which the data is available during normal trading hours e.g. 08:00 AM to 17:30 PM. G20 and EM have more missing values than G10. We preferred to exclude the currency pairs for which an interpolation method is in fact needed to fill gaps of observations at various physical intervals. The intention is to test the strategies on the richest data possible and then testing strategies to fill or build missing observations. This latter investigation is not presented in this research and will be carried our by future works.

We calculate the average spread for each currency pair available in the sample. We average by month and over the whole time series. Results are shown in table 5.4.

We use the average spread to derive the trading costs for our strategies. The costs range among 15% and 20% of the historical spread. For example, for EUR/USD this would correspond to 0.1 basis point.

TABLE 5.4: Spread (basis points) relative to the currency pairs from January to July 2015.

FX	January	February	March	April	May	June	July
EUR/USD	0.49	0.48	0.53	0.66	0.57	0.63	0.56
USD/JPY	44.60	45.07	46.65	60.77	64.30	66.60	60.16
GBP/USD	0.84	0.83	0.94	1.16	1.14	1.08	1.01
USD/CHF	3.54	3.07	1.73	1.78	1.66	1.54	1.46
AUD/USD	0.61	0.65	0.51	0.71	0.73	0.74	0.71
NZD/USD	1.45	1.43	1.21	1.30	1.32	1.33	1.27
USD/CAD	1.17	1.31	1.06	1.24	1.26	1.29	1.32
USD/SEK	45.71	37.31	0.00	0.00	0.00	0.00	0.00
USD/NOK	55.90	37.86	0.00	0.00	0.00	0.00	0.00
USD/DKK	6.94	6.98	0.00	0.00	0.00	0.00	0.00
USD/MXN	25.80	27.44	27.44	25.51	27.12	29.81	27.66
USD/RUB	1718.84	1107.85	825.03	812.14	554.94	536.04	447.20
USD/ZAR	37.16	32.27	40.86	45.33	37.81	37.79	33.14
USD/TRY	6.15	6.66	8.90	9.72	8.57	8.98	6.96

TABLE 5.5: Average spread and trading fees relative to the currency pairs from January to July 2015.

FX	Average spread	Fees
EUR/USD	0.0001	0.00001
USD/JPY	0.0055	0.00100
GBP/USD	0.0001	0.00002
USD/CHF	0.0002	0.00004
AUD/USD	0.0001	0.00001
NZD/USD	0.0001	0.00002
USD/CAD	0.0001	0.00002
USD/SEK	0.0042	0.00080
USD/NOK	0.0047	0.00080
USD/DKK	0.0007	0.00012
USD/MXN	0.0027	0.00050
USD/RUB	0.1413	0.02500
USD/ZAR	0.0035	0.00060
USD/TRY	0.0006	0.00010

Chapter 6

Experiments

6.1 Experiment 1: validation of trend-following

6.1.1 Trading strategy results

We extracted almost 30 years of daily mid, bid and ask prices for the most traded currency pairs from Thompson Reuters. We group the currency pairs using the usual categories: G10, G20 and emerging countries (EM). As an example USD G10 corresponds to the group of currencies in which the USD dollar is base currency like for USD/CHF or quote currency like GBP/USD; whilst the group EUR G10 includes the currencies having the euro as base or quote currency pair. We also look at the cross currencies [1]. The time series are recorded up to the first week of August 2017. The length of historical data is not generally the same for the currency pairs.[2] In order to to produce meaningful results it is important to apply realistic trading costs to the strategy. We deduct five basis points per trade for G10 pairs, except for USD/NOK, USD/SEK, USD/DKK, EUR/NOK, EUR/SEK, and EUR/DKK for which we have used eight basis points, and 15 basis points for EM currency pairs. Another possible approach could be to use historical bid/ask prices but we found out that Reuters spreads are historically too generous and as such would provide less meaningful results. We measure the performance of the strategy using performance metrics like the cumulative returns, annualised returns, Sharpe ratio and maximum drawdown. The Sharpe ratio S_R measures the return of an investment strategy in terms of its embedded risk. It is calculated from the return of the portfolio, dividing it by the standard deviation of the portfolio's return. The maximum drawdown is

[1] In this context, a cross currency is a currency pair that does not include the *U.S.* dollar or the Euro and we include them within the group called "cross".

[2] G10 FX currency pairs start from 16/10/1989; G20 FX currency pairs from 21/12/1992 with the exception of USD/CNY and USD/RUB which start from 06/09/1995 and 05/01/1999, respectively. EM FX currency pairs start from 8/10/1993 excluding USD/CNH and USD/COP which start from 01/10/2010 and 19/04/1994. G10 EUR FX currency pairs start from 04/01/1992; G20 EUR FX currency pairs from 13/01/1999. EM EUR FX currency pairs start from 4/1/1999 except for EUR/CNH that starts from 17/03/2011. The first observation of G10 AUD FX is on 29/11/1996, whilst that of EM AUD FX currency pairs is on 3/5/2013. CHF/JPY starts from 25/7/1996.

the largest drop from a peak to a bottom. It is defined as

$$D_{\max,N} = \sup_{n' \in (0,N)} \left(\sup_{n \in (0,n')} (S_n - S_{n'}) \right) \tag{6.1}$$

and consists of the maximum loss from a market peak to a market trough. It is an important information about capital preservation given that large drawdowns can imply fund redemption. It is worth noting that these metrics are extracted for the whole back-testing dataset and specifically for periods of data of interest. This is done through the process of rebasing the returns. Similar to James(2003) [64] for each currency pair we take into consideration a range of short and long term moving averages of raw prices as input for the trading strategy. The approach works as follows:

1. We implement the strategy varying short and long moving averages from 3 to 70 days and from 71 to 260 days, respectively;

2. At each iteration we backtest the strategy and calculate annualised returns and Sharpe ratio.

3. We combine the results that correspond to pairs of short term and long term moving averages[3] obtaining surfaces of annualised returns and Sharpe ratios.

We measure the performance of the strategy in terms of cumulative returns, annualised returns, Sharpe ratio and maximum drawdown. We apply the approach using the entire time series ans a set of sub-samples[4] This approach allows us to observe the evolution of the strategy through the time. For the sake of clarity in this paper we present results obtained by just one pair of moving averages. The pair is not necessarily the same for different currencies; but it is identical with regards to different sub-samples of data. Our choice goes to pairs that seem to work reasonably well on most all of sub-samples of the historical data. As an example during periods where the strategy does not seem to provide positive returns we do not switch to other moving average pairs that would allow better results. We do so to avoid the so-called data mining bias. Below we show some examples relative to NZD/USD. Figure 6.1, 6.2a, 6.2b, 6.2c, 6.2d, 6.3a, 6.3b, 6.3c, 6.4a, 6.4b, 6.4c, 6.4d show some examples of 3D-surfaces of the annualised returns for EUR/USD, NZD/USD and GBP/USD. Following [64], we note that in those currency pairs which do not trend, there is not much hope of profit regardless of the trend parameters used. On the other hand, even for trending pairs a given combination of the parameters can work better in certain periods than others. We analyse the performance of different parameters through three-dimensional heat maps, which combine the short and the

[3] Our surfaces highlight higher results with a colour spectrum that goes from red to amber, whereas lower results are highlighted with green and blue.

[4] Conditional on data availability, we extract samples relative to the following years: 1989-1999, 2000-2003, 2004-2007, 2008-2009, 2010-2012, and 2013-2017.

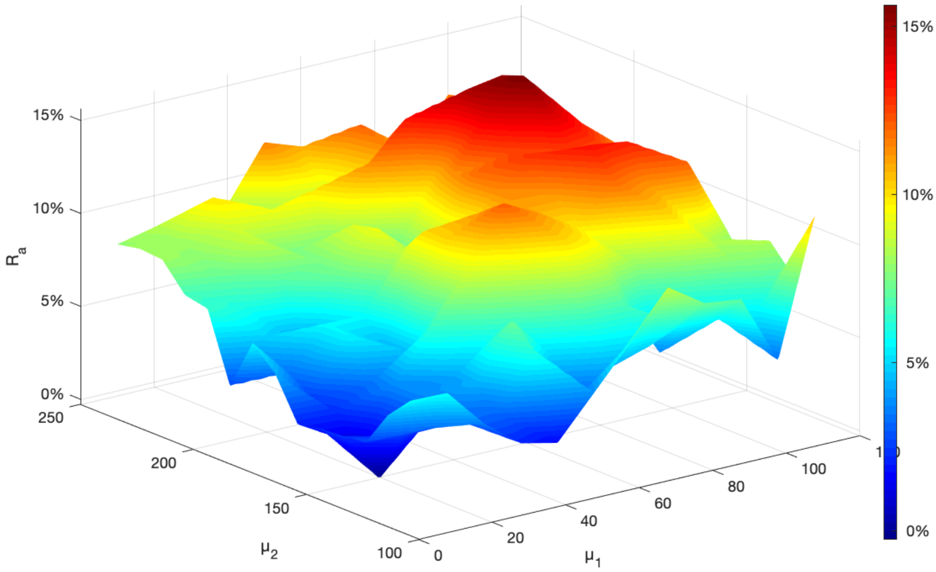
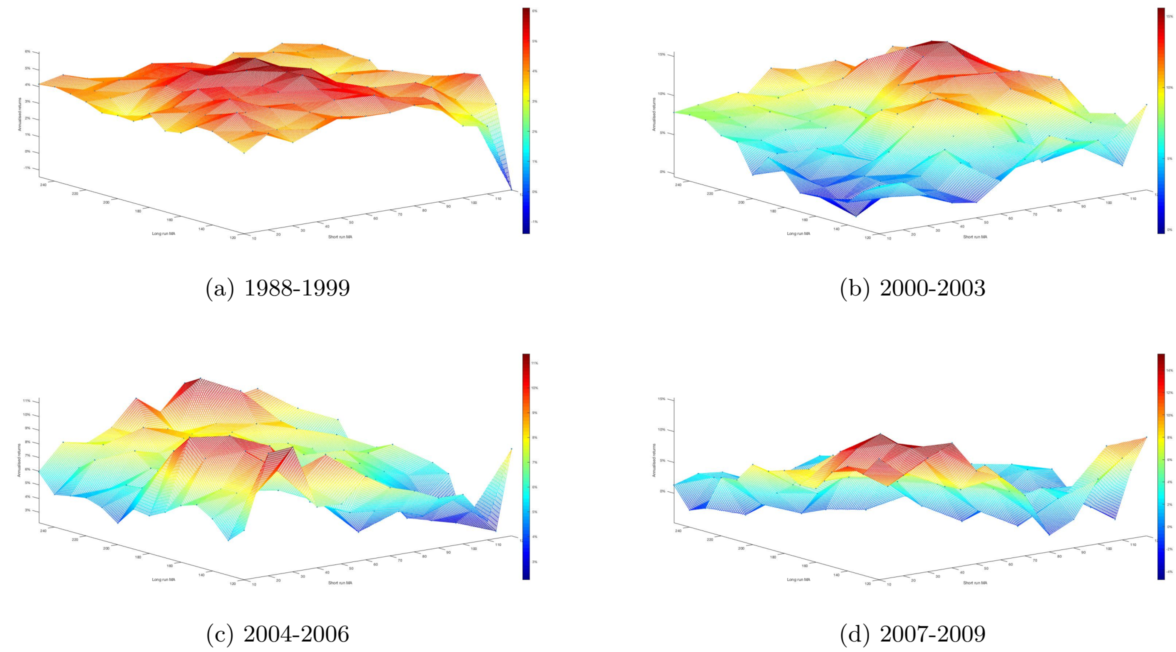


FIG. 6.1: Surface of annualised returns R_a obtained by the trend-following strategy for NZD/USD from 2000 to 2003. For $N_1 < N_2$, the x-axis and the y-axis show different values of the short-term and the long-term moving averages, μ_1 and μ_2, respectively. In this example $N_1 \in [0, 100]$ and $N_2 \in [101, 220]$. The z-axis displays the returns that correspond to the combination of the moving averages used by the strategy. The colours highlight the results from weaker (blue) to stronger (red). It can be noted that some combinations of the moving averages work better than others. For example, long-choosing $70 \leq \mu_1 \leq 100$ and $180 \leq \mu_2 \leq 220$ gives better results than using $5 \leq \mu_1 \leq 70$ and $105 \leq \mu_2 \leq 180$.

long moving averages with their correspondent profit and loss (P/L)[5]. Figure 6.1 as an example shows the annualised returns for various moving average crossovers relative to the period NZD/USD for the period $2000 - 2003$. The performance is illustrated by the red-blue colour spectrum: higher returns are concentrated within red areas, lower returns within blue areas.

The heat maps relative to different periods can be conveniently compared together to show the evolution of the performance of the strategy. For each currency pair, we choose the pair of the trend parameters that work well on the entire back-testing period. These values are illustrated by Table 6.1. Practitioners often do not use just one set of parameters; instead they take a set of moving average crossovers and average the corresponding results. This helps smoothing the returns and adding more stability to the P/L distribution, though it complicates the trading implementation.

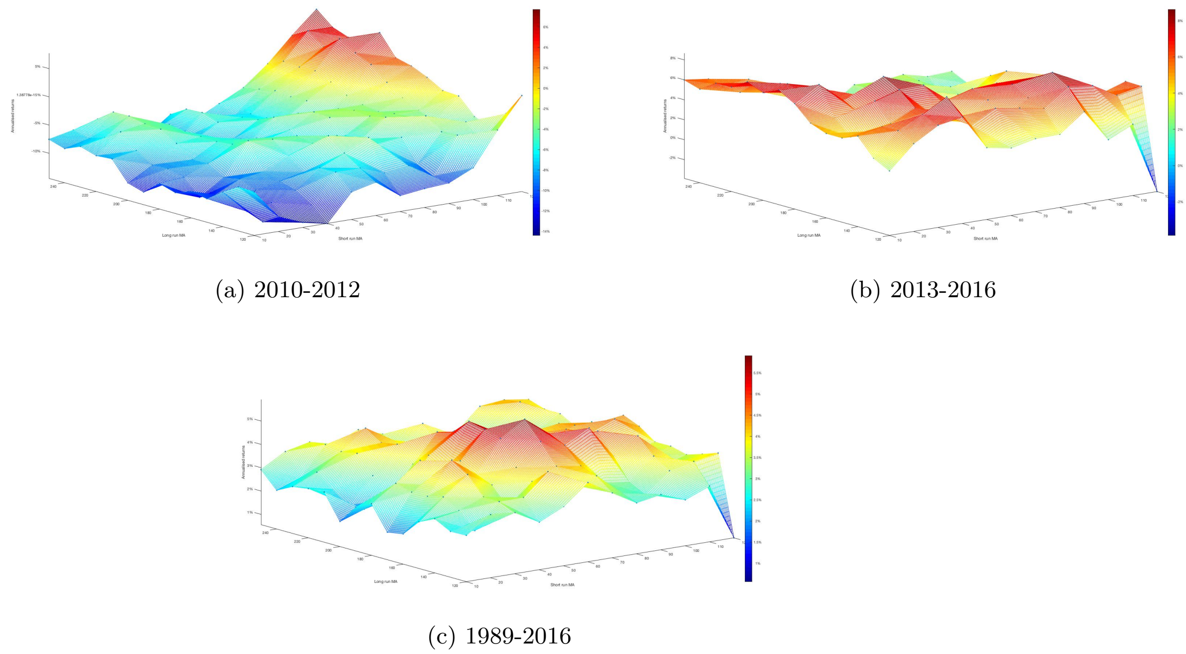
[5]The P/L is measured in terms of cumulative and annualised returns, R_c and R_a, respectively.



(a) 1988-1999 (b) 2000-2003

(c) 2004-2006 (d) 2007-2009

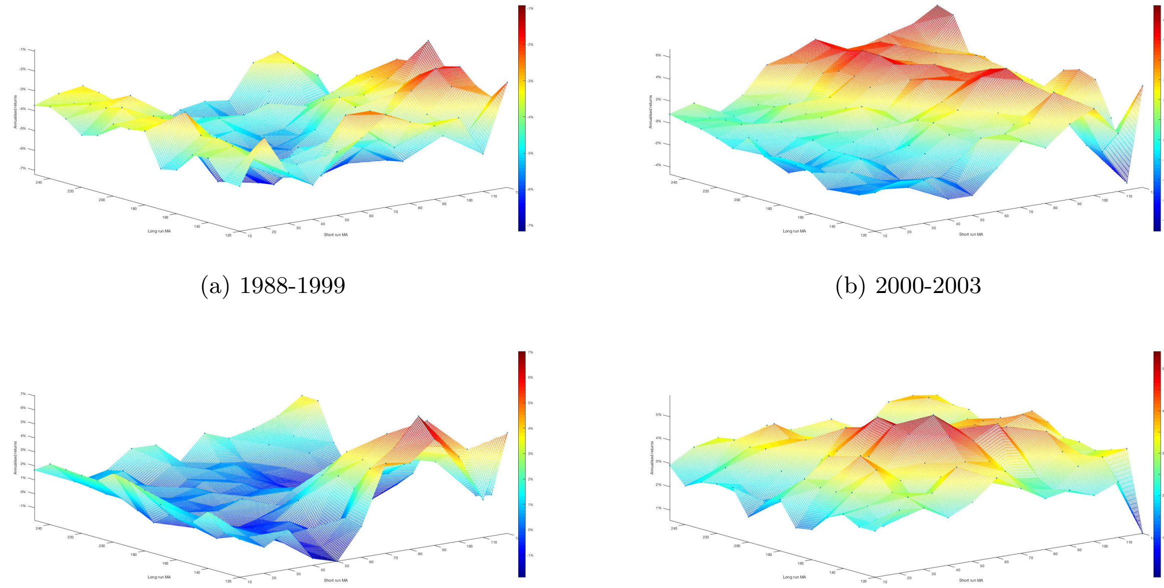
Fig. 6.2: Annualised returns obtained for NZD/USD by a trend following strategy in which long and short moving averages are continuously incremented by 5 days at each iteration which uses data relative to the various periods.



(a) 2010-2012 (b) 2013-2016

(c) 1989-2016

Fig. 6.3: Annualised returns obtained for NZD/USD by a trend following strategy in which long and short moving averages are continuously incremented by 5 days at each iteration which uses data relative to the various periods.



(a) 1988-1999 (b) 2000-2003

(c) 2004-2006 (d) 1989-2016

FIG. 6.4: Annualised returns obtained for GBP/USD by a trend following strategy in which long and short moving averages are continuously incremented by 5 days at each iteration which uses data relative to the various periods.

TABLE 6.1: Short and long-term moving averages μ_{N_1} and μ_{N_2} used in the trend-following strategy.

FX	μ_{N_1}	μ_{N_2}	FX	μ_{N_1}	μ_{N_2}	FX	μ_{N_1}	μ_{N_2}	FX	μ_{N_1}	μ_{N_2}
EUR/USD	70	130	USD/INR	110	160	USD/PHP	40	200	EUR/HUF	30	140
USD/JPY	30	120	USD/IDR	100	150	USD/PLN	70	170	EUR/PLN	50	180
GBP/USD	70	120	USD/KRW	110	180	USD/SGD	10	180	EUR/CNH	100	220
USD/CHF	80	120	USD/MXN	30	200	USD/TWD	10	230	EUR/CNY	30	140
AUD/USD	80	120	USD/RUB	90	160	EUR/CHF	50	180	AUD/NZD	120	170
NZD/USD	70	190	USD/TRY	20	240	EUR/GBP	110	210	AUD/JPY	90	120
USD/CAD	70	190	USD/ZAR	60	160	EUR/JPY	110	140	AUD/CNY	30	130
USD/SEK	90	140	USD/CLP	100	210	EUR/SEK	110	140	AUD/CNH	30	130
USD/NOK	90	150	USD/CNH	20	200	EUR/NOK	70	200	BTC/USD	3	30
USD/DKK	70	140	USD/COP	20	140	EUR/RUB	90	200	ETH/USD	3	30
USD/ARS	110	200	USD/CZK	100	220	EUR/TRY	50	120			
USD/BRL	30	140	USD/HUF	70	160	EUR/ZAR	110	140			
USD/CNY	10	120	USD/ILS	40	220	EUR/CZK	100	220			

In Figure 6.5, we graph the returns obtained using the model since 1990 relative to the G10 and G20 currency groups. We tabulate the average returns in Table 6.2. Table 6.3 shows the average maximum drawdown. Charts relative to the other currency groups are contained in the supplementary material along with the tables of results relative to each individual currency pair expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

Our results confirm the findings of [64] who validated the strategy on a back-testing dataset that ranged from 1990 to 2005. Among the G10 group, historically, long-term trends are displayed in currency pairs which represent the exchange rates between disparate economies, like USD/JPY, EUR/USD, and NZD/USD. Those currency pairs that have not trended are the exchange rates between closely linked economies like EUR/CHF, GBP/USD. Our results confirm those findings. We also note that USD/CAD displays trends. US is the largest trading partner of Canada, but USD/CAD is also driven by the price of commodities like petroleum, minerals, wood products and grains; the; trade flows from those exports can influence investor sentiment. Within the G20 group, long-term trends are displayed in USD/BRL, USD/TRY and USD/MXN; within the EM group, in USD/HUF, USD/COP and USD/TWD.

[64] noted that the performance of the model made no significant profit since 2001 on average in a variety of G10 currency pairs. Our results indeed show that the results are quite lacklustre for NZD/USD, EUR/USD and USD/JPY over the years 2001–2003. Since 2004 long-term trends emerge again for NZD/USD, USD/SEK; EUR/USD, USD/CAD and AUD/USD. Within the G20 and the EM groups, long-term trends are displayed on pairs like USD/ARS, USD/BRL, USD/TRY, USD/ZAR, EUR/TRY and USD/CZK, USD/COP for the G20 and EM groups, respectively. It is worth noting that the results of the trend-following strategy are less positive than those obtained during the previous decade of the data.

Trend-following struggled during the financial crisis. During the years 2007–2013 only a few currency pairs display trends - like USD/SEK, USD/GBP and USD/AUD, EUR/TRY and USD/ARS, USD/INR and USD/IDR - and the corresponding returns from the strategy are much less than the previous period. Even the currencies that provided the strongest results in the previous periods have negative P/L. As an

Table 6.2: Average annualised returns for the various currency groups by interval of time.

Period	G10	G20	EM	EUR G10	EUR G20	EUR EM	CROSS
1991-1995	−1.4%	59.2%	1.8%				
1996-2000	−0.1%	18.3%	6.2%				0.6%
2001-2006	3.6%	9.2%	2.2%	0.3%	4.0%	2.5%	−2.0%
2007-2013	2.2%	4.1%	−0.3%	2.1%	2.7%	0.3%	0.6%
2014-2015	7.3%	12.4%	7.0%	−1.3%	5.3%	3.7%	−5.8%
2016-2017	−2.3%	−10.4%	−2.3%	0.0%	−0.7%	1.1%	−3.6%

TABLE 6.3: Average maximum drawdown by intervals of time by groups of currency pairs.

Period	G10	G20	EM	EUR G10	EUR G20	EUR EM	CROSS
1991-1995	−11.2%	−6.9%	−7.3%				
1996-2000	−9.0%	−9.4%	−7.4%				−13.7%
2001-2006	−9.8%	−10.8%	−8.8%	−6.7%	−14.5%	−7.4%	−10.9%
2007-2013	−12.2%	−10.3%	−11.9%	−8.9%	−12.1%	−9.1%	−14.9%
2014-2015	−8.4%	−9.8%	−7.0%	−8.7%	−19.5%	−6.3%	−12.5%
2016-2017	−9.5%	−10.4%	−7.5%	−6.6%	−14.5%	−4.0%	−9.4%

example NZD/USD and AUD/USD trended strongly during 2000–2006, whilst they do not trend at all in years 2007–2017. Results are very negative for USD/TRY and USD/KRW too. USD/HUF and USD/PLN had largest losses during this period.

The strategy struggled for all G10 EUR crosses in particular in 2009. Results were poor during years 2008–2012 for EUR/JPY and over 2011–2013 for EUR/SEK. EUR/RUB and EUR/ZAR have their largest losses over the interval 2008–2012. EUR/HUF and EUR/PLN have negative returns over the period 2007–2017. CHF/JPY results in losses during the years 2007–2012, whilst the AUD cross currencies had negative results for many years during the 2007–2013 interval. The decline is also reflected in the distribution of the maximum drawdown, which was very much affected by the financial crisis. It peaks during the financial crisis 2007–2013 compared to pre-crisis values.

Long-term trends are displayed during the years 2014 and 2015. There was strong directional moves in almost all currency pairs up until the end of the 2015. Among the G10 group, the model produces the largest profit for EUR/USD, USD/CHF, USD/CAD, USD/SEK, USD/NOK, USD/DKK, and EUR/GBP. Trends are displayed also in USD/ARS, USD/BRL, USD/MXN, USD/TRY, USD/ZAR, and EUR/ZAR and USD/CLP, USD/HUF, USD/COP, USD/PLN, and EUR/CNH. During 2016 also EUR/USD, GBP/USD, AUD/USD and USD/CAD exhibit trends but they are not long enough; trends are in fact alternated by regimes of ranging patterns.

Focusing on the last two years of the sample, a decline in profitability is clearly marked: these were two extremely poor years for trend-followers. Out of the last ten years, eight have resulted in losses or reduced profits for G10, G20 and EM. The emergence of long-term trends across all pairs was probably influenced by the monetary policy intervention that occurred between 2014 and 2015. The last years results have been particularly horrible, with only a few currencies showing a positive return. During the last years of the sample trends were followed by ranging patterns. EUR/USD during 2017 was exceptionally strong but ranging over 2016. AUD/USD trended up during Q1 2016 but retraced during Q2 and gained again till the end of Q2. It has ranged since then. USD/CAD trended up during Q1 2016 and ranged afterwards. USD/JPY during 2016 was exceptionally strong but the sell signal was not anticipated by the strategy.

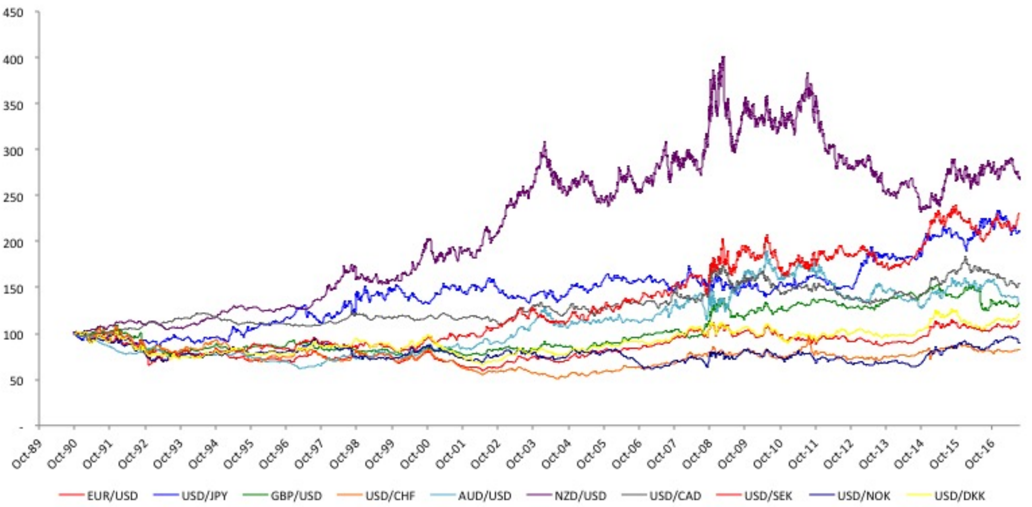


FIG. 6.5: Chart relative to the cumulative returns obtained by the trend-following strategy for G10 currency pairs from 1989 to Q2 2017.

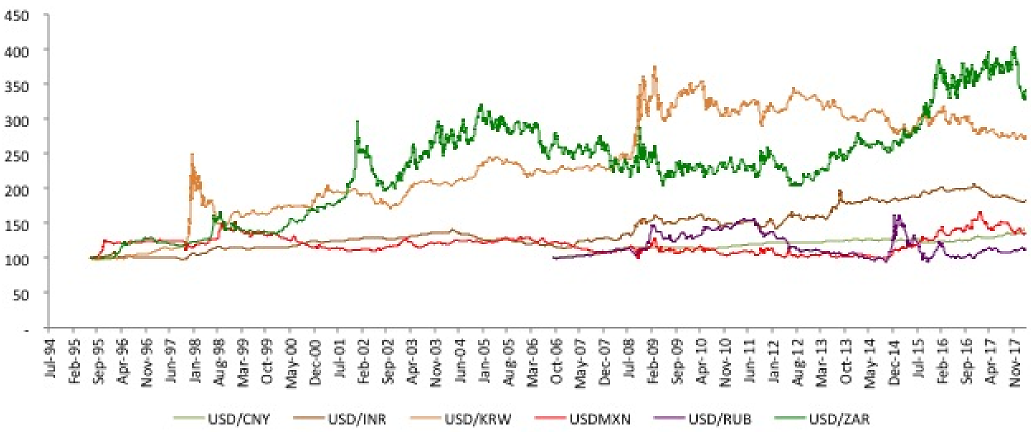


FIG. 6.6: Chart relative to the cumulative returns obtained by the trend-following strategy for 7 G20 currency pairs from 1989 to Q2 2017.

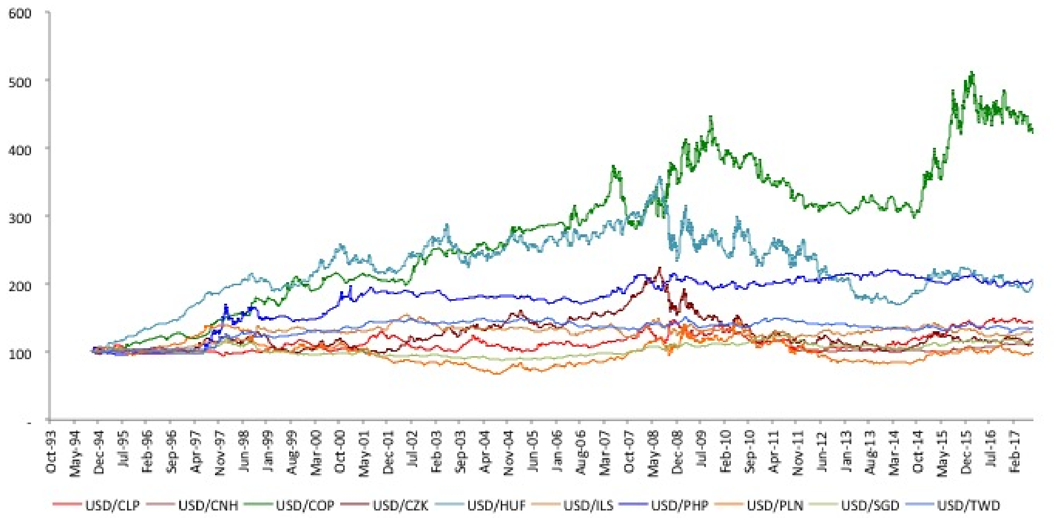
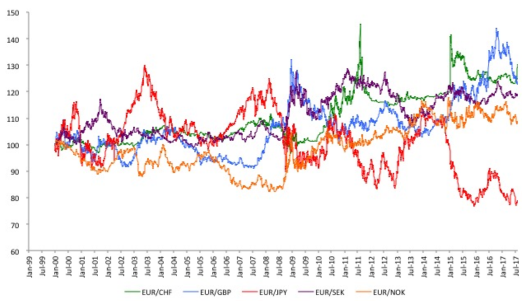
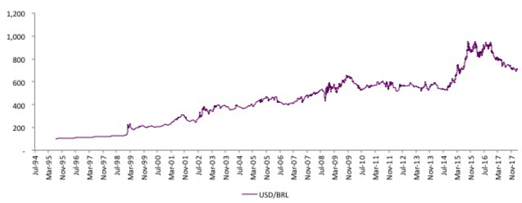


FIG. 6.7: Chart relative to the cumulative returns obtained by the trend-following strategy for EM currency pairs from 1989 to Q2 2017.

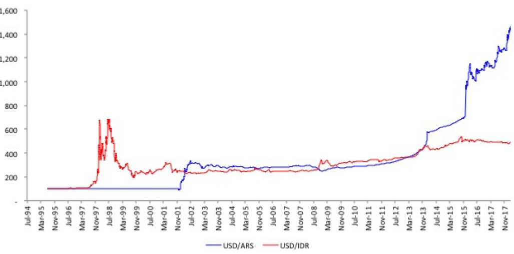


(a) USD/ARS and USD/BRL

(b) USD/TRY



(c) USD/BRL

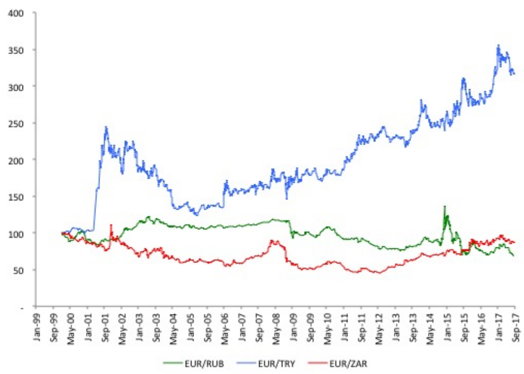


(d) EUR G10 currency pairs

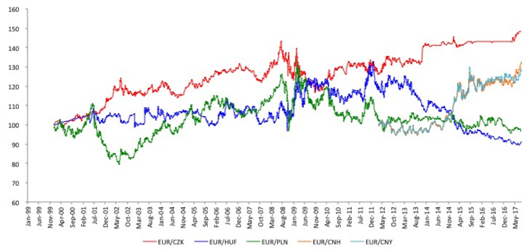
FIG. 6.8: Cumulative returns obtained by the trend-following strategy from 1989 to Q2 2017.

6.1.2 Convexity and skewness of the strategy

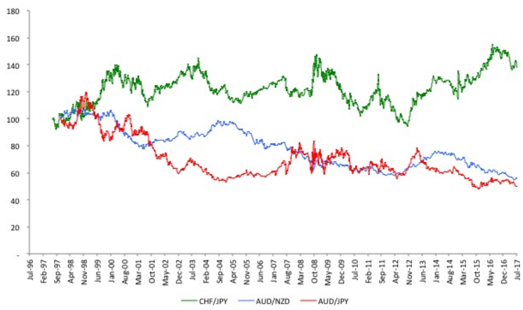
We focus on the pairs which displayed trending behaviour in the back-testing analysis: NZD/USD, AUD/USD, USD/SEK, USD/TRY, USD/HUF, EUR/CHF, EUR/TRY, EUR/CZK, and CHF/JPY. We construct the payoff profile of the strategy using the



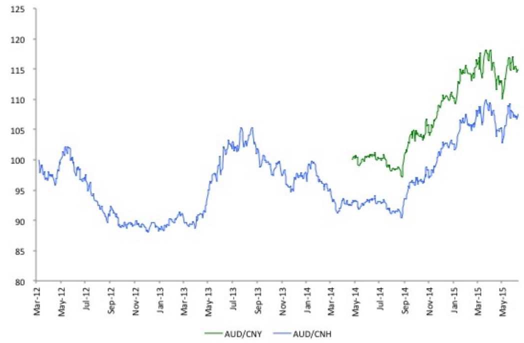
(a) EUR G20 currency pairs



(b) EUR EM currency pairs



(c) Cross currencies currency pairs



(d) EUR cross currencies currency pairs

FIG. 6.9: Cumulative returns obtained by the trend-following strategy from 1989 to Q2 2017.

exponential weighted moving average[6]. They are derived using the equations 2.24 and 2.25 with various look-back periods e.g 90 days and 30 days. We repeat the analysis on distinct periods to assess the evolution of the payoff convexity through time.

The payoff plot links the strength of the trend signal (e.g. length of the trend) and the P/L of the correspondent strategy.

The P/L scatter plots relative to NZD/USD and six different periods (1990–2000, 2001–2007, 2008–2010, 2011–2013, 2014–2015, 2016–2017) are displayed in Figure 6.10. Following the characteristics of the illustrated in sections 2.3, the strategy produces a P/L plot that have the characteristic convex shape which can be interpolated by a parabola. This corresponds to the scenario in which the strategy produces many small losses and few large gains. The vertex of a parabola is the point where the parabola crosses the axis of symmetry. Generally this point corresponds to the losses produced by the strategy. The lower the vertex and the greater the losses. The results show that the vertex of the parabola is always associated with negative P/L for all the currency pairs and all the periods tested.

As expected the P/L curves show that the payoff is much more negative during the financial crisis respect to the pre-crisis and the most recent years. The P/L

[6] We verified that similar results can be obtained using the crossover of the simple moving averages.

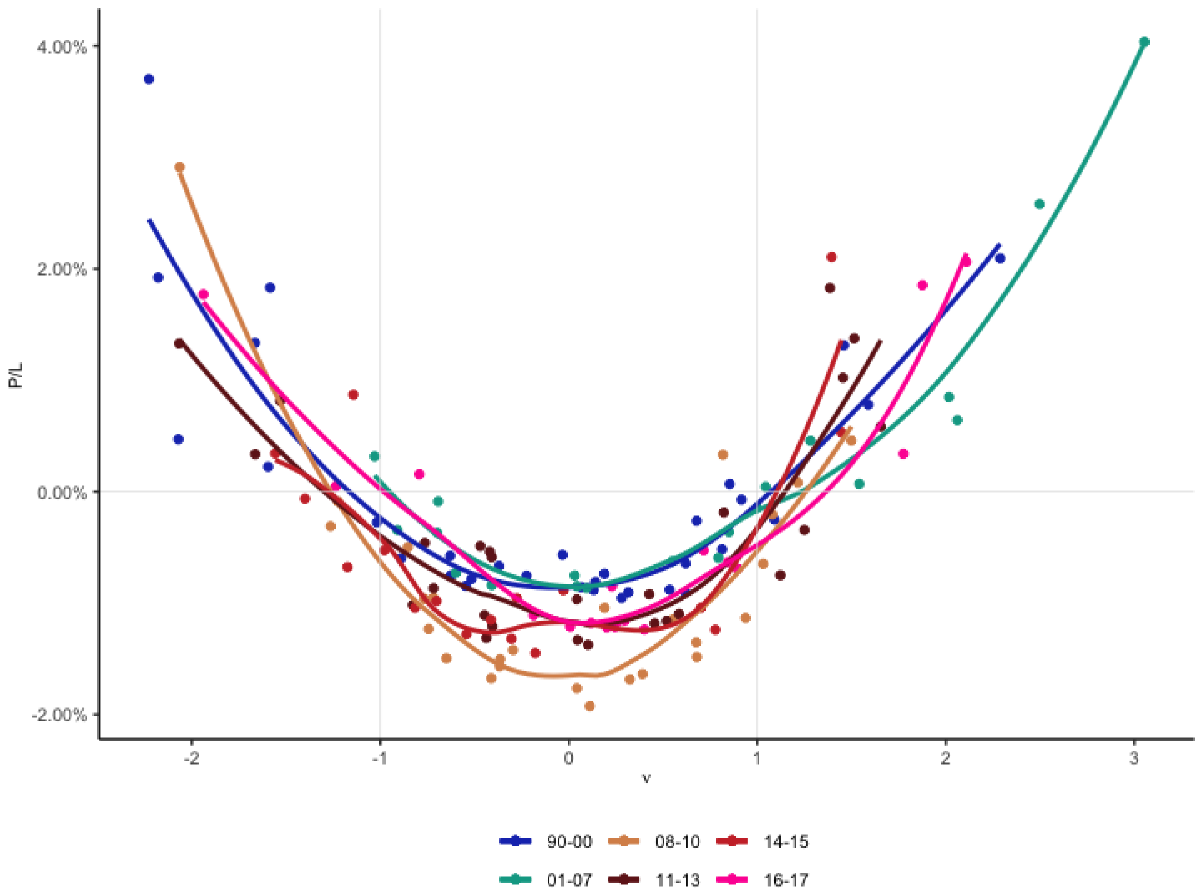


FIG. 6.10: The P/L scatter plot by trend estimation μ_e relative to the trend-following strategy applied to the pair NZD/USD on different periods. The trend is estimated using the exponential weighted moving average. The largest payoffs come from the periods prior the financial crisis.

curves relative to the early years 1990–2000 and 2001–2007 are characterised by higher parabolic curve and less negative vertex, proving that the strategy was more successful in the past than in more recent years. The curves relative to the 2008–2010 and 2016–2017 display signals of decline with lower parabolic curve and more negative vertex. The strategy brings mixed results in the period 2016–2017: some positive returns are still observed and the convexity is maintained but also there are many losses corresponding to the weak trending signals.

Dao 2017 [13] links the performance of the trend-following strategy to the difference between the long-term and the short-term volatility of the returns. We plot such a difference with the P/L of the strategy in Figure 6.11. Similar as before, we repeat the process over distinct periods. We highlight three ellipses around the scatter plot: values that imply negative difference of the volatility (red ellipse), almost zero difference (amber ellipse), and positive difference (green ellipse). We recall that a negative difference corresponds to the scenario of short-term volatility being greater than the long-term volatility, which corresponds to frequent price reversals

TABLE 6.4: Kurtosis of the monthly returns obtained by the trend-following strategy over the entire data and by periods. The kurtosis relative to the entire back-testing data is positive for all the currency pairs. Looking at the specific time frames, the distribution of returns have heavier fat tails at the beginning of the data e.g. 1990-2007.

CCY	1990-2000	2001-2007	2008-2013	2014-2015	2016-2017
EUR/USD	4.62	2.74	3.75	1.84	1.40
USD/JPY	8.88	2.47	3.28	0.77	3.40
GBP/USD	9.16	1.87	4.85	0.25	2.92
USD/CHF	3.85	2.05	6.54	6.92	1.76
AUD/USD	1.88	2.40	4.04	1.25	2.30
NZD/USD	4.24	2.19	4.67	1.04	0.78
USD/CAD	3.54	2.24	9.25	4.50	1.19
USD/SEK	9.71	1.85	2.61	0.63	1.72
USD/NOK	6.20	2.16	4.90	2.04	1.04
USD/DKK	5.76	2.22	3.58	2.02	1.70

TABLE 6.5: Skewness of the monthly returns obtained by the trend-following strategy over the entire data and by periods. Not all currency pairs have positive skewness as the strategy does not produce similar results across all the currency pairs.

CCY	1990-2000	2001-2007	2008-2013	2014-2015	2016-2017
EUR/USD	0.14	-0.06	-0.24	0.34	0.47
USD/JPY	1.49	0.08	-0.30	0.58	1.51
GBP/USD	0.07	-0.03	1.39	0.15	-0.88
USD/CHF	-0.16	0.11	-1.24	-1.41	-0.47
AUD/USD	0.06	-0.29	0.60	0.44	-0.16
NZD/USD	0.22	0.04	-0.23	0.02	0.50
USD/CAD	0.90	-0.16	1.68	1.31	-0.23
USD/SEK	-1.27	0.51	0.13	-0.03	-0.17
USD/NOK	-0.75	0.13	0.68	0.14	0.16
USD/DKK	0.25	0.43	0.14	0.41	-0.14

and thus losses for the trend-following strategy. On the other hand, the positive difference would correspond to cases in which long trends can emerge. The red ellipses are generally composed of observations during the financial crisis but also to the years 2016–2017. The green ellipse contains mainly the pre-crisis observations. The amber ellipse includes a mix of observations like the small losses that occurred during the pre-crisis period and the large losses that happened during the 2016–2017.

The analysis of the skewness of the strategy returns confirm the evidence of convex payoff: the most trending currency pairs have positive skewness e.g NZD/USD, EUR/CHF, EUR/CZK, EUR/TRY and CHF/JPY. The kurtosis relative to the entire back-testing data is positive for all the currency pairs. Looking at the specific time frames, the distribution of returns have heavier fat tails at the beginning of

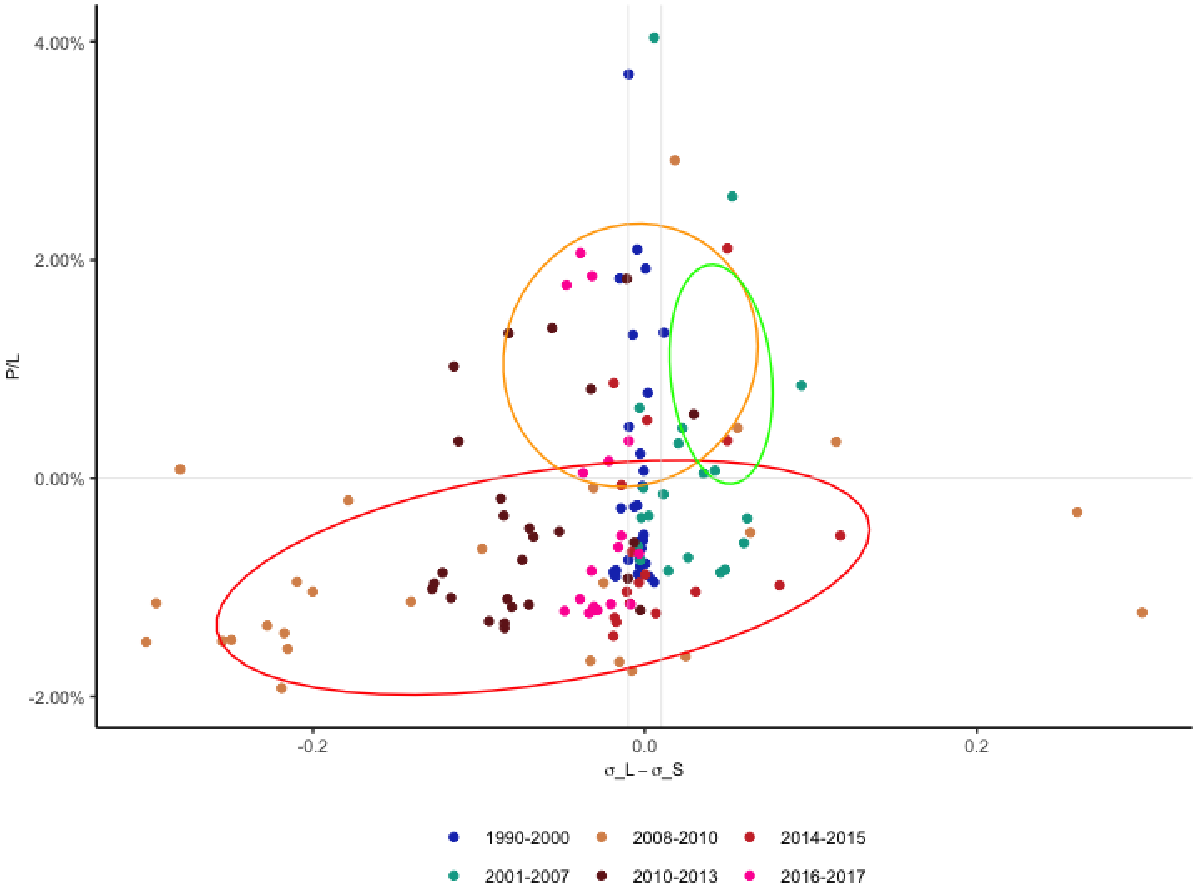


FIG. 6.11: The difference between the long and the short-term volatility $\sigma_L - \sigma_S$ relative to NZD/USD (x-axis) is compared with the payoff of the trend-following strategy (y-axis). The observations are marked by different colours based on the period of time e.g. the dark blue points correspond to the years 1990–2000 whilst the pink points belonging to the period 2016–2017. The ellipses show different scenarios: a) negative payoff (red ellipse), b) positive payoff and long-term vol approx the same of the short-term one (amber ellipse), c) positive payoff and long-term vol greater than the short-term one. The red ellipse includes almost all the points relative to the financial crisis and the 2016–2017. The payoffs relative to the pre-crisis periods are contained within the amber and the green ellipses. The distribution of the payoffs implies the positive skewness of the returns - see table 6.5. As an example the strategy applied over 1990–2000 exhibit many small losses (blue points included in the centre of the red ellipse many small losses) which are compensated by few large gains (points in the amber ellipse).

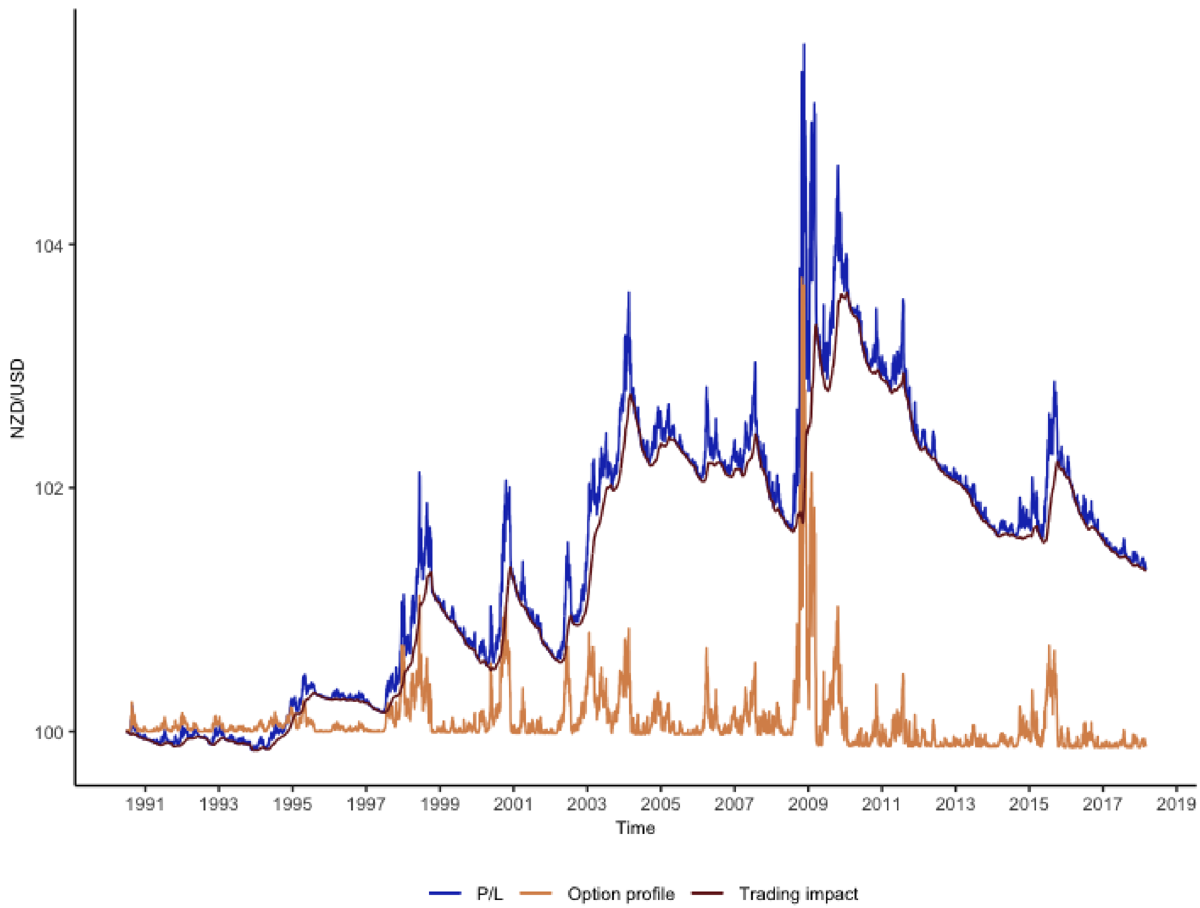


FIG. 6.12: Cumulative returns of the trend-following strategy for NZD/USD obtained using a EWMA(180) trend estimator (blue line) along with the option profile (yellow line) and the trading impact (brown line). The P/L is the sum of trading impact and option profile. The trading impact explains the most of the P/L.

the data e.g. 1990-2007. Not all the currency pairs have positive skewness of the distribution of returns. Notable results are the negative skewness of USD/CHF from 2007 to 2015, the positive skewness of USD/CAD over 2007–2015 and the positive skewness of USD/JPY from 1990 to 2000 and over 2016–2017.

6.1.3 Trading impact results

We verify that the decomposition of the returns into option profile and trading impact is confirmed by the evidence of the data applying Equation (2.20) to various currency pairs. Figure 6.12 shows the decomposition of the strategy P/L relative to NZD/USD. The trend is estimated using the exponential moving average with length equal to 180 days. It can be seen that the returns implied by the strategy and those obtained by adding the option profile and the trading impact are very much identical. In line with the expectations much of the returns is provided by the trading impact rather than the option profile which is a characteristic of the trend-following strategies.

6.1.4 Trend-following alpha from diverging economies and monetary policies

Diverging economies and diverging monetary policies can act as favourable market factors for trend. As an example, we look at the trends of EUR/USD and USD/JPY. We analyse the changes to alpha based on:

- converging interest rates vs. diverging interest rates scenario in which the absolute difference is above 1%,
- diverging monetary policy of the Federal Reserve (Fed) vs. European Central Bank (ECB) and Bank of Japan (BOJ).

We derive the payoffs of the trend-following strategy corresponding to the scenario in which the absolute difference of the interest rates is below or above 1%. Similarly, we observe the changes of the P/L of the strategy between periods in which the absolute difference of the interest rates is below or above 1% and in correspondence to two relevant dates are considered about the QE program: the 22nd May of 2013 and the 22nd May of 2015 (see the appendix for more details on these events). These dates correspond to Fed chairman's "tapering" speech and the start of the European Central Bank sovereign and corporate bonds purchase program. The Societe Generale Prime Services index SG CTA[7] measures the performance of CTAs which generally adopt trend-following strategies as part of their systematic investing. We show the index along with the most significant QE interventions in Figure 6.13. The figure displays the effect of the quantitative easing program on the strategy: the dollar strength resulting from the diverging monetary interventions created conditions favourable for trend, which were successfully exploited by the CTA index.[8] Our analysis supports this conclusion. Figure 6.15 shows the payoff of the trend-following which estimates the trend using the 30-day EWMA: the divergence of the interest rates favoured long-term trends. Accordingly, the trend-following strategy produces positive returns selling EUR against USD and buying USD against JPY. Similarly, the divergence of the monetary policy provided new alpha for the trend-following strategies as it is displayed in Figure 6.14 in which profits could be pocketed by selling the Euro. The beginning of the tapering program from the Fed and the resulting divergence of the monetary policy between the Fed , the ECB and the BOJ strengthened the *U.S.* dollar. Similar conclusions are applicable to the curve relative to USD/JPY which is contained in the supplementary material.

Trend-following during the last 10 years is largely influenced by the behaviour of the USD dollar based on the rising *U.S.* debt, the global financial crisis, the Euro-zone crisis, and Fed monetary policy.

Overall during 2002 to 2011 the *U.S.* dollar declined but uptrend periods were followed by downtrend ones. This is because traders and investors looked at two

[7] The data is available at www.cib.societegenerale.com.

[8] Very similar results are obtained for the cumulative P/L of our trend-following strategy for EUR/USD and USD/JPY.

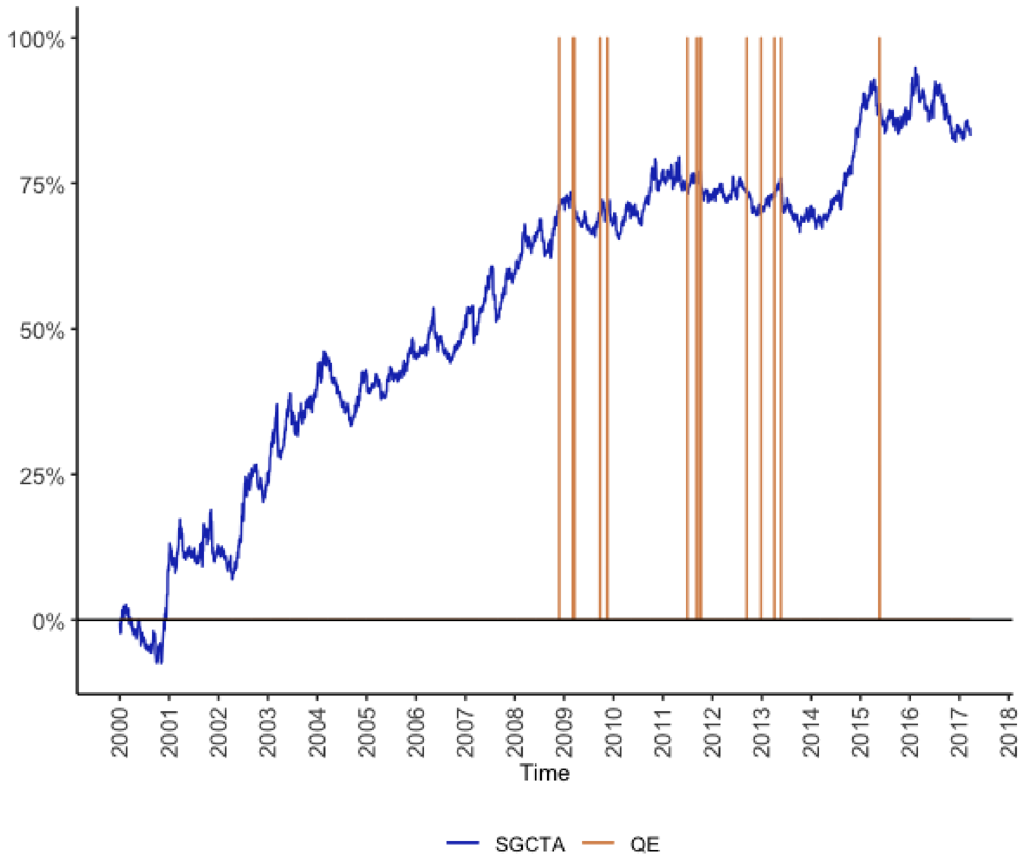


FIG. 6.13: The SGCTA is the index relative to a CTA panel data provided by Societe General. The CTAs historically base their systematic investing prevalently on a trend-following strategy; thus, the index is a good benchmark for the performance of the strategy. The index is compared with significant events of the QE program. The index rose until the end of 2008 and declined from 2009 to Q2 2014. It strongly consolidated between Q3 2014 and end of 2015. It declined again afterwards. It can be noted that the index often rises during the QE in particular during Q3 2010 and Q3 2011 and between August 2014 and March 2015.

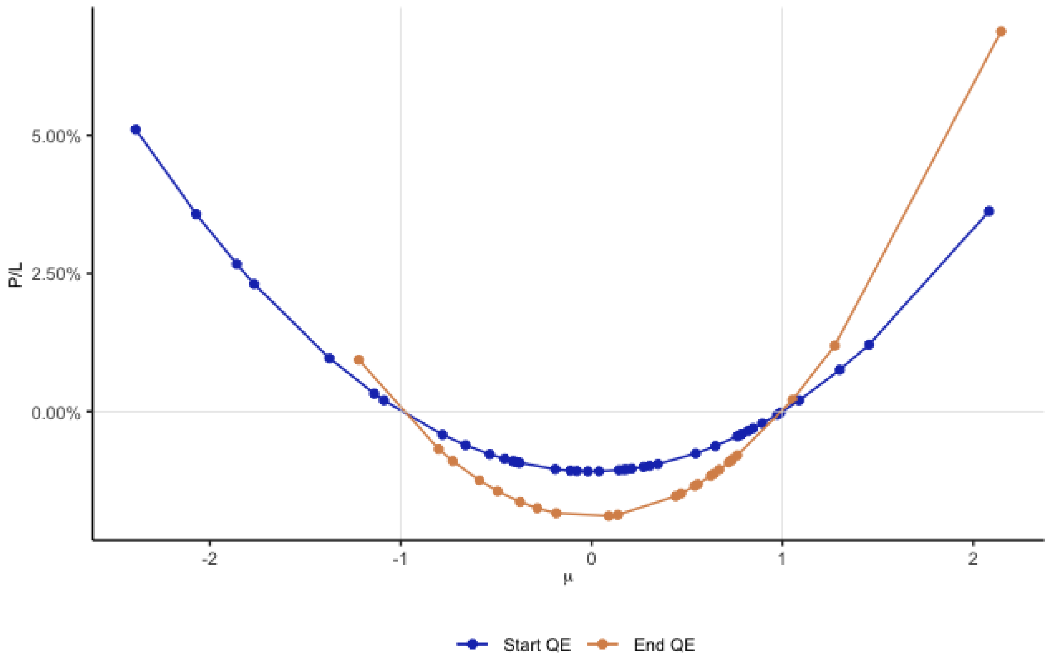


FIG. 6.14: The P/L scatter plot by trend estimation μ relative to the trend-following strategy for EUR/USD. Two scenarios are presented: the period after the Fed announcement of the QE tapering(blue line) and the period after the ECB decision to expand the QE(yellow line). The blue line is lower than the yellow one suggesting that the strategy is more profitable when the monetary policies diverge. In this case this causes stronger USD and thus a down trend for the pair EUR/USD which corresponds to the high left-hand component of the convex payoff function of the blue line.

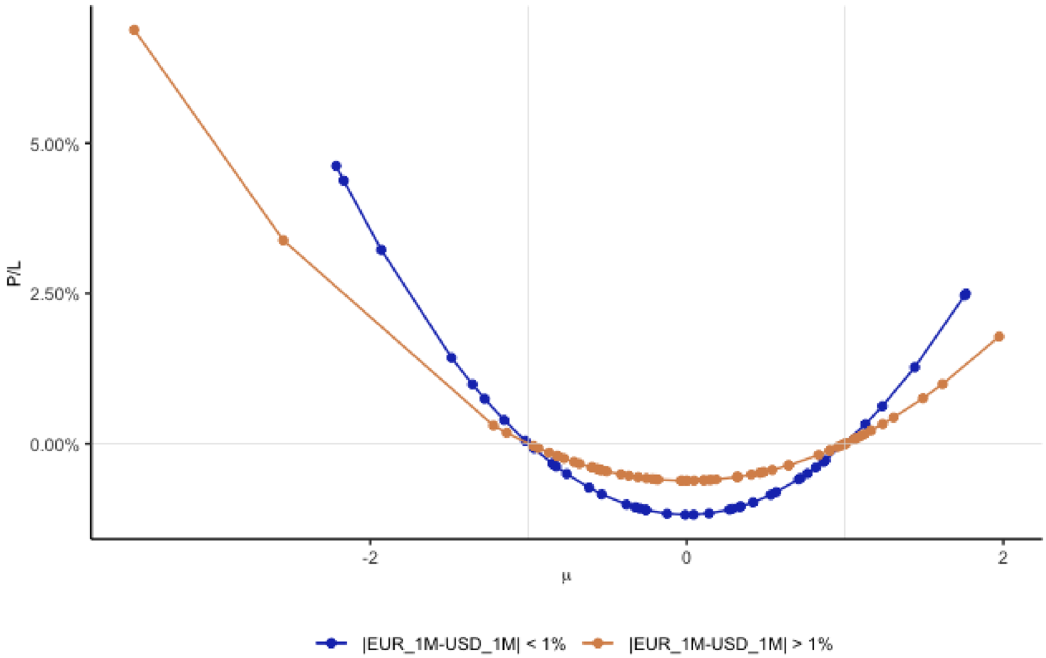


FIG. 6.15: The P/L scatter plot by trend estimation μ relative to the trend-following strategy for EUR/USD. Two scenarios are considered: the period in which the difference between the 1-month implied rate of the two economies, EUR_1M and USD_1M, is below 1% (blue line) and the period in which is greater than 1% (yellow line). The blue line is lower than the yellow one suggesting that the strategy is more profitable when the two implied rates diverge.

aspects: the relative strength of the dollar compared to other currencies and the growing *U.S.* debt. The USD dollar appreciated during the financial crisis when it was considered a safe asset. As an example, during 2008 the dollar strengthened by more than 20% as businesses and investors stockpiled dollars during the crisis. Back in 2008 as the global economy was fighting against a severe financial crisis, the major central banks orchestrated a series of interest rate cuts to provide liquidity. This program is called quantitative easing (QE). The interest rates were at or approached zero and so began a prolonged period of monetary policy convergence that would persist for the next seven years. The QE should have weakened the dollar; due to the global scale of the crisis and the coordinated QE, FX investors considered the USD as a safe haven thus strengthening it.

On the other hand, the USD dollar depreciated during the period of growing the *U.S.* debt. The dollar fell by 40% as the *U.S.* debt grew by 60% between 2002 and 2007 and by 20% when the yield rose from 2.15% to approximately 3.30%. The Greek debt crisis strengthened the dollar in 2010, but fears of rising inflation triggered by the Fed's quantitative easing strategy weakened the greenback.

Between 2011 and 2016 the USD dollar primarily strengthened due to the following factors:

1. Eurozone crisis and struggling Greek economy
2. Chinese economy slowdown from 2015
3. China and Japan policies orientated at weakening their currencies to boost the export
4. Fed anticipating a change in their monetary policy and then the start of the reverse QE.

In particular when the Fed announced the intention to start their reverse QE, the dollar could appreciate. Although the investors were still concerned about the growth of the *U.S.* debt, the Fed's quantitative easing program brought an artificial strengthening of the dollar. This caused the emergence of trends in any USD related currency pair.

Such an artificially strong dollar provided new alpha for trend-followers as is displayed by the Figure 6.16 which shows the P/L of the strategy relative to the period 2014–2015.

A notable exception occurred with the Japanese Yen. The struggle of the Japanese economy implied a counter-intuitive appreciation of the Yen. The Bank of Japan (BOJ) monetary policy resulted to be ineffective as the inflation target was continuously missed. Loosening monetary policy typically causes a currency to weaken as the money supply increases. But instead of falling, the Yen appreciated as investors decided to bet against the BOJ as they were expecting more drastic actions to support the economy.

We test the discriminatory power of the Quantitative Easing (QE) interventions on the the results of the G10 Momentum index. The hypothesis to test is that

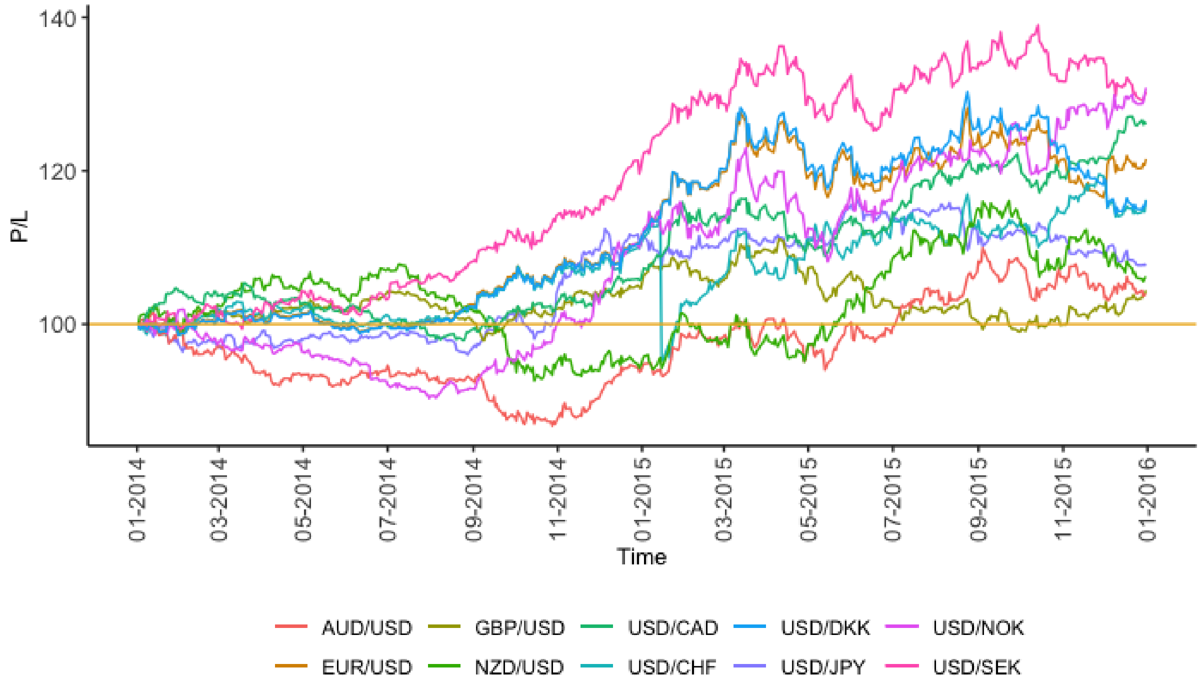


Fig. 6.16: Cumulative returns obtained by the trend-following strategy for the G10 group during 2014 and 2015. With the exception of USD/JPY the pairs do not display long-term trends and the strategy performance declines at the beginning of 2018.

the returns of the momentum strategy are not on average similar when they are calculated over different periods that correspond distinct QE phases. We extract the seven groups from the G10 momentum index: 1) data between 15/11/2005 and 26/11/2008 (*Prior Q1*; 2) data between 01/12/2008 and 30/03/2010 (*Q1*); 3) data between 01/04/2010 and 28/10/2010 (*Prior Q2*); 4) data between 01/11/2010 and 29/06/2011 (*Q2*); 5) data between 01/07/2011 and 30/08/2012 (*Prior Q3*); 6) data between 04/09/2012 and 30/12/2013 (*Q3*); 7) data after 02/01/2014 (*Post Q3*). Table 6.6 shows the results relative to the analysis of variance (ANOVA) for the G10 momentum index based on the aforementioned seven groups. It can be noted that the p-value of the F Fisher test used to assess the significance of the groups is always significantly different from zero (p-value< 0.0001). The averages of the index are significantly different between groups i.e. the phases of the Quantitative Easing program correspond to non similar average returns of the momentum strategy relative to the G10 basket of currency pairs. We also apply the ANOVA for the returns of momentum strategy applied to G10 currency pairs. Table 6.7, 6.8, 6.9, 6.11, 6.12 , 6.13 , 6.14 , 6.15 show that the pvalue of the F Fisher test used to assess the significance of the groups is always significantly different from zero (pvale< 0.0001) for the indices $I_{EURUSD,M}$, $I_{USDJPY,Mom}$, $I_{GBPUSD,M}$, $I_{AUDUSD,M}$, $I_{NZDUSD,M}$, $I_{USDCAD,M}$,$I_{USDSEK,M}$,$I_{USDNOK,M}$. The averages of the index are significantly different between groups i.e. the phases of the Quantitative Easing program corre-

TABLE 6.6: ANOVA relative to the G10 Momentum index $I_{G10,M}$ and a set of Quantitative Easing (QE) phases.

Groups	Stat	SS	df	MS	F	pval
Prior Q1 vs Q1	Groups	33310.44	1	33310.44	1242.72	< 0.0001
Prior Q1 vs Q1	Error	29377.74	1096	26.80		
Prior Q1 vs Q1	Total	62688.18	1097			
Q1 vs Prior Q2	Groups	321.18	1	321.18	16.85	< 0.0001
Q1 vs Prior Q2	Error	9129.15	479	19.06		
Q1 vs Prior Q2	Total	9450.32	480			
Prior Q2 vs Q2	Groups	1363.32	1	1363.32	273.52	< 0.0001
Prior Q2 vs Q2	Error	1555.11	312	4.98		
Prior Q2 vs Q2	Total	2918.44	313			
Q2 vs Prior Q3	Groups	186.12	1	186.12	39.80	< 0.0001
Q2 vs Prior Q3	Error	2150.97	460	4.68		
Q2 vs Prior Q3	Total	2337.09	461			
Prior Q3 vs Q3	Groups	3276.77	1	3276.77	403.93	< 0.0001
Prior Q3 vs Q3	Error	5070.17	625	8.11		
Prior Q3 vs Q3	Total	8346.94	626			
Q3 vs Post Q3	Groups	47850.52	1	47850.52	1180.28	< 0.0001
Q3 vs Post Q3	Error	59798.93	1475	40.54		
Q3 vs Post Q3	Total	107649.46	1476			

spond to non similar average returns of the momentum strategy.The ANOVA cannot reject the hypothesis of equal averages for the $I_{USDCHF,M}$ relative to the groups: prior to Q2 vs Q2 and prior to Q3 and Q3 (table 6.10 . Similarly the ANOVA fails to reject the hypothesis of equal averages for the $I_{USDDKK,M}$ relative to the group prior to Q3 and Q3 as shown by table 6.16.

Table 6.7: ANOVA for $I_{EURUSD,M}$ relative to QE phases.

Groups	Stat	SS	df	MS	F	pval
Prior Q1 vs Q1	Groups	4022.06	1	4022.06	107.07	< 0.0001
Prior Q1 vs Q1	Error	41172.76	1096	37.57		
Prior Q1 vs Q1	Total	45194.82	1097			
Q1 vs Prior Q2	Groups	14992.23	1	14992.23	376.47	< 0.0001
Q1 vs Prior Q2	Error	19075.46	479	39.82		
Q1 vs Prior Q2	Total	34067.69	480			
Prior Q2 vs Q2	Groups	714.82	1	714.82	50.86	< 0.0001
Prior Q2 vs Q2	Error	4384.98	312	14.05		
Prior Q2 vs Q2	Total	5099.79	313			
Q2 vs Prior Q3	Groups	6195.68	1	6195.68	400.03	< 0.0001
Q2 vs Prior Q3	Error	7124.54	460	15.49		
Q2 vs Prior Q3	Total	13320.22	461			
Prior Q3 vs Q3	Groups	6768.15	1	6768.15	531.88	< 0.0001
Prior Q3 vs Q3	Error	7953.04	625	12.72		
Prior Q3 vs Q3	Total	14721.19	626			
Q3 vs Post Q3	Groups	1056.77	1	1056.77	14.58	0.0001
Q3 vs Post Q3	Error	106931.26	1475	72.50		
Q3 vs Post Q3	Total	107988.02	1476			

Table 6.8: ANOVA for $I_{USDJPY,Mom}$ relative to QE phases.

Groups	Stat	SS	df	MS	F	pval
Prior Q1 vs Q1	Groups	15560.07	1	15560.07	921.67	< 0.0001
Prior Q1 vs Q1	Error	18503.19	1096	16.88		
Prior Q1 vs Q1	Total	34063.26	1097			
Q1 vs Prior Q2	Groups	131.44	1	131.44	5.18	0.0233
Q1 vs Prior Q2	Error	12157.76	479	25.38		
Q1 vs Prior Q2	Total	12289.20	480			
Prior Q2 vs Q2	Groups	3640.32	1	3640.32	284.29	< 0.0001
Prior Q2 vs Q2	Error	3995.17	312	12.81		
Prior Q2 vs Q2	Total	7635.49	313			
Q2 vs Prior Q3	Groups	2768.51	1	2768.51	593.56	< 0.0001
Q2 vs Prior Q3	Error	2145.56	460	4.66		
Q2 vs Prior Q3	Total	4914.07	461			
Prior Q3 vs Q3	Groups	82292.91	1	82292.91	936.94	< 0.0001
Prior Q3 vs Q3	Error	54894.99	625	87.83		
Prior Q3 vs Q3	Total	137187.90	626			
Q3 vs Post Q3	Groups	267213.15	1	267213.15	1427.97	< 0.0001
Q3 vs Post Q3	Error	276013.06	1475	187.13		
Q3 vs Post Q3	Total	543226.20	1476			

TABLE 6.9: ANOVA for $I_{GBPUSD,Mom}$ relative to QE phases.

Groups	Stat	SS	df	MS	F	pval
Prior Q1 vs Q1	Groups	232577.57	1	232577.57	8247.33	< 0.0001
Prior Q1 vs Q1	Error	30907.57	1096	28.20		
Prior Q1 vs Q1	Total	263485.14	1097			
Q1 vs Prior Q2	Groups	1807.45	1	1807.45	81.15	< 0.0001
Q1 vs Prior Q2	Error	10668.48	479	22.27		
Q1 vs Prior Q2	Total	12475.92	480			
Prior Q2 vs Q2	Groups	1555.41	1	1555.41	84.92	< 0.0001
Prior Q2 vs Q2	Error	5714.94	312	18.32		
Prior Q2 vs Q2	Total	7270.35	313			
Q2 vs Prior Q3	Groups	514.03	1	514.03	57.61	< 0.0001
Q2 vs Prior Q3	Error	4104.41	460	8.92		
Q2 vs Prior Q3	Total	4618.44	461			
Prior Q3 vs Q3	Groups	6130.82	1	6130.82	820.61	< 0.0001
Prior Q3 vs Q3	Error	4669.42	625	7.47		
Prior Q3 vs Q3	Total	10800.23	626			
Q3 vs Post Q3	Groups	76114.46	1	76114.46	772.99	< 0.0001
Q3 vs Post Q3	Error	145239.30	1475	98.47		
Q3 vs Post Q3	Total	221353.76	1476			

TABLE 6.10: ANOVA for $I_{USDCHF,Mom}$ relative to QE phases.

Groups	Stat	SS	df	MS	F	pval
Prior Q1 vs Q1	Groups	27607.85	1	27607.85	1502.26	< 0.0001
Prior Q1 vs Q1	Error	20141.78	1096	18.38		
Prior Q1 vs Q1	Total	47749.63	1097			
Q1 vs Prior Q2	Groups	7637.89	1	7637.89	367.48	< 0.0001
Q1 vs Prior Q2	Error	9955.71	479	20.78		
Q1 vs Prior Q2	Total	17593.60	480			
Prior Q2 vs Q2	Groups	94.79	1	94.79	2.31	0.1296
Prior Q2 vs Q2	Error	12807.52	312	41.05		
Prior Q2 vs Q2	Total	12902.32	313			
Q2 vs Prior Q3	Groups	14699.65	1	14699.65	329.32	< 0.0001
Q2 vs Prior Q3	Error	20532.97	460	44.64		
Q2 vs Prior Q3	Total	35232.62	461			
Prior Q3 vs Q3	Groups	60.43	1	60.43	2.40	0.1218
Prior Q3 vs Q3	Error	15728.60	625	25.17		
Prior Q3 vs Q3	Total	15789.03	626			
Q3 vs Post Q3	Groups	277863.73	1	277863.73	1377.10	< 0.0001
Q3 vs Post Q3	Error	297617.73	1475	201.77		
Q3 vs Post Q3	Total	575481.46	1476			

TABLE 6.11: ANOVA for $I_{AUDUSD,Mom}$ relative to QE phases.

Groups	Stat	SS	df	MS	F	pval
Prior Q1 vs Q1	Groups	3566.06	1	3566.06	55.17	< 0.0001
Prior Q1 vs Q1	Error	70845.69	1096	64.64		
Prior Q1 vs Q1	Total	74411.74	1097			
Q1 vs Prior Q2	Groups	2025.39	1	2025.39	35.23	< 0.0001
Q1 vs Prior Q2	Error	27540.96	479	57.50		
Q1 vs Prior Q2	Total	29566.34	480			
Prior Q2 vs Q2	Groups	10920.26	1	10920.26	614.13	< 0.0001
Prior Q2 vs Q2	Error	5547.88	312	17.78		
Prior Q2 vs Q2	Total	16468.15	313			
Q2 vs Prior Q3	Groups	11222.23	1	11222.23	308.84	< 0.0001
Q2 vs Prior Q3	Error	16714.85	460	36.34		
Q2 vs Prior Q3	Total	27937.09	461			
Prior Q3 vs Q3	Groups	6903.71	1	6903.71	242.89	< 0.0001
Prior Q3 vs Q3	Error	17764.61	625	28.42		
Prior Q3 vs Q3	Total	24668.32	626			
Q3 vs Post Q3	Groups	46416.56	1	46416.56	1202.22	< 0.0001
Q3 vs Post Q3	Error	56948.21	1475	38.61		
Q3 vs Post Q3	Total	103364.76	1476			

TABLE 6.12: ANOVA for $I_{NZDUSD,Mom}$ relative to QE phases.

Groups	Stat	SS	df	MS	F	pval
Prior Q1 vs Q1	Groups	297464.91	1	297464.91	4674.42	< 0.0001
Prior Q1 vs Q1	Error	69745.85	1096	63.64		
Prior Q1 vs Q1	Total	367210.76	1097			
Q1 vs Prior Q2	Groups	1613.74	1	1613.74	18.88	< 0.0001
Q1 vs Prior Q2	Error	40935.65	479	85.46		
Q1 vs Prior Q2	Total	42549.39	480			
Prior Q2 vs Q2	Groups	271.42	1	271.42	6.61	0.0106
Prior Q2 vs Q2	Error	12804.87	312	41.04		
Prior Q2 vs Q2	Total	13076.29	313			
Q2 vs Prior Q3	Groups	170.93	1	170.93	12.29	< 0.0001
Q2 vs Prior Q3	Error	6397.23	460	13.91		
Q2 vs Prior Q3	Total	6568.16	461			
Prior Q3 vs Q3	Groups	2040.17	1	2040.17	190.95	< 0.0001
Prior Q3 vs Q3	Error	6677.73	625	10.68		
Prior Q3 vs Q3	Total	8717.90	626			
Q3 vs Post Q3	Groups	3793.12	1	3793.12	76.47	< 0.0001
Q3 vs Post Q3	Error	73159.75	1475	49.60		
Q3 vs Post Q3	Total	76952.87	1476			

TABLE 6.13: ANOVA for $I_{USDCAD,Mom}$ relative to QE phases.

Groups	Stat	SS	df	MS	F	pval
Prior Q1 vs Q1	Groups	4971.99	1	4971.99	173.79	< 0.0001
Prior Q1 vs Q1	Error	31355.22	1096	28.61		
Prior Q1 vs Q1	Total	36327.21	1097			
Q1 vs Prior Q2	Groups	2424.19	1	2424.19	71.13	< 0.0001
Q1 vs Prior Q2	Error	16324.50	479	34.08		
Q1 vs Prior Q2	Total	18748.68	480			
Prior Q2 vs Q2	Groups	1359.03	1	1359.03	361.08	< 0.0001
Prior Q2 vs Q2	Error	1174.29	312	3.76		
Prior Q2 vs Q2	Total	2533.32	313			
Q2 vs Prior Q3	Groups	5638.14	1	5638.14	400.32	< 0.0001
Q2 vs Prior Q3	Error	6478.74	460	14.08		
Q2 vs Prior Q3	Total	12116.88	461			
Prior Q3 vs Q3	Groups	3818.99	1	3818.99	379.02	< 0.0001
Prior Q3 vs Q3	Error	6297.43	625	10.08		
Prior Q3 vs Q3	Total	10116.42	626			
Q3 vs Post Q3	Groups	85205.50	1	85205.50	1955.51	< 0.0001
Q3 vs Post Q3	Error	64268.63	1475	43.57		
Q3 vs Post Q3	Total	149474.13	1476			

TABLE 6.14: ANOVA for $I_{USDSEK,Mom}$ relative to QE phases.

Groups	Stat	SS	df	MS	F	pval
Prior Q1 vs Q1	Groups	363959.15	1	363959.15	4262.69	< 0.0001
Prior Q1 vs Q1	Error	93579.30	1096	85.38		
Prior Q1 vs Q1	Total	457538.45	1097			
Q1 vs Prior Q2	Groups	884.83	1	884.83	18.22	< 0.0001
Q1 vs Prior Q2	Error	23264.64	479	48.57		
Q1 vs Prior Q2	Total	24149.47	480			
Prior Q2 vs Q2	Groups	339.42	1	339.42	7.80	0.0056
Prior Q2 vs Q2	Error	13578.93	312	43.52		
Prior Q2 vs Q2	Total	13918.35	313			
Q2 vs Prior Q3	Groups	657.52	1	657.52	31.47	< 0.0001
Q2 vs Prior Q3	Error	9611.40	460	20.89		
Q2 vs Prior Q3	Total	10268.92	461			
Prior Q3 vs Q3	Groups	47662.10	1	47662.10	1010.13	< 0.0001
Prior Q3 vs Q3	Error	29489.96	625	47.18		
Prior Q3 vs Q3	Total	77152.05	626			
Q3 vs Post Q3	Groups	828.87	1	828.87	7.86	0.0051
Q3 vs Post Q3	Error	155479.01	1475	105.41		
Q3 vs Post Q3	Total	156307.89	1476			

Table 6.15: ANOVA for $I_{USDNOK,Mom}$ relative to QE phases.

Groups	Stat	SS	df	MS	F	pval
Prior Q1 vs Q1	Groups	151784.46	1	151784.46	3205.52	< 0.0001
Prior Q1 vs Q1	Error	51896.59	1096	47.35		
Prior Q1 vs Q1	Total	203681.05	1097			
Q1 vs Prior Q2	Groups	4138.74	1	4138.74	141.44	< 0.0001
Q1 vs Prior Q2	Error	14016.55	479	29.26		
Q1 vs Prior Q2	Total	18155.28	480			
Prior Q2 vs Q2	Groups	1009.98	1	1009.98	45.91	< 0.0001
Prior Q2 vs Q2	Error	6863.83	312	22.00		
Prior Q2 vs Q2	Total	7873.82	313			
Q2 vs Prior Q3	Groups	2500.23	1	2500.23	208.06	< 0.0001
Q2 vs Prior Q3	Error	5527.81	460	12.02		
Q2 vs Prior Q3	Total	8028.04	461			
Prior Q3 vs Q3	Groups	5649.68	1	5649.68	765.70	< 0.0001
Prior Q3 vs Q3	Error	4611.53	625	7.38		
Prior Q3 vs Q3	Total	10261.21	626			
Q3 vs Post Q3	Groups	86769.67	1	86769.67	509.55	< 0.0001
Q3 vs Post Q3	Error	251173.42	1475	170.29		
Q3 vs Post Q3	Total	337943.08	1476			

Table 6.16: ANOVA for $I_{USDDKK,Mom}$ relative to QE phases.

Groups	Stat	SS	df	MS	F	pval
Prior Q1 vs Q1	Groups	135044.36	1	135044.36	2171.19	< 0.0001
Prior Q1 vs Q1	Error	68169.37	1096	62.20		
Prior Q1 vs Q1	Total	203213.73	1097			
Q1 vs Prior Q2	Groups	18371.90	1	18371.90	542.45	< 0.0001
Q1 vs Prior Q2	Error	16222.88	479	33.87		
Q1 vs Prior Q2	Total	34594.78	480			
Prior Q2 vs Q2	Groups	321.79	1	321.79	15.15	0.0001
Prior Q2 vs Q2	Error	6628.76	312	21.25		
Prior Q2 vs Q2	Total	6950.55	313			
Q2 vs Prior Q3	Groups	709.56	1	709.56	35.79	< 0.0001
Q2 vs Prior Q3	Error	9120.18	460	19.83		
Q2 vs Prior Q3	Total	9829.74	461			
Prior Q3 vs Q3	Groups	8.31	1	8.31	0.37	0.5452
Prior Q3 vs Q3	Error	14182.81	625	22.69		
Prior Q3 vs Q3	Total	14191.12	626			
Q3 vs Post Q3	Groups	36784.65	1	36784.65	423.71	< 0.0001
Q3 vs Post Q3	Error	128054.20	1475	86.82		
Q3 vs Post Q3	Total	164838.85	1476			

6.1.5 Has trend vanished from FX?

Trend delivered a lacklustre performance during the last two years of our data set. Most of the G10 currency pairs along with USD/TRY, USD/ZAR, USD/BRL, USD/ARS did not display trends over the period 2016–2017, as shown by Figure 6.17.

Historically, it is not the first time that two fairly serious losing years have occurred together. In fact, out of the last 10 years, eight have resulted in losses. Trend certainly performed poorly during the financial crisis[9]. In contrast, the first six years of the data set were all profitable. The markets seem to have changed and so has the performance of trend-following in FX. During a long period of time trends were practically erased by the growth of market factors which are a problematic for trends. The increasing volatility, the crisis of liquidity, the convergence of global monetary policies, the converge of the interest rates and the condition of synchronous economies among most of the G10 and EM countries has characteristed most of the last ten years of data.

The strengthening of the *U.S.* dollar played a key role in the recovery of trend-following in 2014 and 2015. The strong dollar resulted from the fact that USD emerged as a valuable and safe currency among the G10 group. This was a consequence of the Fed monetary policy and in particular from the reverse QE. The *U.S.* dollar is the primary reserve currency. Many foreign countries (like Japan and China) retain dollars because it keeps their currency values lower boosting exports.

[174] noted a modern version of the Triffin dilemma for which the growing demands for dollar assets clashes with targeted financial stability. Stability could be threatened when the increasing demand for dollar assets induces a build-up in *U.S.*, debt to levels that might be difficult to service. In the run up to the crisis, foreign demand for *U.S.* debt were rising rapidly[10]. Dollar strength was halted by a change in the political economics of the *U.S.* establishment.

In this context President Trump opted to run ever a bigger budget deficit while reducing the trade deficit. This was the result of the new political vision which was much more in favour of a weaker dollar to revive the *U.S.* economy and in particular exports and to delays of the Fed to hike monetary policy by rising the rates to fight the inflation. As a result, between 2016 and 2018, the dollar weakened. In 2016 the euro rose to 1.13. Between 2017 and 2018 the euro rose to 1.20. In 2018 the euro continued its ascent. At the same time, the euro strengthened following the improvement in the Eurozone's economic outlook.

During 2014 and 2017 the strong *U.S.* dollar led to a trending world. A weakening dollar led to a price ranging world, in which trend has progressively disappeared.

[9]For example, USD/JPY did not trend between 2003 and 2004, NZD/USD during 2011–2014, AUD/USD from 2011 to Q2 2013, GBP/USD between 2010 and 2013, EUR/USD from 2012 to 2013, USD/CHF between 2011–2019, USD/SGD during years 2011–2014, USD/MXN from 2009 to Q3 2011 and between 2012–2014.

[10]The Triffin dilemma in **(author?)** [175] holds that the demand of the global reserve currency leads that very same country to a trade deficit and the imbalances in the current account, high exchange rate and less competitive domestic export.

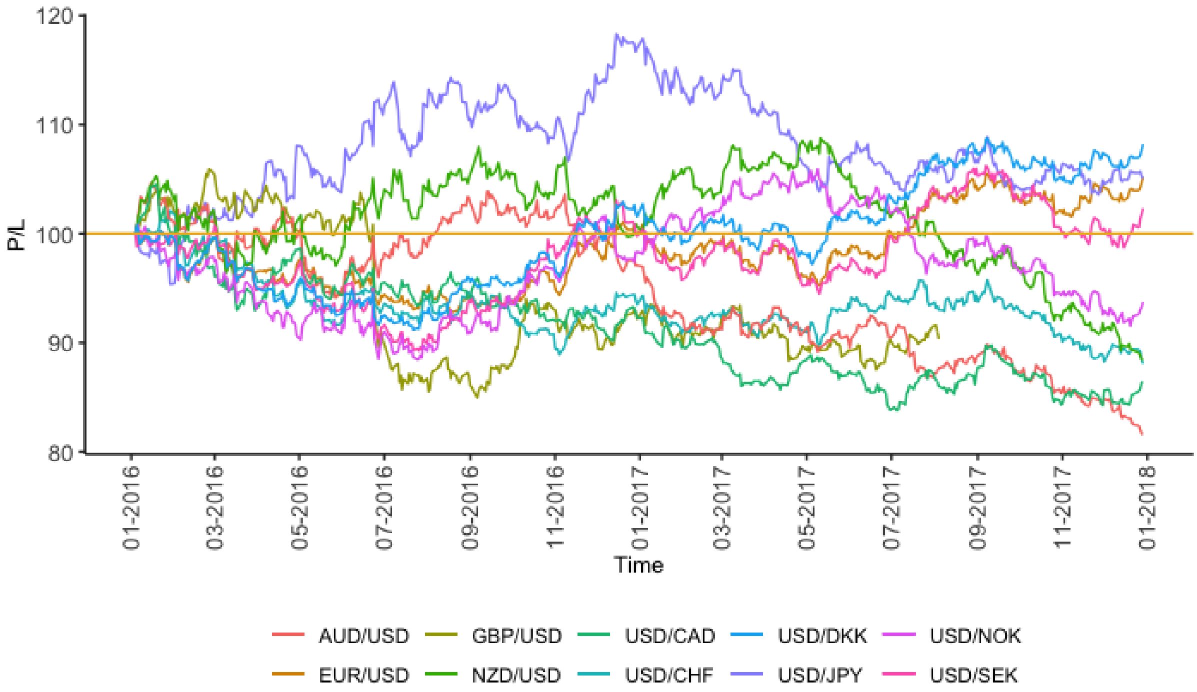


FIG. 6.17: Cumulative returns obtained by the trend-following strategy for the G10 group relative to 2016 and 2017. With the exclusion of USD/JPY the pairs do not display long-term trends and the strategy performance declines at the beginning of 2018.

On the other hand, in 2019 dollar started heading to what appears to be a secular decline[11]. The differential between the *U.S.* and the rest of the world interest rates lessened as the Fed cut interest rates. The reduction of USD carry meant that holding USD became less valuable than before. Figure 6.18 displays the SG CTA index and the dollar index during the 2018 and 2019. Soon a perceived overvalued dollar favoured trends in particular for the G10 and the EM currency pairs[12]. The rest of 2019 appeared to be a lot more mixed than expected as the *U.S.* dollar recovered against G10 and EM currencies. As a consequence short dollar trend-following strategies did not prove to be profitable anymore. During 2018 and 2019 a weak *U.S.* dollar has led to a trending world too. The strengthening of the dollar has brought back a price ranging regime in FX.

In conclusion, seeking alpha in FX through trend-following strategy has proved to be very much different compared to 20 or 30 years ago. As interest rates diverge much less than in the past and economies tend to be less asynchronous than before, the strategy appears to be strongly influenced by the *U.S.* monetary and trade policies. During cycles of strong dollar (e.g 2014–2015) and during those of (very)

[11]Long USD trend-following strategy performs well between April and August 2018 and between the first three quarters of 2019. During these periods the dollar index rose from 89 to 96 and from 96 to 99, respectively.

[12]Short dollar in the currency pairs GBP/USD, USD/JPY, AUD/USD and NZD/USD was generally a winning bet during the first two quarters of 2019.

FIG. 6.18: The SG CTA index (blue line) and the dollar index (yellow line) are shown from Q1 2018 to Q2 2020. The SG CTA index rose during 2019 pushed by a weakening dollar. As the dollar recovers during the last two quarters of 2019, the CTA index declined. It further declines during 2020 as a consequence of the market volatility caused by the global pandemic.

weak dollar (2019) trends may appear in FX. In between those cycles, FX prices tend to follow ranging patterns rather than trends. As prices move in a short range, the short-term volatility is too high and trends cannot emerge. Furthermore, the rising volatility that stormed the markets after the most recent global pandemic crisis has further increased the short-term volatility and as such reduced the chances for trend followers to make money in FX.

Is this the death of trend in FX? Currently yes. Lack of a consistent USD direction has meant that trends are now both unlikely and short term. It is likely that if, in the future trend-friendly conditions like long term asynchronous in large economies return, trends that is worth trading may come back. But currently trend strategies lack evidence to support their sustainability.

6.2 Experiment 2: validation of momentum strategy

We present the results of the strategy in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown. We looked the index level and at the index rebased based on the volatility target. The weights and $W_{p,n}$ for the momentum strategy applied to the G10 and the EM currency groups can be obtained through quantitative approaches or through expert-based solution. In this context, we present the latter approach by which we define them as illustrated by the following table.

TABLE 6.17: Percentage weight of the FX currecy pairs constituent for the momentum strategy.

FX rate	Weight	FX rate	Weight
EURUSD	25%	USDARS	14.29%
USDJPY	25%	USDBRL	14.29%
GBPUSD	0%	USDCNY	14.29%
USDCHF	0%	USDINR	14.29%
AUDUSD	25%	USDIDR	14.29%
NZDUSD	25%	USDKRW	0%
USDCAD	0%	USDMXN	14.29%
USDSEK	0%	USDRUB	14.29%
USDNOK	0%	USDTRY	0%
USDDKK	0%	USDZAR	0%

The results also include trading costs as defined by equation (2.36). The results are shown relative to the whole back testing window and by specific years. We rebased the returns of the strategy and show the results for each year included in the historical data. For example $I_{VT,>2007}$ is the performance of the rebased index relative to the period after the 2007; whilst $I_{VT,2013}$ is the performance of the rebased index relative to the year 2013. The full list of results is contained in the supplementary material. For all the trading strategies the results are not the same results on all the currency pairs and over the entire time period. Some currency pairs prove to perform better than others. All the strategies recovered in 2018 whilst some of them went through heavy losses during the years $2016 - 2017$.

The momentum strategy exhibits stronger returns for USD/DKK, USD/JPY, GBP/USD, NZD/USD, AUD/USD and USD/SEK among the G10 group; USD/ARS, USD/CNY, USD/RUB, USD/TRY, USD/IDR, USD/KRW among the G20 set. The strategy has positive returns prior the financial crisis for the G10 and EM currency pairs. The G10 index struggles during the financial crisis and in particular during the 2009. Results are positive but not exceptionally positive during 2011 and 2012. The EM currencies struggle during 2010, 2012 and 2013. The strategy is profitable for the G10 group from 2013 to 2015 and between 2014 and 2015 for the EM group. Severe losses are obtained during the years $2016 - 2017$ for both G10 and EM. G10 index loses more than EM index, in particular during the 2016.

TABLE 6.18: **G10 Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown. We looked the index level I and at the index rebased based on the volatility target I_{VT}. The results are shown relative to the whole back testing window and for the year 2007. The results also include trading costs.

Results	I	I_{VT}	$I_{>2007}$	$I_{VT,>2007}$	I_{2007}	$I_{VT,2007}$
CumRet	20.46%	115.46%	20.07%	93.09%	−0.56%	1.47%
AnnualRet	1.36%	6.24%	1.60%	5.86%	−0.56%	1.48%
AnnualVol	7.58%	11.84%	7.81%	11.95%	6.66%	12.05%
Sharpe	17.92%	52.73%	20.44%	49.07%	−8.45%	12.31%
D_{max}	−17.98%	−25.53%	−17.98%	−25.53%	−7.48%	−11.11%

TABLE 6.19: **G10 Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown. We looked the index level I and at the index rebased based on the volatility target I_{VT}. The results are shown relative to the whole back testing window and by specific years. The results are shown relative to years 2008 to 2010 and include trading costs.

Results	I_{2008}	$I_{VT,2008}$	I_{2009}	$I_{VT,2009}$	I_{2010}	$I_{VT,2010}$
CumRet	12.18%	9.46%	−2.31%	8.35%	2.08%	1.05%
AnnualRet	12.21%	9.49%	−2.32%	8.40%	2.10%	1.07%
AnnualVol	15.60%	15.17%	10.51%	10.92%	6.95%	10.85%
Sharpe	78.30%	62.58%	−22.06%	76.87%	30.30%	9.82%
D_{max}	−8.96%	−12.46%	−15.85%	−10.96%	−6.32%	−10.55%

Table 6.20: **G10 Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown. We looked the index level I and at the index rebased based on the volatility target I_{VT}. The results are shown relative to the whole back testing window and by specific years. The results are shown relative to years 2011 to 2013 and include trading costs.

Results	I_{2011}	$I_{VT,2011}$	I_{2012}	$I_{VT,2012}$	I_{2013}	$I_{VT,2013}$
CumRet	0.63%	6.83%	0.82%	10.87%	6.80%	21.34%
AnnualRet	0.64%	6.91%	0.83%	10.93%	6.84%	21.47%
AnnualVol	6.71%	10.74%	5.31%	12.77%	5.92%	10.64%
Sharpe	9.55%	64.32%	15.60%	85.56%	115.64%	201.84%
D_{max}	−6.16%	−7.19%	−4.79%	−9.48%	−2.86%	−4.58%

Table 6.21: **G10 Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown. We looked the index level I and at the index rebased based on the volatility target I_{VT}. The results are shown relative to the whole back testing window and by specific years. The results are shown relative to years 2014 to 2016 and include trading costs.

Results	I_{2014}	$I_{VT,2014}$	I_{2015}	$I_{VT,2015}$	I_{2016}	$I_{VT,2016}$
CumRet	8.74%	19.81%	1.17%	3.61%	−9.51%	−15.36%
AnnualRet	8.79%	19.93%	1.18%	3.63%	−9.61%	−15.51%
AnnualVol	5.62%	13.12%	7.30%	11.34%	5.93%	11.13%
Sharpe	156.52%	151.95%	16.15%	32.00%	−162.02%	−139.38%
D_{max}	−2.71%	−8.04%	−7.07%	−8.81%	−10.02%	−16.28%

Table 6.22: **G10 Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for G10 currency pairs including trading costs.

Results	USDEUR	USDJPY	USDGBP	USDCHF	USDAUD
CumRet	−16.65%	17.45%	−0.16%	−42.41%	−18.26%
AnnualRet	−1.31%	1.17%	−0.01%	−3.92%	−1.45%
AnnualVol	9.76%	10.45%	9.77%	11.83%	13.68%
Sharpe	−13.44%	11.21%	−0.12%	−33.13%	−10.60%
D_{max}	−33.88%	−25.84%	−29.02%	−54.04%	−37.79%

TABLE 6.23: **G10 Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for G10 currency pairs including trading costs.

Results	USDNZD	USDCAD	USDSEK	USDNOK	USDDKK
CumRet	−0.81%	−18.84%	40.22%	27.96%	58.06%
AnnualRet	−0.06%	−1.50%	2.48%	1.80%	3.37%
AnnualVol	13.69%	9.84%	12.66%	12.78%	9.74%
Sharpe	−0.43%	−15.25%	19.58%	14.10%	34.64%
D_{max}	−33.42%	−32.29%	−31.66%	−24.78%	−19.82%

TABLE 6.24: **EM Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the index I and the index rebased on the volatility target I_{VT}. The results are shown relative to the whole back testing window, from the 2007 onward. Trading costs are included.

Results	I	I_{VT}	$I_{>2007}$	$I_{VT,>2007}$
CumRet	33.40%	40.88%	27.19%	39.17%
AnnualRet	2.11%	2.69%	2.10%	2.90%
AnnualVol	7.47%	7.56%	4.39%	7.69%
Sharpe	28.26%	35.61%	47.92%	37.73%
D_{max}	−15.90%	−17.16%	−14.56%	−17.16%

TABLE 6.25: **EM Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the index I and the index rebased on the volatility target I_{VT}. The results are shown relative to the whole back testing window, from the 2008 to 2010. Trading costs are included.

Results	I_{2008}	$I_{VT,2008}$	I_{2009}	$I_{VT,2009}$	I_{2010}	$I_{VT,2010}$
CumRet	5.35%	6.93%	6.52%	2.96%	−2.52%	−5.83%
AnnualRet	5.35%	6.93%	6.53%	2.97%	−2.53%	−5.85%
AnnualVol	3.59%	8.77%	4.12%	4.90%	2.42%	7.25%
Sharpe	149.06%	79.04%	158.73%	60.65%	−104.28%	−80.66%
D_{max}	−2.87%	−5.10%	−2.53%	−1.71%	−3.10%	−7.18%

TABLE 6.26: **EM Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the index I and the index rebased on the volatility target I_{VT}. The results are shown relative to the whole back testing window, from the 2011 to 2013. Trading costs are included.

Results	I_{2011}	$I_{VT,2011}$	I_{2012}	$I_{VT,2012}$	I_{2013}	$I_{VT,2013}$
CumRet	2.39%	7.44%	−8.65%	−7.18%	−1.51%	−4.24%
AnnualRet	2.39%	7.47%	−8.65%	−7.18%	−1.52%	−4.25%
AnnualVol	4.64%	8.95%	4.79%	6.65%	4.76%	7.92%
Sharpe	51.65%	83.40%	−180.56%	−107.94%	−31.89%	−53.73%
D_{max}	−3.76%	−3.98%	−8.65%	−8.11%	−3.62%	−7.94%

Table 6.27: **EM Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the index I and the index rebased on the volatility target I_{VT}. The results are shown relative to the whole back testing window, from the 2014 to 2016. Trading costs are included.

Results	I_{2014}	$I_{VT,2014}$	I_{2015}	$I_{VT,2015}$	I_{2016}	$I_{VT,2016}$
CumRet	2.69%	4.26%	9.86%	10.13%	0.46%	−0.40%
AnnualRet	2.70%	4.27%	9.89%	10.16%	0.47%	−0.40%
AnnualVol	4.33%	9.43%	5.79%	7.73%	3.98%	5.42%
Sharpe	62.30%	45.32%	170.75%	131.52%	11.70%	−7.41%
D_{max}	−3.29%	−5.29%	−3.49%	−3.91%	−4.28%	−4.63%

Table 6.28: **EM Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for EM currency pairs including trading costs.

Results	USDARS	USDBRL	USDCNY	USDINR	USDIDR
CumRet	638.69%	65.87%	40.54%	−32.94%	22.28%
AnnualRet	15.59%	3.73%	2.50%	−2.85%	1.47%
AnnualVol	9.79%	14.22%	2.05%	6.31%	8.74%
Sharpe	159.31%	26.27%	121.52%	−45.25%	16.80%
D_{max}	−17.25%	−32.35%	−4.47%	−40.90%	−32.80%

Table 6.29: **EM Momentum** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for EM currency pairs including trading costs.

Results	USDKRW	USDMXN	USDRUB	USDZAR	USDTRY
CumRet	12.14%	72.53%	414.01%	29.46%	11.62%
AnnualRet	0.83%	4.03%	12.59%	1.89%	0.80%
AnnualVol	10.58%	10.50%	12.42%	14.86%	12.01%
Sharpe	7.88%	38.38%	101.36%	12.71%	6.66%
D_{max}	−31.40%	−28.81%	−25.65%	−38.62%	−26.50%

6.3 Experiment 3: validation of value strategy

The value strategy exhibits stronger returns for USD/SEK, GBP/USD, NZD/USD. The index has positive returns prior the financial crisis relative to both the G10 in particular during 2008. The G10 value index struggles during the financial crisis but does not lead to losses as the momentum index in particular during 2009 and most of all in 2010. During period $2011 - 2013$ the model recovers the losses incurred at the beginning of the financial crisis. The positive performance observed at the end of the financial crisis continues until 2014 when it peaks compared to previous years. The model slows down in 2015 when registers large losses. However during $2016 - 2018$ the strategy produces strong results.

TABLE 6.30: **Value** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **G10** *Index*, b) the **G10** index rebased on the volatility target $Index_{VT}$. The results are shown relative to the 2018. Trading costs are included.

Results	I_{2018}	$I_{VT,2018}$
CumRet	−3.21%	−4.73%
AnnualRet	−5.87%	−8.58%
AnnualVol	11.41%	10.63%
Sharpe	−51.46%	−80.71%
MDD	−7.28%	−6.91%

TABLE 6.31: **Value** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **G10** *Index*, b) the **G10** index rebased on the volatility target $Index_{VT}$. The results are shown relative to the whole back testing window, from the 2007 onward and for year 2008 only. Trading costs are included.

Results	I	I_{VT}	$I_{>2007}$	$I_{VT,>2007}$	I_{2008}	$I_{VT,2008}$
CumRet	30.48%	18.74%	42.38%	21.53%	58.34%	8.98%
AnnualRet	1.95%	1.27%	3.11%	1.70%	58.54%	9.00%
AnnualVol	21.96%	12.44%	21.92%	12.76%	32.80%	11.93%
Sharpe	8.86%	10.19%	14.17%	13.35%	178.48%	75.47%
MDD	−50.85%	−30.69%	−50.85%	−25.12%	−26.82%	−16.54%

TABLE 6.32: **Value** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **G10** *Index*, b) the **G10** index rebased on the volatility target $Index_{VT}$. The results are shown relative to years 2009 to 2011. Trading costs are included.

Results	I_{2009}	$I_{VT,2009}$	I_{2010}	$I_{VT,2010}$	I_{2011}	$I_{VT,2011}$
CumRet	−21.17%	−8.31%	−15.50%	0.14%	−1.70%	−2.55%
AnnualRet	−21.28%	−8.35%	−15.66%	0.14%	−1.72%	−2.58%
AnnualVol	26.51%	12.08%	24.31%	14.60%	28.58%	13.04%
Sharpe	−80.25%	−69.16%	−64.40%	0.96%	−6.03%	−19.77%
MDD	−30.94%	−13.87%	−31.37%	−14.01%	−22.52%	−12.10%

TABLE 6.33: **Value** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **G10** *Index*, b) the **G10** index rebased on the volatility target $Index_{VT}$. The results are shown relative to years 2012 to 2014. Trading costs are included.

Results	I_{2012}	$I_{VT,2012}$	I_{2013}	$I_{VT,2013}$	I_{2014}	$I_{VT,2014}$
CumRet	5.07%	6.05%	13.34%	3.63%	17.10%	11.17%
AnnualRet	5.10%	6.09%	13.42%	3.65%	17.20%	11.24%
AnnualVol	17.96%	11.02%	22.16%	11.35%	16.83%	12.13%
Sharpe	28.38%	55.24%	60.53%	32.20%	102.25%	92.65%
MDD	−19.47%	−10.63%	−15.15%	−7.65%	−15.22%	−14.10%

TABLE 6.34: **Value** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **G10** *Index*, b) the **G10** index rebased on the volatility target $Index_{VT}$. The results are shown relative to years 2015 to 2017. Trading costs are included.

Results	I_{2015}	$I_{VT,2015}$	I_{2016}	$I_{VT,2016}$	I_{2017}	$I_{VT,2017}$
CumRet	−15.91%	−13.85%	9.58%	13.51%	14.28%	13.62%
AnnualRet	−15.99%	−13.92%	9.69%	13.67%	14.45%	13.78%
AnnualVol	24.79%	17.78%	14.88%	12.60%	11.21%	10.65%
Sharpe	−64.50%	−78.31%	65.11%	108.47%	128.92%	129.37%
MDD	−18.90%	−16.62%	−12.47%	−9.55%	−5.06%	−4.62%

TABLE 6.35: **Value** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for **G10** currency pairs including trading costs.

Results	USDEUR	USDJPY	USDGBP	USDCHF	USDAUD
CumRet	−6.28%	1.64%	4.66%	−7.37%	−0.79%
AnnualRet	−0.47%	0.12%	0.33%	−0.55%	−0.06%
AnnualVol	3.34%	4.29%	3.47%	9.06%	6.33%
Sharpe	−14.03%	2.75%	9.53%	−6.11%	−0.91%
MDD	−10.27%	−16.09%	−19.59%	−20.83%	−21.44%

TABLE 6.36: **Value** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for **G10** currency pairs including trading costs.

Results	USDNZD	USDCAD	USDSEK	USDNOK	USDDKK
CumRet	11.17%	2.24%	38.86%	3.83%	0.00%
AnnualRet	0.77%	0.16%	2.41%	0.27%	0.00%
AnnualVol	3.71%	0.57%	6.17%	7.88%	0.00%
Sharpe	20.78%	28.29%	39.03%	3.46%	0.00%
MDD	−13.10%	−1.04%	−16.62%	−21.77%	0.00%

6.4 Experiment 4: validation of carry trade

The carry strategy exhibits stronger returns for USD/JPY, USD/CHF and negative returns on USD/CAD, USD/NOK, GBP/USD, USD/CNY, USD/ARS, USD/BRL and USD/INR. The index has mixed results prior the financial crisis: positive performance with the exclusion of 2010 for both G10 and EM groups.
The index relative to the G10 and EM currencies have negative results in particular during years $2013-2015$. The index recovers during the period in losses during years $2016-2017$ for the G10 and EM groups. In 2018 their performance diverges: the G10 index continues the positive trend, whilst the EM index shows losses.

TABLE 6.37: **G10 Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **G10** *Index*, b) the **G10** index rebased on the volatility target $Index_{VT}$. The results are shown relative to the 2018. Trading costs are included.

Results	I_{2018}	$I_{VT,2018}$
CumRet	17.22%	4.05%
AnnualRet	34.23%	7.63%
AnnualVol	29.15%	10.96%
Sharpe	117.45%	69.63%
MDD	−19.10%	−9.21%

TABLE 6.38: **EM Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **EM** *Index*, b) the **G10** index rebased on the volatility target $Index_{VT}$. The results are shown relative to the 2018. Trading costs are included.

Results	I_{2018}	$I_{VT,2018}$
CumRet	−57.20%	−23.95%
AnnualRet	−79.08%	−39.64%
AnnualVol	40.90%	12.87%
Sharpe	−193.36%	−307.98%
MDD	−63.11%	−27.06%

TABLE 6.39: **G10 Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **G10** *Index*, b) the **G10** index rebased on the volatility target $Index_{VT}$. The results are shown relative to the whole back testing window, and for years 2007 and 2008. Trading costs are included.

Results	Index	I_{VT}	I_{2007}	$I_{VT,2007}$	I_{2008}	$I_{VT,2008}$
CumRet	−78.57%	0.07%	−84.75%	−20.92%	−71.18%	−11.27%
AnnualRet	−10.56%	0.01%	−15.03%	−2.01%	−71.28%	−11.30%
AnnualVol	52.80%	12.68%	56.77%	12.82%	142.75%	23.56%
Sharpe	−20.00%	0.04%	−26.48%	−15.69%	−49.94%	−47.95%
MDD	−92.83%	−37.66%	−92.83%	−37.66%	−91.88%	−33.46%

TABLE 6.40: **G10 Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **G10** *Index*, b) the **G10** index rebased on the volatility target $Index_{VT}$. The results are shown relative to years 2009 to 2011. Trading costs are included.

Results	I_{2009}	$I_{VT,2009}$	I_{2010}	$I_{VT,2010}$	I_{2011}	$I_{VT,2011}$
CumRet	48.94%	10.02%	−7.06%	−4.69%	−16.09%	3.75%
AnnualRet	49.27%	10.08%	−7.13%	−4.74%	−16.25%	3.79%
AnnualVol	64.20%	10.55%	54.19%	13.42%	59.24%	11.13%
Sharpe	76.74%	95.55%	−13.16%	−35.35%	−27.43%	34.04%
MDD	−42.79%	−6.43%	−50.96%	−17.07%	−49.91%	−8.99%

TABLE 6.41: **G10 Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **G10** *Index*, b) the **G10** index rebased on the volatility target $Index_{VT}$. The results are shown relative to years 2012 to 2014. Trading costs are included.

Results	I_{2012}	$I_{VT,2012}$	I_{2013}	$I_{VT,2013}$	I_{2014}	$I_{VT,2014}$
CumRet	13.74%	3.28%	−26.51%	−7.75%	−33.98%	−15.49%
AnnualRet	13.82%	3.30%	−26.63%	−7.79%	−34.13%	−15.56%
AnnualVol	33.35%	11.03%	33.84%	10.57%	26.16%	11.09%
Sharpe	41.44%	29.89%	−78.70%	−73.70%	−130.48%	−140.32%
MDD	−36.18%	−13.49%	−35.57%	−11.52%	−44.39%	−21.80%

Table 6.42: **G10 Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **G10** *Index*, b) the **G10** index rebased on the volatility target $Index_{VT}$. The results are shown relative to years 2015 to 2017. Trading costs are included.

Results	I_{2015}	$I_{VT,2015}$	I_{2016}	$I_{VT,2016}$	I_{2017}	$I_{VT,2017}$
CumRet	−14.41%	−2.15%	25.83%	16.00%	−31.89%	−13.70%
AnnualRet	−14.48%	−2.16%	26.16%	16.19%	−32.18%	−13.84%
AnnualVol	28.49%	11.24%	19.29%	10.73%	26.54%	10.85%
Sharpe	−50.84%	−19.22%	135.61%	150.90%	−121.22%	−127.58%
MDD	−32.88%	−14.02%	−9.41%	−4.73%	−37.02%	−15.97%

Table 6.43: **Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for **G10** currency pairs including trading costs.

Results	USD/EUR	USD/JPY	USD/GBP	USD/CHF	USD/AUD
CumRet	−7.55%	3.21%	−7.59%	7.40%	−11.39%
AnnualRet	−0.57%	0.23%	−0.57%	0.52%	−0.87%
AnnualVol	2.51%	5.30%	2.65%	5.71%	13.93%
Sharpe	−22.63%	4.32%	−21.53%	9.09%	−6.26%
MDD	−16.74%	−24.43%	−14.05%	−14.77%	−44.45%

Table 6.44: **Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for **G10** currency pairs including trading costs.

Results	USD/NZD	USD/CAD	USD/SEK	USD/NOK	USD/DKK
CumRet	4.23%	−13.58%	−1.35%	−32.01%	2.61%
AnnualRet	0.30%	−1.05%	−0.10%	−2.76%	0.19%
AnnualVol	13.57%	2.85%	8.05%	10.94%	5.61%
Sharpe	2.22%	−36.96%	−1.22%	−25.20%	3.33%
MDD	−41.21%	−20.33%	−26.98%	−39.25%	−19.57%

TABLE 6.45: **EM Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for **EM** currency pairs including trading costs.

Results	USD/ARS	USD/BRL	USD/CNY	USD/INR	USD/IDR
CumRet	89.83%	53.70%	16.62%	15.44%	20.96%
AnnualRet	5.24%	3.48%	1.23%	1.15%	1.53%
AnnualVol	13.33%	11.89%	1.43%	4.39%	7.56%
Sharpe	39.30%	29.29%	86.27%	26.21%	20.20%
MDD	−48.27%	−49.58%	−3.36%	−17.68%	−21.68%

TABLE 6.46: **EM Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for **EM** currency pairs including trading costs.

Results	USD/KRW	USD/MXN	USD/RUB	USD/ZAR	USD/TRY
CumRet	10.58%	−0.86%	−9.85%	19.05%	−30.90%
AnnualRet	0.80%	−0.07%	−0.82%	1.40%	−2.90%
AnnualVol	6.75%	2.63%	12.72%	8.35%	11.99%
Sharpe	11.93%	−2.62%	−6.47%	16.75%	−24.20%
MDD	−23.15%	−14.30%	−51.71%	−25.89%	−55.20%

TABLE 6.47: **EM Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **EM** *Index*, b) the **EM** index rebased on the volatility target $Index_{VT}$. The results are shown relative to the whole back testing window, from 2007 onward and for year 2008. Trading costs are included.

Results	I	I_{VT}	$I_{>2007}$	$I_{VT,>2007}$	I_{2008}	$I_{VT,2008}$
CumRet	135.60%	31.27%	76.17%	42.46%	−27.55%	−10.63%
AnnualRet	7.07%	2.19%	5.02%	3.11%	−27.55%	−10.63%
AnnualVol	36.85%	15.66%	37.35%	15.39%	52.83%	17.15%
Sharpe	19.18%	13.99%	13.45%	20.22%	−52.15%	−61.98%
MDD	−68.98%	−43.44%	−68.98%	−43.44%	−58.16%	−24.70%

Table 6.48: **EM Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **EM** *Index*, b) the **EM** index rebased on the volatility target $Index_{VT}$. The results are shown relative to years 2009 to 2011. Trading costs are included.

Results	I_{2009}	$I_{VT,2009}$	I_{2010}	$I_{VT,2010}$	I_{2011}	$I_{VT,2011}$
CumRet	78.03%	23.12%	45.16%	26.77%	−25.36%	−6.93%
AnnualRet	78.31%	23.19%	45.31%	26.85%	−25.42%	−6.95%
AnnualVol	36.40%	11.85%	26.29%	11.17%	32.37%	15.26%
Sharpe	215.13%	195.72%	172.35%	240.31%	−78.54%	−45.55%
MDD	−32.30%	−11.88%	−16.65%	−5.66%	−41.76%	−22.80%

Table 6.49: **EM Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **EM** *Index*, b) the **EM** index rebased on the volatility target $Index_{VT}$. The results are shown relative to years 2012 to 2014. Trading costs are included.

Results	I_{2012}	$I_{VT,2012}$	I_{2013}	$I_{VT,2013}$	I_{2014}	$I_{VT,2014}$
CumRet	22.16%	4.08%	−0.48%	−6.50%	−19.94%	−10.58%
AnnualRet	22.16%	4.08%	−0.48%	−6.52%	−19.98%	−10.60%
AnnualVol	20.06%	13.52%	25.21%	20.64%	48.17%	20.24%
Sharpe	110.49%	30.16%	−1.91%	−31.60%	−41.49%	−52.39%
MDD	−29.51%	−23.01%	−33.50%	−30.69%	−60.15%	−33.47%

Table 6.50: **EM Carry** strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown for the a) **EM** *Index*, b) the **EM** index rebased on the volatility target $Index_{VT}$. The results are shown relative to years 2015 to 2017. Trading costs are included.

Results	I_{2015}	$I_{VT,2015}$	I_{2016}	$I_{VT,2016}$	I_{2017}	$I_{VT,2017}$
CumRet	−27.76%	−7.45%	77.43%	26.31%	26.28%	6.86%
AnnualRet	−27.82%	−7.47%	77.71%	26.39%	26.44%	6.90%
AnnualVol	50.47%	16.93%	39.85%	14.05%	33.71%	11.34%
Sharpe	−55.13%	−44.11%	195.00%	187.86%	78.44%	60.86%
MDD	−50.57%	−19.29%	−25.41%	−10.41%	−26.75%	−12.31%

At the core of the $I_{G10,Carry}$ there is the carry trading that is in fact implied by differential between domestic and foreign interest rates. To validate the goodness of the index and the "carryness" of G10 currency pairs, we build a set of regression models in which the target variable is the performance of the G10 carry index $I_{G10,Carry}$ and the predictive factor is the the interest rate differential between domestic and foreign rates ($r^d_{t,t+k} - r^f_{t,t+k}$). We used the same data that is used to build and back-test the G10 carry index. Table 6.51 shows the goodness of fit of the various linear regressions in terms of the R^2. The results confirm the results obtained from the back-testing of carry index constructed for individual G10 currencies. The carry component is stronger for the currency pairs USD/CHF, USD/JPY and USD/SEK respect to the other G10 currencies. Figure 6.19 shows the hyper-planes obtained with the linear regressions built using $r^{USD}_t - r^{CHF}_t$ and $r^{USD}_t - r^{JPY}_t$ and by $r^{USD}_t - r^{JPY}_t$ and $r^{USD}_t - r^{EUR}_t$ to predict the returns of the G10 carry index (Carry PnL). The goodness of fit of the two regressions is particularly high; both have R^2 above 80% as displayed by table 6.52.

TABLE 6.51: Linear regression between $I_{G_{10},Carry}$ and $(r^d_t - r^f_t)$ for G10 currency pairs.

Explanatory variable	R^2
$r^{USD}_t - r^{EUR}_t$	16.76%
$r^{USD}_t - r^{JPY}_t$	59.08%
$r^{USD}_t - r^{GBP}_t$	20.84%
$r^{USD}_t - r^{CHF}_t$	69.77%
$r^{USD}_t - r^{AUD}_t$	23.89%
$r^{USD}_t - r^{NZD}_t$	0.18%
$r^{USD}_t - r^{CAD}_t$	6.96%
$r^{USD}_t - r^{SEK}_t$	45.81%
$r^{USD}_t - r^{NOK}_t$	0.03%
$r^{USD}_t - r^{DKK}_t$	0.70%

TABLE 6.52: Linear regression between $I_{G_{10},Carry}$ and $(r^d_t - r^f_t)$ for G10 currency pairs.

Explanatory variables	R^2
$r^{USD}_t - r^{CHF}_t, r^{USD}_t - r^{JPY}_t$	85.78%
$r^{USD}_t - r^{EUR}_t, r^{USD}_t - r^{JPY}_t$	80.71%

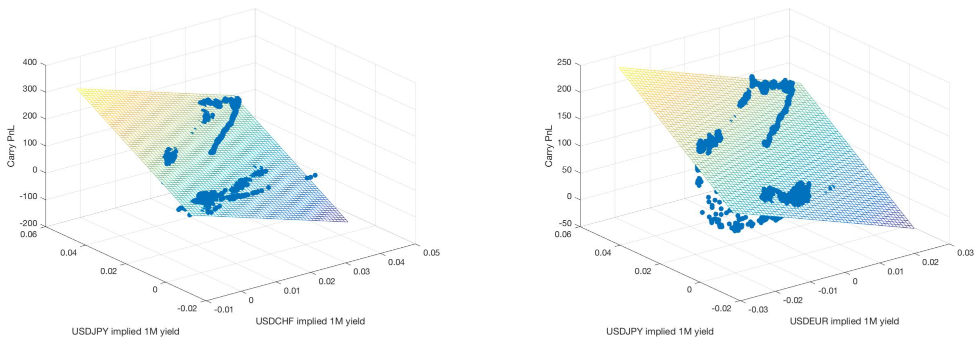


FIG. 6.19: Regression between the carry trade index and the difference of domestic and foreign rates measured by the 1-month implied yield for for the currency pairs USD/JPY and USD/CHF (left), USD/JPY and USD/EUR (right).

6.5 Experiment 5: validation of the forward rate puzzle

According to UIP, the interest rate differential should be offset by the appreciation of the low yielding currency and the depreciation of yielding currency. The condition expressed by equation 2.30 can be tested through the Fama-regression equation:

$$\Delta(S_{n,n+k}) = \alpha + \beta(r_{d,n,n+k} - r_{f,n,n+k}) + \epsilon_n, \tag{6.2}$$

where $\Delta(Sn, n+k$ is the change in the spot rate from time n to n+k; $r_{d,n,n+k}$ and $r_{f,n,n+k}$ are the interest rate from time t to time t+k for the domestic and the foreign currency respectively. By substituting equation 2.30 into the econometric regression equation 6.2 we derive the regression for testing for the unbiasedness of the forward rate as a predictor for the future spot exchange rate:

$$\Delta(S_{n,n+k}) = \alpha + \beta(f_{n,n+k} - S_n) + \epsilon_n, \tag{6.3}$$

The forward rate unbiasedness hypothesis states that the forward rate $f_{n,n+k}$ should correctly predict future spot exchange rate S_n. If agents are risk-neutral and have rational expectations, as in the UIP regression, we should expect the slope parameter p to be equal to unity and the disturbance term ϵ_n - the rational expectations forecast error - to be uncorrelated with information available at n. Previous section **??** defines the concept of forward rate puzzle in the context of the uncovered interest rate parity UIP. The claim is that the forward rate is not a good predictor of the spot rate in the future i.e. $F_{n,N} \neq S_N$. Aim of this paragraph is verifying this claim using spot and forward rate data relative to a pool of G10 and EM currencies. The forward rate puzzle can open trading opportunities by as an example adopting carry trade strategies. This type of trading strategy can be used for trading the spot rate and FX options. Two types of analysis are carried out. The first analysis measures the bias between forward rate and spot rate at maturity in terms of root-mean-square-error ρ_2. Large values of the ρ_2 imply that the forward rate is not an accurate predictor of the future spot rate. The formula of the ρ_2 is

$$\rho_2 = \sqrt{\frac{1}{N}\Big(\frac{F_{n,n+k} - S_{n+k}}{S_{n+k}}\Big)^2}. \tag{6.4}$$

The second analysis starts from equation 2.30 and derives the bias between forward rate and future spot rate as a function of the differential between the domestic interest rate r_d and the foreign interest rate r_f. This is done by taking the natural logarithm and rearranging the terms of the equation to obtain[13]

$$f_{n,n+k} - s_n = r_{d,n,n+k} - r_{f,n,n+k}. \tag{6.5}$$

If the left term $f_{n,n+k} - s_n$ is systematically different form the right term $r_{d,n,n+k} - r_{f,n,n+k}$ then the UIP does not hold and the forward rate is not a good predictor for the future spot rate.

TABLE 6.53: Validation of Fama regression for the G10 currencies.

		estimate	error	tstat	pvalue
EUR/USD	α	0.00003	< 0.0001	10.42347	< 0.0001
	β	0.00022	< 0.0001	91.62447	< 0.0001
	R^2	89.19%			
USD/JPY	α	−0.00003	< 0.0001	−5.87722	< 0.0001
	beta	−0.00022	< 0.0001	−130.23641	< 0.0001
	R^2	93.27%			
GBP/USD	α	0.00004	< 0.0001	11.29977	< 0.0001
	β	0.00033	< 0.0001	129.59691	< 0.0001
	R^2	94.15%			
USD/CHF	α	0.00002	< 0.0001	4.04929	< 0.0001
	β	−0.00027	< 0.0001	−104.34557	< 0.0001
	R^2	91.50%			
AUD/USD	α	0.00003	< 0.0001	8.73371	< 0.0001
	β	0.00017	< 0.0001	114.65206	< 0.0001
	R^2	91.47%			
USD/CAD	α	0.00000	< 0.0001	−2.24278	< 0.0001
	β	−0.00025	< 0.0001	−120.53918	< 0.0001
	R^2	92.23%			
USD/SEK	α	−0.00009	< 0.0001	−3.89913	< 0.0001
	β	−0.00159	< 0.0001	−109.74658	< 0.0001
	R^2	91.85%			
USD/NOK	α	−0.00013	< 0.0001	−5.89549	< 0.0001
	β	−0.00126	< 0.0001	−101.73985	< 0.0001
	R^2	92.72%			
USD/DKK	α	−0.00016	< 0.0001	−2.23861	0.02601
	β	−0.00139	< 0.0001	−20.60278	< 0.0001
	R^2	61.24%			

[13] We write the logarithm of the FX S_n as s_n.

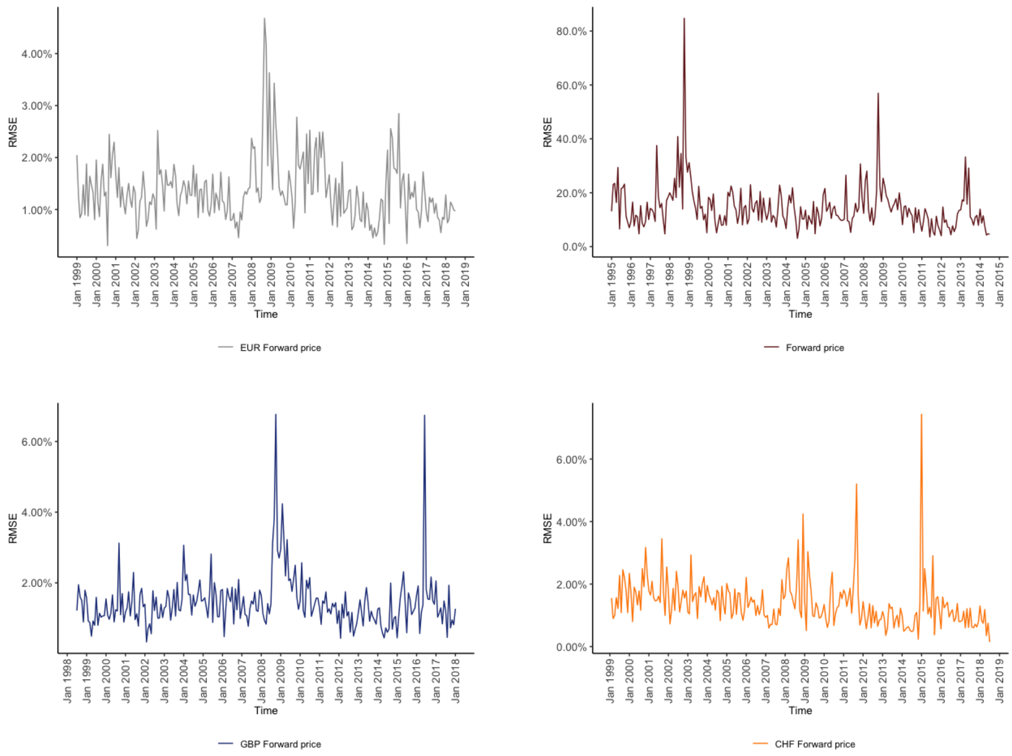


FIG. 6.20: Root mean square error of the forward rate vs. the spot at expiry for EUR, JPY, GBP, CHF.

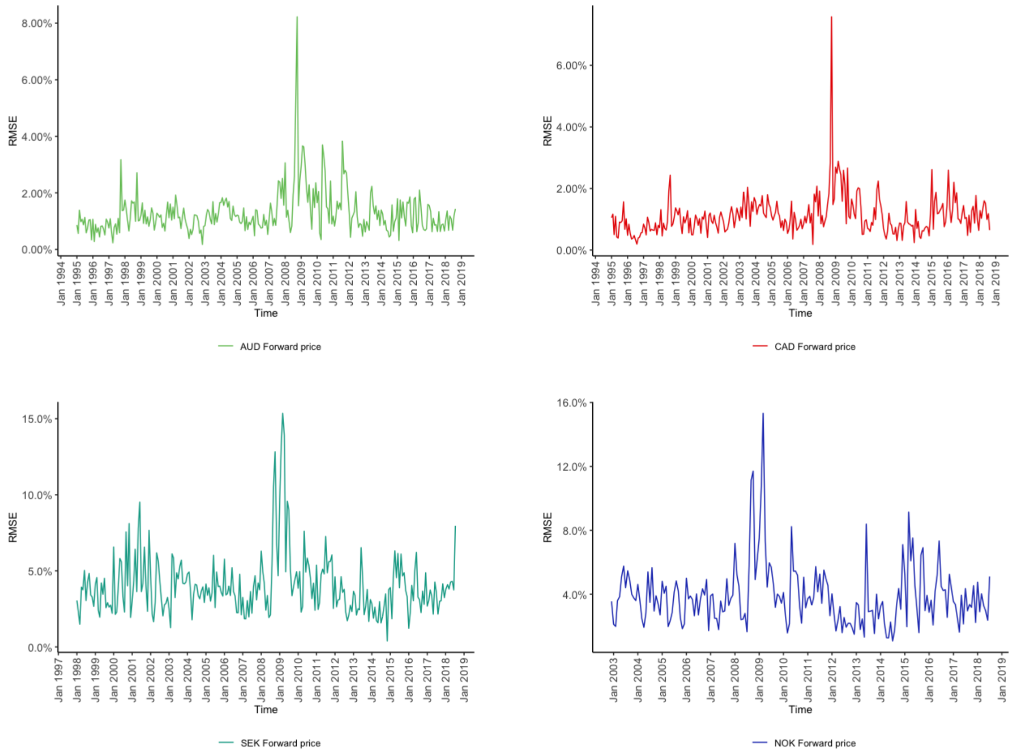


FIG. 6.21: Root mean square error of the forward rate vs. the spot at expiry for AUD, CAD, SEK, NOK.

TABLE 6.54: Root mean square error using forward as predictor (%) (*RMSF*) vs root mean square change in spot rate (%)(*RMSS*) relative to the G10 currency group.

FX	RMSF	RMSS
EUR/USD	1.3637%	1.3625%
USD/JPY	14.1014%	14.1012%
GBP/USD	1.4450%	1.4445%
USD/CHF	1.3933%	1.3922%
AUD/USD	1.2878%	1.2849%
USD/CAD	1.1082%	1.1073%
USD/SEK	4.0581%	4.0528%
USD/NOK	3.9035%	3.9041%
USD/DKK	2.6379%	2.6416%

6.6 Experiment 6: validation of a multi-premia index

We extracted the CBOE volatility index (VIX) and the S&P 500 equity index relative to the period 22/02/2000 and 19/02/2019. We calculated the Pearson correlation factor between the two time series. The tables 6.55, 6.56, 6.57 demonstrate a strong link between short-term index-based returns and implied volatilities of options traded on the index. The correlation on the entire time series is -48.2%.

TABLE 6.55: Pearson correlation coefficient by year between SP500 equity index and CBOE volatility index (VIX) over period $2000 - 2006$.

2000	2001	2002	2003	2004	2005	2006
-65.8%	-68.9%	-90.7%	-91.6%	-72.8%	-73.5%	-69.6%

TABLE 6.56: Pearson correlation coefficient by year between SP500 equity index and CBOE volatility index (VIX) over period $2007 - 2013$.

2007	2008	2009	2010	2011	2012	2013
-0.2%	-93.3%	-90.7%	-71.0%	-93.8%	-80.5%	-7.2%

Our empirical study of the strategies returns shows that volatility is generally negatively correlated with returns and that returns are auto correlated: large returns tend to be followed by large returns and small returns tend to be followed by small returns.

The multi-premia index shows a strong positive trend over the last decade. This is displayed by figures 6.22, 6.23, 6.24. The index has some noticeable troughs in Q2 2013 and Q2 2016. To recover from the losses experienced during the financial crisis in 2013 took much longer than in the second half of 2016. But the positive trend of the index started in 2016 does not last in 2017. In particular the first two quarters

TABLE 6.57: Pearson correlation coefficient by year between SP500 equity index and CBOE volatility index (VIX) over period $2014 - 2019$.

2014	2015	2016	2017	2018	2019	2000-2019
-23.5%	-91.7%	-85.8%	-47.9%	-75.0%	-95.7%	-48.2%

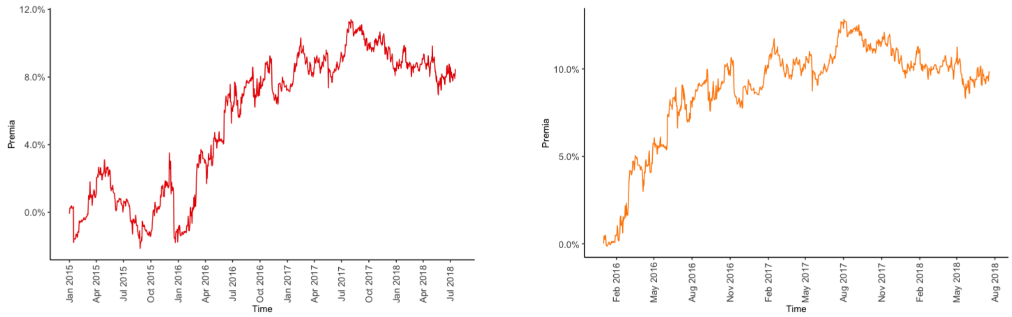


FIG. 6.23: Multi-risk premia from January 2015 to 18 July 2018.

of 2018 have registered large losses on the index. After a positive semester, Q3 2017 again appears to be dominated by negative performance as the index retraced to same values of one year prior. The results relative to the multi-risk premia are illustrated by the tables 6.58 and 6.59.

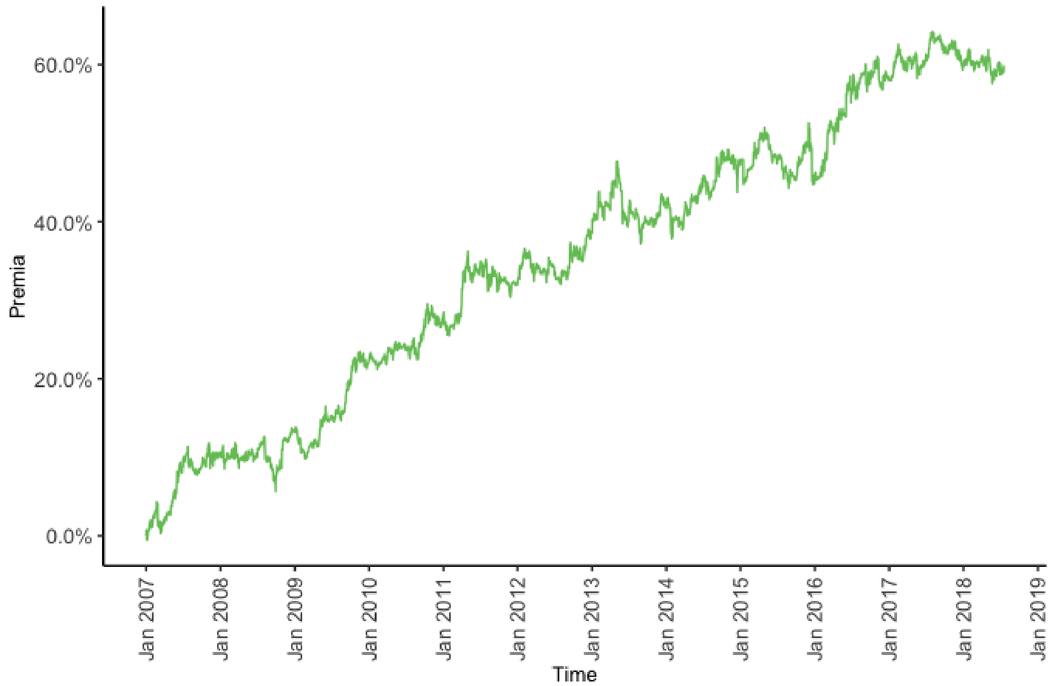


FIG. 6.22: Multi risk premia from January 2007 to 18 July 2018.

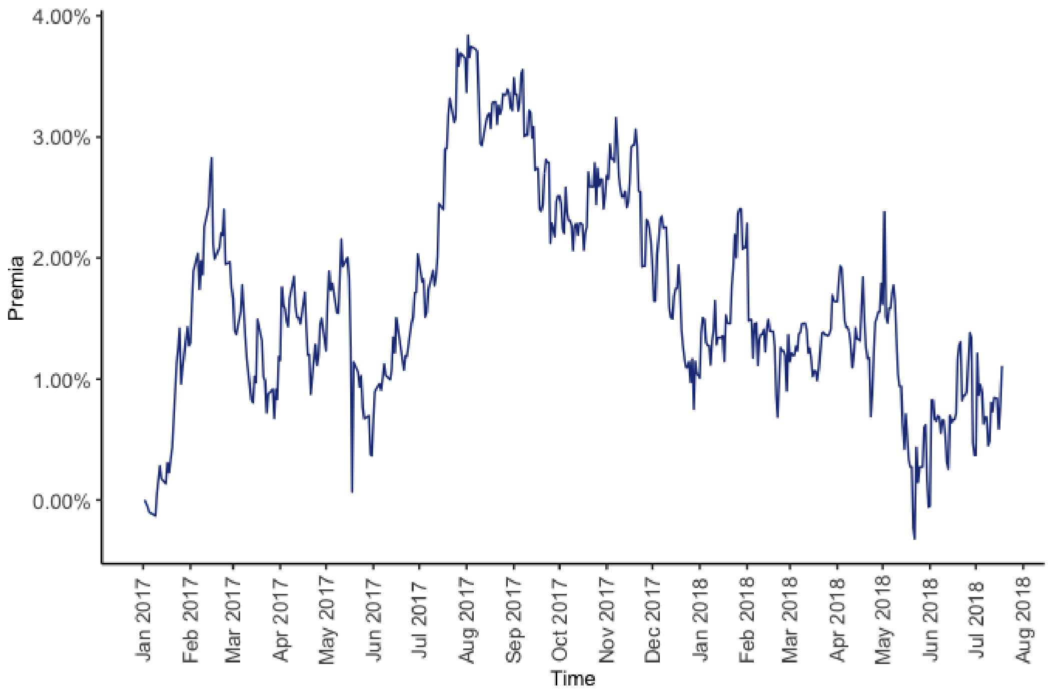


FIG. 6.24: Multi risk premia from January 2017 to 18 July 2018.

TABLE 6.58: Monthly annualised returns for the multi-risk premia index from 2007 to 2017.

Year	Jan	Feb	Mar	Apr	May	Jun
2007	0.00%	0.74%	−0.46%	0.98%	3.62%	2.26%
2008	−0.42%	0.25%	−0.95%	1.02%	0.55%	−0.42%
2009	−2.30%	−0.53%	1.04%	0.90%	2.93%	−0.36%
2010	−0.10%	−0.17%	0.39%	0.70%	0.97%	−0.62%
2011	−2.03%	1.18%	1.61%	4.77%	−1.10%	0.35%
2012	3.02%	−0.38%	−1.12%	−0.40%	−0.01%	0.26%
2013	2.30%	−1.07%	1.08%	2.13%	−3.46%	0.20%
2014	−2.48%	1.52%	0.57%	0.54%	0.34%	1.47%
2015	−1.19%	0.96%	1.28%	1.49%	−1.38%	−0.93%
2016	0.49%	1.59%	2.29%	1.23%	−0.31%	1.95%
2017	1.29%	0.47%	−0.56%	0.31%	−1.12%	1.66%

Table 6.60 contains the performance indicators of the multi-risk strategy by trading strategy. EM Carry and Value bring the highest Sharpe ratio. EM momentum produces the worst results among the tested strategies. The index is a synthesis of the strength and the weaknesses of the individual indices combined together. These components are sufficiently uncorrelated as shown by table 6.61.

TABLE 6.59: Monthly annualised returns for the multi-risk premia index from 2007 to 2017.

Year	Jul	Aug	Sep	Oct	Nov	Dec
2007	−0.07%	−0.40%	0.46%	2.20%	−0.58%	−0.40%
2008	1.63%	−1.74%	−2.51%	3.52%	1.03%	0.95%
2009	0.78%	−0.07%	3.58%	1.06%	0.89%	0.01%
2010	0.27%	−1.27%	3.72%	0.72%	−0.93%	1.19%
2011	0.61%	−0.68%	−2.07%	1.05%	−1.28%	0.60%
2012	−1.24%	0.70%	1.97%	0.00%	1.01%	1.16%
2013	0.29%	−2.10%	1.87%	−0.37%	0.91%	0.65%
2014	−0.70%	1.29%	1.80%	0.93%	−1.69%	0.46%
2015	−1.39%	−0.26%	0.04%	1.78%	1.24%	−2.81%
2016	0.68%	1.07%	−0.61%	1.20%	−2.00%	0.83%
2017	1.59%	−0.42%	−0.68%	0.00%	−0.37%	−1.07%

TABLE 6.60: Multi-risk premia strategy: results in terms of cumulative and annualised returns, annualised volatility, Sharpe and maximum drawdown, monthly returns and daily returns.

Results	$I_{G_{10},M}$	$I_{EM,M}$	$I_{G10,V}$	$I_{G_{10},C}$	$I_{EM,C}$
CumRet	1.65%	−2.43%	10.20%	−9.78%	14.98%
AnnualRet	2.66%	−3.87%	16.82%	−6.46%	25.05%
AnnualVol	11.57%	6.15%	11.06%	10.88%	11.47%
Sharpe	0.23	−0.63	1.52	−0.59	2.18
D_{max}	−12.94%	−3.94%	−3.89%	−20.89%	−5.08%
MonthlyRet	−3.24%	−0.16%	2.06%	0.36%	1.50%
DailyRet	0.54%	−0.05%	0.15%	0.46%	0.40%

TABLE 6.61: Correlation matrix between the multi-risk premia index and the indices, which are its constituents.

Index	I_P	$I_{G_{10},V}$	$I_{G_{10},M}$	$I_{EM,M}$	$I_{G_{10},C}$	$I_{EM,C}$
I_P	100.00%	8.99%	42.52%	35.21%	46.00%	70.33%
$I_{G_{10},V}$	8.99%	100.00%	−5.11%	−3.59%	−44.26%	−23.43%
$I_{G_{10},M}$	42.52%	−5.11%	100.00%	10.87%	−5.55%	−1.08%
$I_{EM,M}$	35.21%	−3.59%	10.87%	100.00%	2.80%	−1.24%
$I_{G_{10},C}$	46.00%	−44.26%	−5.55%	2.80%	100.00%	39.86%
$I_{EM,C}$	70.33%	−23.43%	−1.08%	−1.24%	39.86%	100.00%

We provide an example of the trading positions selected by the algorithms as of 18 July 2018. It can be noted that the ensemble of algorithms suggests to buy the currency pairs at a certain spot value. For each trade we display the weight of the investment relative to the specific strategy W_I and to the global investment W_{Π}. This is illustrated by tables 6.62− 6.66.

TABLE 6.62: Example: trading positions determined by the G10 momentum algorithm as of 18 July 2018.

Currency pair	*Long*	*Short*	*Spot*	W_I	W_{Π}
EUR/USD	USD	EUR	1.16	25.00%	5.00%
USD/JPY	JPY	USD	113.05	25.00%	5.00%
AUD/USD	USD	AUD	0.73	25.00%	5.00%
NZD/USD	USD	NZD	0.67	25.00%	5.00%

TABLE 6.63: Example: trading positions determined by the EM momentum algorithm as of 18 July 2018.

Currency pair	*Long*	*Short*	*Spot*	W_I	W_{Π}
USD/ARS	USD	ARS	27.52	14.29%	2.86%
USD/BRL	USD	BRL	3.84	14.29%	2.86%
USD/CNY	USD	CNY	6.75	14.29%	2.86%
USD/INR	INR	USD	68.80	14.29%	2.86%
USD/IDR	USD	IDR	14493.00	14.29%	2.86%
USD/MXN	MXN	USD	18.99	14.29%	2.86%
USD/RUB	RUB	USD	63.04	14.29%	2.86%

TABLE 6.64: Example: trading positions determined by the G10 value algorithm as of 18 July 2018.

Currency pair	*Long*	*Short*	*Spot*	W_I	W_{Π}
USD/CHF	USD	CHF	1.00	100.00%	20.00%

Table 6.65: Example: trading positions determined by the G10 carry algorithm as of 18 July 2018.

Currency pair	*Long*	*Short*	*Spot*	W_I	W_{Π}
EUR/USD	USD	EUR	1.16	25.00%	5.00%
USD/CHF	USD	CHF	0.99	25.00%	5.00%
USD/SEK	USD	SEK	8.97	25.00%	5.00%
USD/DKK	USD	DKK	6.40	25.00%	5.00%

Table 6.66: Example: trading positions determined by the EM carry algorithm as of 18 July 2018.

Currency pair	*Long*	*Short*	*Spot*	W_I	W_{Π}
USD/INR	INR	USD	68.75	25.00%	5.00%
USD/MXN	MXN	USD	19.93	25.00%	5.00%
USD/TRY	TRY	USD	4.60	25.00%	5.00%
USD/ZAR	ZAR	USD	13.73	25.00%	5.00%

- Trend-following strategies are designed to profit from the comparison of medium/long term trends and are deployed by moving average crossovers. They try to capture price reversal and early stages of rallies of market prices. These strategies generally need a stronger consensus about the price direction than the trend-following ones.

- The purchase power parity predicts that inflation differential between economies is compensated by the appreciation or the depreciation of the exchange rate. While this may hold in the long term, short-term observations prove the contrary. This opens trading opportunities to models that are designed to profit from the imbalance between the value of the currency pairs.

- The carry trading is linked to the trajectory of the interest rates of two economies. The interest rates determine the forward prices of currencies for future delivery. Currencies that have lower interest rate than the base currency are offered at premiums; those with higher interest rates sell at discount. The uncovered interest rate parity is built on the assumption that the forward rates are robust predictors of future spot rates. Contrary to the theory forward rates are poor predictors of future spot rates. If premium suggests that a currency should rise it never consistently rises to the forward rate. The forward rate has systematically overestimated the subsequent change in the spot rate. Under these scenarios carry trading strategies then can systematically achieve positive returns.

Our validation seems to suggest that the individual strategies as well as the combined multi-risk premia have performed better in the past compared to the most recent years. In particular all the strategies struggled during the recent financial crisis. The poor results could be explained by the predominant synchronisation between the economies during the crisis and on the recent years. As an example it can be noted that when the adoption of different monetary policies by the respective central banks broke the economic synchronisation during the period $2014 - 2015$, the multi-premia index produced more positive results.

6.7 Experiment 7: validation by block-bootstrapping

We validate the trend-following, value, and carry strategies using the approach described in previous section 2.9. In particular we focus on two portions of the time series: $2007-2012$ and $2013-2017$. The intention is to compare the performance on most recent years as opposed to earlier observations. We modify the algorithm 2.9.3 to allow a two-level bootstrap sampling described by the procedure **??**. 'Figure 6.25' shows simulated price paths relative to EUR/USD.

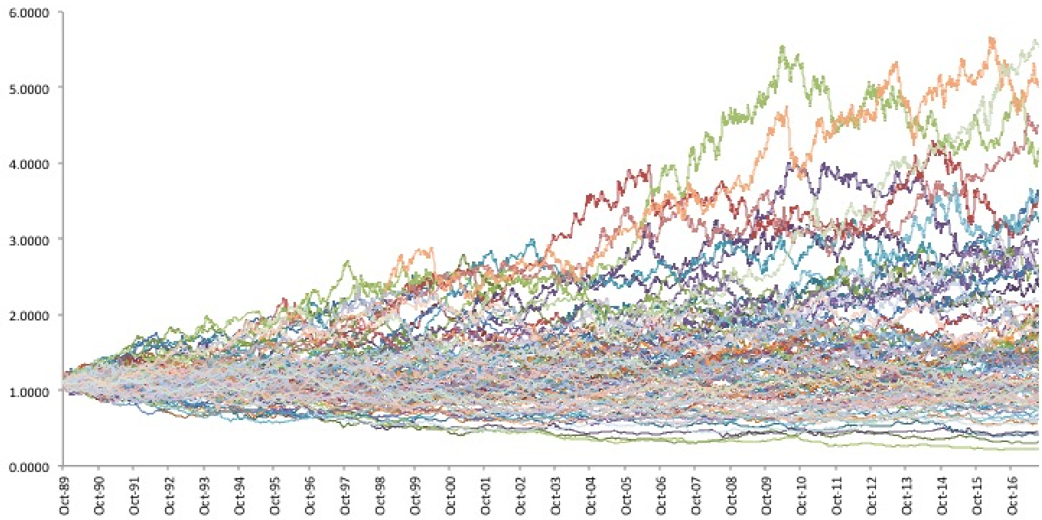


FIG. 6.25: Block-bootstrap price paths relative to EUR/USD.

'Figure 6.26' shows an example of the autocorrelation function of EUR/USD calculated from the historical time series:

Having created the validation sample, the same trading strategy used on the back-testing data is tested [14].

The analysis of the Sharpe ratio distributions obtained from the bootstrapped samples generally confirms the result of the back-testing. The momentum strategy produces non dissimilar results on the two statistical samples. The Sharpe ratio is

[14]We verified that two alternative implementations of the bootstrapping approach are possible. The first approach extracts samples of the strategy returns. The second approach extracts samples of the currency pair prices and applies the strategy to derive the returns. In other words, the first approach applies the strategy to the historical prices, whilst the second to the bootstrapped prices. The two approaches produce similar results.

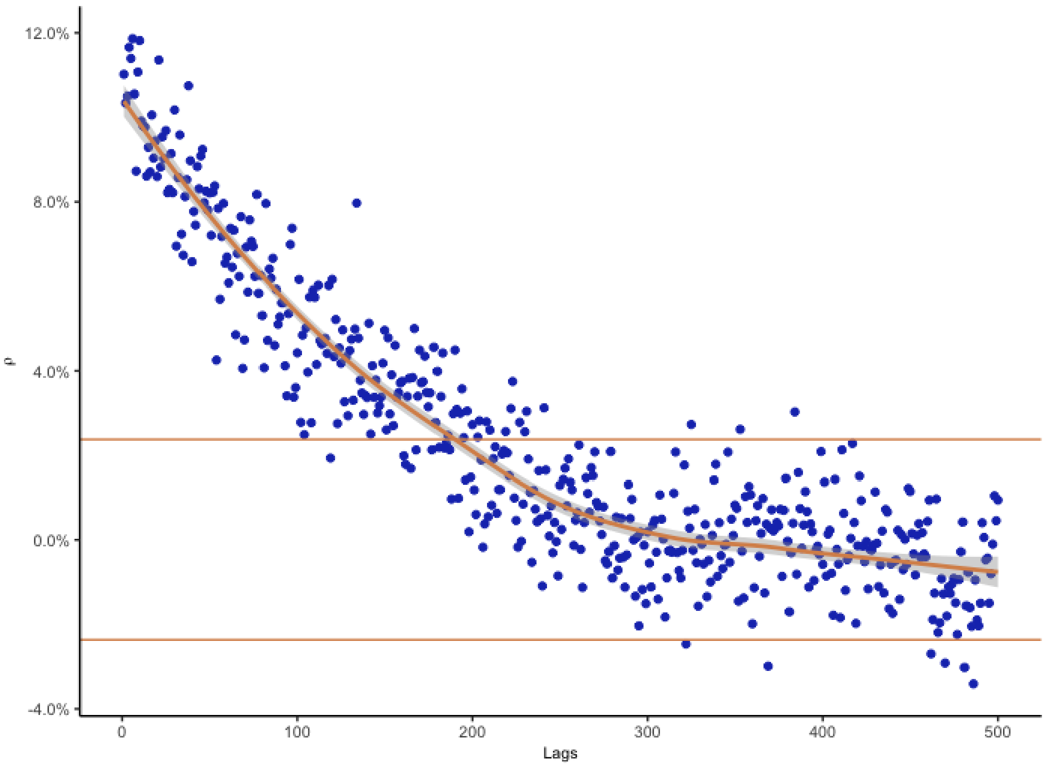


FIG. 6.26: Autocorrelation of returns, ρ, at various lags of time for EUR/USD. The figure displays the autocorrelation at various lags (blue points) and the interpolation line (yellow line) along with the area defined by the 95% bounds around the zero (yellow straight lines). The length of the blocks is chosen in correspondence of the lags for which the autocorrelation is significantly greater than zero. As an example, blocks long not more than 200 days have higher correlation than those longer more than 200 days for which the autocorrelation values are included in the 95% bounds area.

general much lower than the one obtained from the previous back-testing analysis, in which the momentum index have a positive run during 2014 and 2015. Carry brings negative results on the bootstrapped sampled for both G10 and EM currency groups. The analysis of the risk premia on the historical data showed that the carry index was under-performing mainly for the G10 currencies. The Sharpe ratios for G10 Value improve during period $2013-2017$ compared to $2007-2012$.

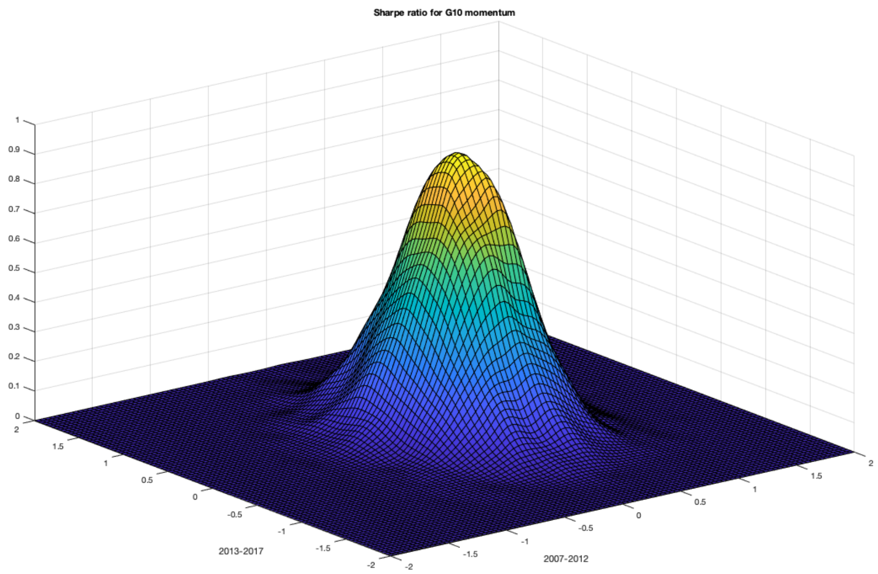


Fig. 6.27: Joined distributions of the boostrapped Sharpe ratio relative to the G10 momentum index relative to period $2007-2012$ and $2013-2017$. The distribution is centered showing that the overall results from the two samples are not statistically dissimilar.

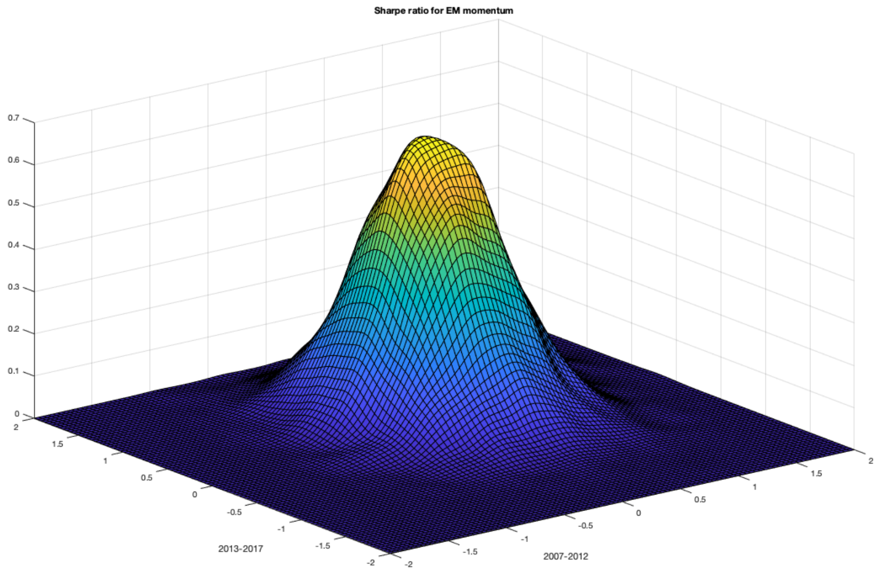


FIG. 6.28: Joined distributions of the boostrapped Sharpe ratio relative to the EM momentum index relative to period $2007-2012$ and $2013-2017$. The distribution is centered showing that the overall results from the two samples are not statistically dissimilar.

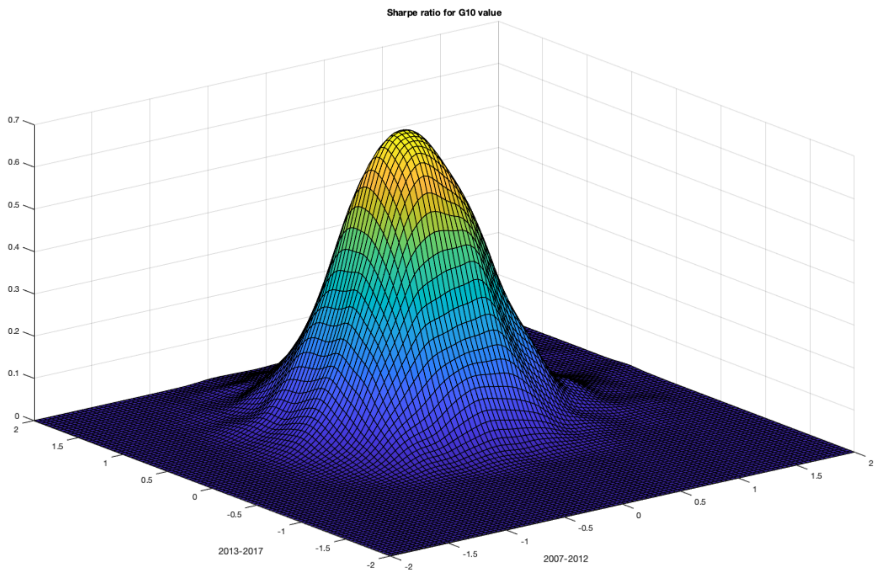


FIG. 6.29: Joined distributions of the boostrapped Sharpe ratio relative to the G10 value index relative to period $2007-2012$ and $2013-2017$. The distribution is not centered showing that the overall results from the most recent data is larger than the oldest one.

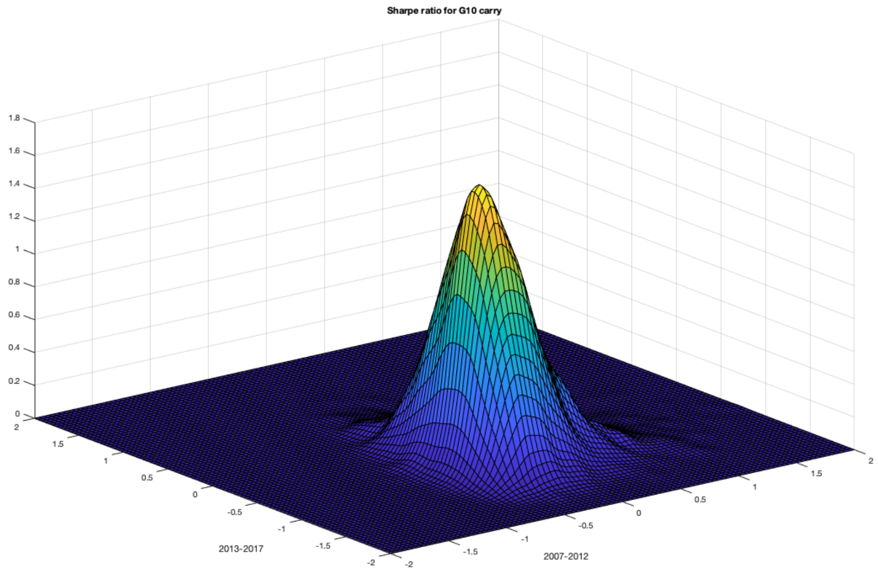


Fig. 6.30: Joined distributions of the boostrapped Sharpe ratio relative to the G10 carry index relative to period $2007-2012$ and $2013-2017$. The distribution is not centered showing that the overall results from the oldest data is larger than the most recent one.

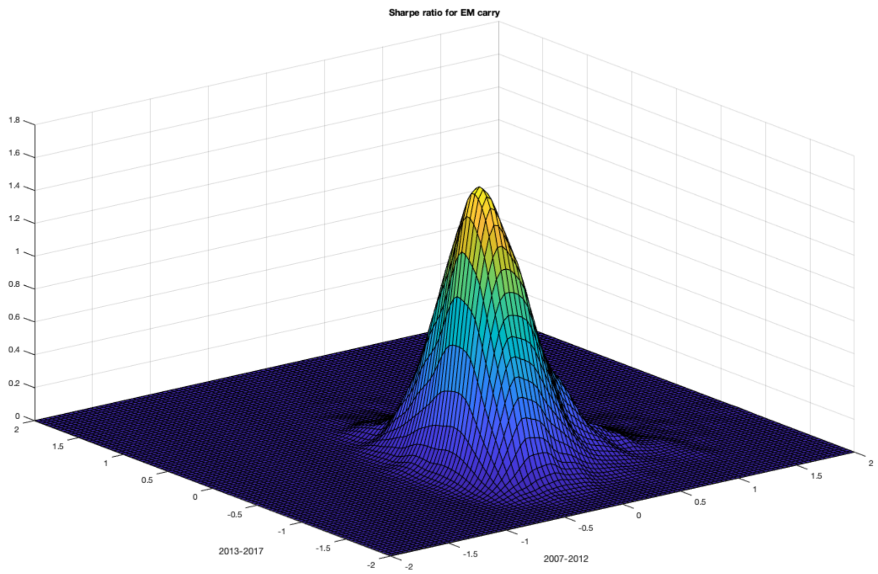
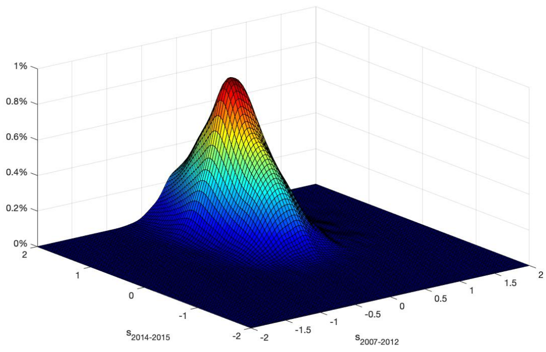
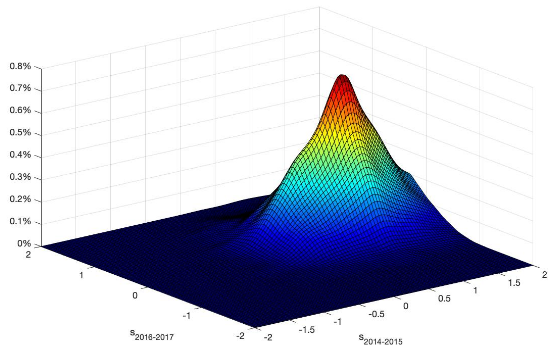


Fig. 6.31: Joined distributions of the boostrapped Sharpe ratio relative to the EM carry index relative to period $2007-2012$ and $2013-2017$. The distribution is not centered showing that the overall results from the oldest data is larger than the most recent one.



(a) 2007–2015

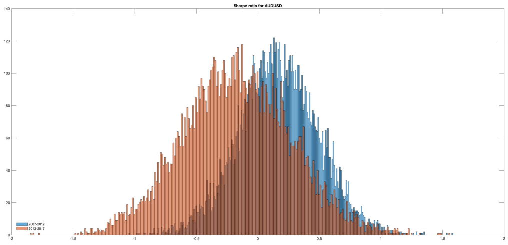


(b) 2014–2017

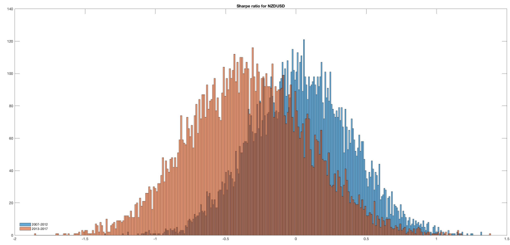
FIG. 6.32: Joined distributions of the Sharpe ratio obtained from bootstrapped samples for the periods 2007–2012 and 2014–2015 and for the periods 2014–2015 and 2016–2017 for the EUR/USD. The Sharpe ratio obtained by a trend-following strategy for the EUR/USD is larger during 2014–2015 compared to the period 2007–2012. The currency pair did not trend during the financial crisis. The Sharpe is larger during years 2014–2015 compared to the period 2016–2017. The center of the distribution is shifted towards the y axis e.g larger Sharpe ratio during 2014–2015. The center of the distribution of the Sharpe is shifted towards the x axis as the currency pair did not trend much during 2016–2017.

We also use the bootstrapping validation to assess the results of the trend-following strategy for the specific currency pairs and over older and more recent data e.g. 2007–2012 and 2013–2017. The data clearly shoes that for most of them the distributions of the Sharpe ratios overlap for the two periods i.e. no-significant difference in performance over the two samples. The strategy clearly performs less for AUD/USD, NZD/USD, USD/INR and USD/SGD; whilst it improves for USD/JPY, USD/RUB, USD/CZK and AUD/JPY. We look at in detail at the results relative to EUR/USD. The Sharpe ratio obtained by a trend-following strategy for the EUR/USD is larger during 2014–2015 compared to the period 2007–2012. The currency pair did not trend during the financial crisis. The Sharpe is larger during years 2014–2015 compared to the period 2016–2017.

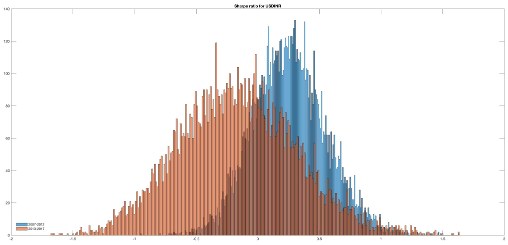
The simulated prices are used to test the significance of the back-tested Sharpe ratio. A t-test is constructed using the bootstrapped samples. Results are contained in table 6.67. It can be seen that the Sharpe calculated on the historical data is generally not included in the confidence interval constructed from the simulated prices.



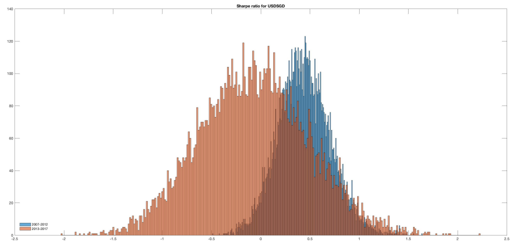
(a) AUD/USD



(b) NZD/USD

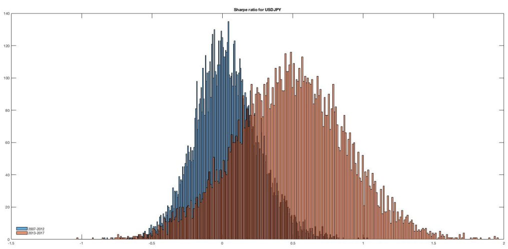


(c) USD/INR

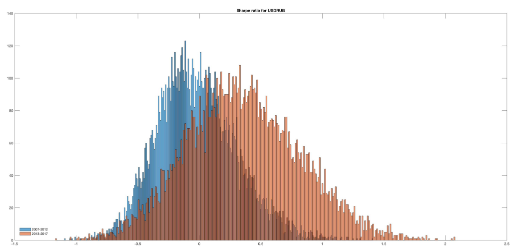


(d) USD/SGD

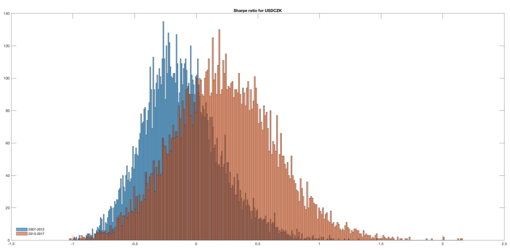
FIG. 6.33: Joined distributions of the trend-following Sharpe ratio obtained from bootstrapped samples for the periods 2007–2012 and 2013–2017 for a group of currency pairs for which the results are more negative on the most recent data.



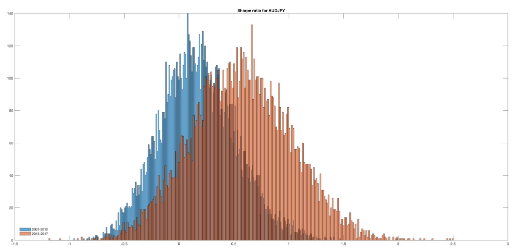
(a) USD/JPY



(b) USD/RUB

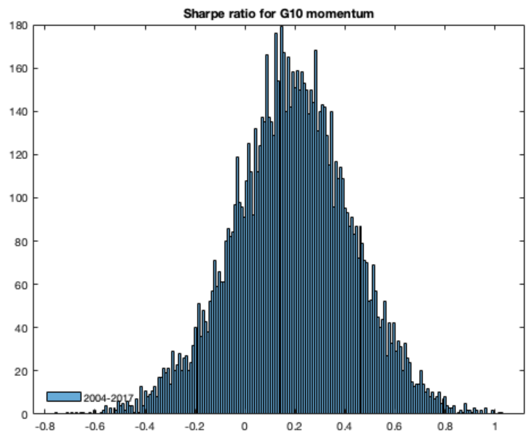


(c) USD/CZK

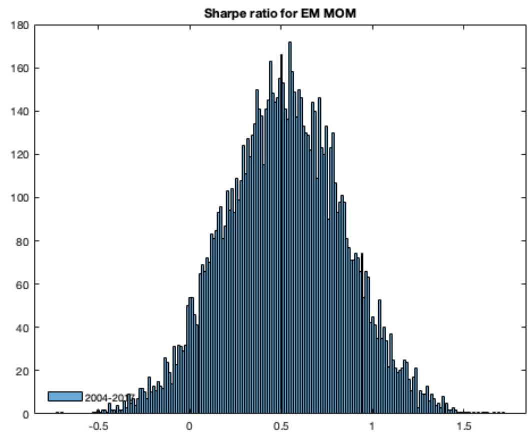


(d) AUD/JPY

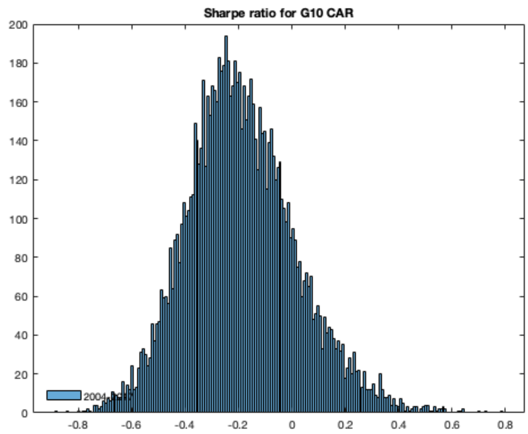
FIG. 6.34: Joined distributions of the trend-following Sharpe ratio obtained from bootstrapped samples for the periods 2007–2012 and 2013–2017 for a group of currency pairs for which the results are more positive on the most recent data.



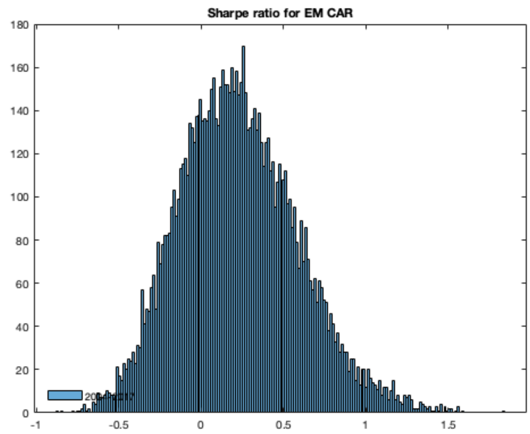
(a) G10 Momentum



(b) EM Momentum



(c) G10 Carry



(d) EM Carry

Fig. 6.35: Sharpe ratio distributions obtained from the simulated samples through the block-bootstrapping approach for the momentum and carry strategies.

TABLE 6.67: T-test of the average Sharpe ratio and the simulated samples.

Model	p-value	Sim mean	Lower bound	Upper bound	Mean
G10 Momentum	0.00000	0.19010	0.18550	0.19480	0.52730
EM Momentum	0.00059	0.52730	0.50980	0.52250	0.35610
G10 Value	0.00000	0.08910	0.08390	0.09430	0.10190
G10 Carry	0.00000	-0.18820	-0.19220	-0.18420	0.00042
EM Carry	0.00000	0.22770	0.22070	0.23480	0.13990

6.8 Experiment 8: validation of option premia

We present the results in tables about calls, puts and straddles 6.68, 6.69, 6.70. In there each column is the ratio between the payout and the premium. We display the average payout and premium for each column. For example, 95.02% is the average ratio for AUDUSD when options are traded on Mondays. The column "benchmark" is the value presented by [167]. These results are obtained using a fixed value of 10 million US dollar as notional. Payout and premium are expressed in US dollars. If the currency pairs does not include US dollar as base or quote currency we expressed the quantities in euros.

We construct a T-test for each weekly payout and assess if the payout/premium is significantly different from the weekly average. As an example, -7.5409 is the value of T-test obtained by comparing the Monday ratio with the average of the ratios obtained from Tuesday to Friday.

Table 6.68: Payout/premium for ATMF calls, 06/01/1995–09/07/2018, 1 week tenor, by trading any day of the week or a specific day of the week.

FX rate	Any day	Monday	Tuesday	Wednesday	Thursday	Friday	Benchmark
AUD/USD	92.73%	95.02%	91.47%	91.67%	92.32%	93.15%	96.10%
EUR/AUD	86.34%	91.42%	86.01%	85.19%	80.60%	88.47%	82.70%
EUR/CAD	88.35%	89.46%	89.08%	87.73%	82.51%	92.98%	
EUR/CZK	63.78%	65.31%	65.39%	63.42%	61.46%	63.31%	72.20%
EUR/GBP	94.50%	95.39%	94.34%	91.90%	92.79%	98.07%	87.30%
EUR/HUF	83.65%	85.54%	82.10%	82.91%	83.17%	84.53%	74.60%
EUR/JPY	93.25%	95.81%	91.78%	92.15%	91.66%	94.86%	94.30%
EUR/NOK	84.36%	82.74%	84.24%	84.06%	85.87%	84.89%	76.50%
EUR/PLN	78.62%	82.87%	75.57%	77.95%	78.00%	78.71%	
EUR/SEK	84.95%	87.24%	84.64%	83.28%	82.65%	86.95%	
EUR/USD	90.27%	91.57%	92.10%	86.94%	87.61%	93.14%	91.00%
GBP/USD	91.25%	92.06%	92.89%	88.19%	89.07%	94.05%	89.20%
USD/CAD	86.36%	86.20%	86.46%	88.41%	85.30%	85.42%	85.90%
USD/CHF	91.46%	90.73%	92.10%	90.56%	89.41%	94.49%	89.10%
USD/CZK	76.73%	79.50%	77.96%	76.03%	71.50%	78.66%	
USD/DKK	74.59%	76.02%	76.51%	72.41%	71.17%	76.81%	80.90%
USD/HKD	46.39%	46.76%	45.95%	45.00%	46.77%	47.47%	51.20%
USD/HUF	92.49%	91.20%	91.79%	92.45%	93.96%	93.07%	
USD/ILS	72.89%	70.72%	70.91%	73.43%	70.52%	78.87%	
USD/INR	87.34%	87.16%	89.21%	89.65%	87.04%	83.63%	
USD/JPY	93.43%	96.14%	93.21%	90.43%	91.20%	96.18%	83.60%
USD/KRW	85.51%	88.07%	87.79%	86.39%	83.21%	82.07%	72.20%
USD/MXN	88.51%	89.11%	87.41%	89.73%	89.44%	86.86%	75.80%
USD/NOK	89.09%	89.32%	88.25%	88.42%	90.43%	89.04%	84.80%
USD/PHP	78.34%	77.91%	77.49%	77.58%	79.18%	79.55%	
USD/PLN	83.98%	86.03%	83.50%	81.91%	84.00%	84.44%	
USD/SEK	89.15%	89.92%	87.98%	87.52%	88.85%	91.50%	84.60%
USD/SGD	75.50%	75.41%	74.49%	75.99%	78.07%	73.52%	69.60%
USD/TRY	88.33%	91.09%	84.24%	87.91%	89.86%	88.56%	86.50%
USD/TWD	70.94%	73.54%	70.17%	71.00%	71.60%	68.38%	64.90%
USD/ZAR	83.69%	84.20%	82.68%	83.46%	84.06%	84.06%	81.20%

Table 6.69: Payout/premium for ATMF puts, 06/01/1995–09/07/2018, 1 week tenor, by trading any day of the week or a specific day of the week.

FX rate	Any day	Monday	Tuesday	Wednesday	Thursday	Friday	Benchmark
AUD/USD	93.05%	95.22%	91.00%	92.07%	92.95%	94.00%	86.80%
EUR/AUD	82.30%	86.44%	81.95%	79.87%	78.77%	84.45%	86.80%
EUR/CAD	92.33%	93.08%	93.56%	90.85%	88.91%	95.23%	
EUR/CZK	67.27%	68.27%	69.34%	67.29%	65.28%	66.16%	82.20%
EUR/GBP	84.84%	85.30%	85.16%	82.41%	82.57%	88.76%	87.10%
EUR/HUF	70.48%	72.06%	70.06%	70.13%	69.55%	70.60%	87.30%
EUR/JPY	87.66%	90.01%	85.94%	87.06%	86.18%	89.13%	87.80%
EUR/NOK	76.65%	75.33%	76.77%	76.21%	78.28%	76.67%	85.40%
EUR/PLN	77.11%	79.81%	75.49%	75.91%	76.72%	77.62%	
EUR/SEK	71.92%	74.19%	71.72%	70.34%	69.77%	73.61%	
EUR/USD	93.90%	95.19%	95.63%	91.74%	91.39%	95.57%	96.00%
GBP/USD	93.24%	94.59%	94.13%	90.76%	91.00%	95.70%	87.80%
USD/CAD	87.46%	87.40%	88.69%	88.75%	85.76%	86.71%	95.60%
USD/CHF	97.37%	97.14%	98.72%	94.85%	94.43%	101.71%	95.60%
USD/CZK	70.09%	73.01%	72.02%	67.94%	65.52%	71.94%	94.50%
USD/DKK	66.44%	67.99%	68.23%	62.66%	63.32%	69.99%	83.90%
USD/HKD	30.94%	33.03%	31.09%	29.99%	29.10%	31.51%	36.00%
USD/HUF	80.85%	79.74%	80.56%	79.60%	82.68%	81.66%	
USD/ILS	86.45%	84.45%	84.60%	86.75%	84.79%	91.66%	
USD/INR	74.35%	73.21%	73.84%	77.11%	75.83%	71.76%	
USD/JPY	84.78%	88.26%	83.88%	81.10%	82.18%	88.49%	81.80%
USD/KRW	83.60%	85.63%	85.57%	83.82%	81.45%	81.53%	83.30%
USD/MXN	72.82%	73.94%	72.59%	73.74%	72.18%	71.64%	81.10%
USD/NOK	92.78%	93.24%	92.21%	91.99%	93.84%	92.64%	94.50%
USD/PHP	72.20%	72.26%	71.31%	70.84%	73.01%	73.57%	
USD/PLN	99.16%	101.14%	99.93%	96.47%	98.27%	99.97%	
USD/SEK	110.97%	122.16%	133.04%	94.44%	95.46%	109.75%	90.90%
USD/SGD	82.28%	82.49%	81.85%	82.57%	84.17%	80.33%	82.30%
USD/TRY	93.37%	94.22%	90.62%	93.21%	94.99%	93.80%	107.50%
USD/TWD	74.98%	77.50%	74.70%	75.40%	74.72%	72.56%	62.80%
USD/ZAR	91.98%	93.15%	91.74%	91.35%	92.02%	91.65%	89.40%

TABLE 6.70: Payout/premium for ATMF straddles, 06/01/1995–09/07/2018, 1 week tenor, by trading any day of the week or a specific day of the week.

FX rate	Any day	Monday	Tuesday	Wednesday	Thursday	Friday	Benchmark
AUD/USD	92.89%	95.14%	91.23%	91.86%	92.65%	93.58%	91.90%
EUR/AUD	83.99%	88.51%	83.63%	82.08%	79.55%	86.16%	89.30%
EUR/CAD	92.56%	93.41%	93.49%	91.54%	88.78%	95.56%	
EUR/CZK	65.58%	66.85%	67.45%	65.32%	63.45%	64.83%	78.70%
EUR/GBP	89.00%	89.64%	89.10%	86.49%	86.97%	92.80%	82.70%
EUR/HUF	76.74%	78.46%	75.81%	76.22%	76.02%	77.19%	83.00%
EUR/JPY	90.26%	92.73%	88.64%	89.42%	88.71%	91.80%	88.30%
EUR/NOK	80.21%	78.75%	80.19%	79.82%	81.82%	80.45%	81.70%
EUR/PLN	77.82%	81.20%	75.60%	76.82%	77.33%	78.13%	
EUR/SEK	77.82%	80.07%	77.53%	76.22%	75.62%	79.66%	
EUR/USD	92.04%	93.33%	93.79%	89.33%	89.49%	94.29%	89.60%
GBP/USD	92.23%	93.30%	93.47%	89.48%	90.05%	94.85%	91.30%
USD/CAD	86.89%	86.76%	87.56%	88.58%	85.53%	86.03%	93.50%
USD/CHF	94.35%	93.87%	95.29%	92.71%	91.90%	98.00%	96.10%
USD/CZK	73.47%	76.31%	75.02%	71.89%	68.74%	75.35%	94.30%
USD/DKK	70.43%	71.94%	72.23%	67.50%	67.21%	73.28%	82.80%
USD/HKD	38.67%	39.79%	38.54%	37.56%	37.95%	39.53%	44.00%
USD/HUF	86.46%	85.30%	85.86%	85.80%	88.18%	87.14%	
USD/ILS	79.69%	77.62%	77.78%	80.13%	77.67%	85.28%	
USD/INR	80.29%	79.37%	80.69%	83.04%	81.03%	77.33%	
USD/JPY	89.10%	92.19%	88.54%	85.74%	86.72%	92.33%	82.10%
USD/KRW	84.40%	86.68%	86.49%	84.86%	82.22%	81.74%	77.60%
USD/MXN	80.41%	81.29%	79.74%	81.48%	80.54%	79.02%	78.70%
USD/NOK	90.91%	91.25%	90.19%	90.19%	92.12%	90.82%	89.90%
USD/PHP	75.22%	75.01%	74.21%	74.21%	76.14%	76.55%	
USD/PLN	91.53%	93.56%	91.63%	89.14%	91.13%	92.17%	
USD/SEK	103.32%	111.65%	115.97%	91.18%	93.22%	104.60%	86.30%
USD/SGD	78.86%	78.90%	78.11%	79.26%	81.11%	76.90%	76.90%
USD/TRY	90.81%	92.78%	87.37%	90.33%	92.39%	91.18%	95.50%
USD/TWD	72.94%	75.54%	72.38%	73.23%	73.04%	70.51%	64.50%
USD/ZAR	87.83%	88.67%	87.23%	87.41%	88.05%	87.80%	89.50%

TABLE 6.71: Ttest for payout/premium for ATMF calls, 06/01/1995–09/07/2018, 1 week tenor, by trading Monday, Tuesday or Wednesday.

FX rate	Tstat Mon	p-value Mon	Tstat Tue	p-value Tue	Tstat Wed	p-value Wed
AUD/USD	-7.5409	0.0048	2.1689	0.1186	1.7395	0.1803
EUR/AUD	-3.8627	0.0307	0.1765	0.8712	0.6268	0.5753
EUR/CAD	-0.6409	0.5672	-0.4179	0.7041	0.3576	0.7443
EUR/CZK	-2.3819	0.0975	-2.5712	0.0824	0.4807	0.6636
EUR/GBP	-0.8145	0.4750	0.1418	0.8962	2.9225	0.0614
EUR/HUF	-4.6727	0.0185	3.1464	0.0514	1.2295	0.3065
EUR/JPY	-4.2319	0.0241	1.8161	0.1670	1.2973	0.2853
EUR/NOK	4.9506	0.0158	0.2242	0.8370	0.5708	0.6081
EUR/PLN	-7.7739	0.0044	3.2373	0.0479	0.5530	0.6188
EUR/SEK	-3.0095	0.0572	0.3254	0.7662	1.9412	0.1475
EUR/USD	-1.0371	0.3759	-1.5197	0.2259	3.4421	0.0412
GBP/USD	-0.7093	0.5293	-1.5151	0.2270	3.5969	0.0368
USD/CAD	0.2765	0.8001	-0.1736	0.8732	-8.9963	0.0029
USD/CHF	0.8282	0.4683	-0.7242	0.5213	1.0284	0.3794
USD/CZK	-2.1497	0.1207	-0.8548	0.4555	0.4763	0.6664
USD/DKK	-1.2561	0.2980	-1.7575	0.1771	2.0410	0.1339
USD/HKD	-0.8758	0.4456	1.0565	0.3683	5.5513	0.0115
USD/HUF	3.4939	0.0397	1.5222	0.2253	0.0900	0.9339
USD/ILS	1.4088	0.2537	1.2733	0.2926	-0.3325	0.7614
USD/INR	0.1598	0.8832	-1.8938	0.1546	-2.5003	0.0877
USD/JPY	-2.6433	0.0774	0.1825	0.8668	3.0914	0.0537
USD/KRW	-2.3916	0.0966	-2.0609	0.1314	-0.7162	0.5256
USD/MXN	-1.0465	0.3722	2.1052	0.1259	-2.4078	0.0952
USD/NOK	-0.5778	0.6039	2.4959	0.0880	1.8709	0.1581
USD/PHP	1.0052	0.3889	2.2236	0.1127	1.9380	0.1480
USD/PLN	-4.6668	0.0186	0.6961	0.5365	4.7128	0.0181
USD/SEK	-1.0734	0.3618	1.7387	0.1805	2.6997	0.0738
USD/SGD	0.1053	0.9228	1.3483	0.2703	-0.6318	0.5724
USD/TRY	-2.8653	0.0643	7.2214	0.0055	0.3585	0.7437
USD/TWD	-4.6527	0.0187	0.9042	0.4325	-0.0739	0.9457
USD/ZAR	-1.9514	0.1461	7.6080	0.0047	0.8210	0.4718

Our results are coherent with those obtained by [167]. Numerical differences are explained by the fact that the two exercises used different historical data. The ratios displayed by tables 6.68, 6.69, 6.70 along with those containing confidence intervals built with one standard deviation from the average ratios are generally similar when we compare the outcome relative to a specific day of the week with the column “any day". Still, we notice some interesting exceptions. For the call options, the ratio payout/premium of weekly options traded on Friday is significantly different for 12 currency pairs out of 31, whilst trading on Tuesday or Wednesday lead to much more similar results.

Table 6.72: Ttest for payout/premium for ATMF calls, 06/01/1995–09/07/2018, 1 week tenor, by trading Thursday or Friday.

FX rate	Tstat Thu	p-value Thu	Tstat Fri	p-value Fri
AUD/USD	0.6155	0.5817	-0.6510	0.5615
EUR/AUD	5.1175	0.0144	-1.2024	0.3155
EUR/CAD	6.5222	0.0073	-3.6041	0.0367
EUR/CZK	5.0385	0.0151	0.6316	0.5725
EUR/GBP	1.6687	0.1938	-5.7368	0.0105
EUR/HUF	0.7765	0.4940	-1.4935	0.2322
EUR/JPY	1.9984	0.1395	-2.0233	0.1362
EUR/NOK	-4.1877	0.0248	-1.0302	0.3787
EUR/PLN	0.5125	0.6436	-0.0729	0.9465
EUR/SEK	3.0316	0.0562	-2.4501	0.0917
EUR/USD	2.4269	0.0936	-2.6961	0.0740
GBP/USD	2.1501	0.1207	-3.0718	0.0545
USD/CAD	2.0755	0.1296	1.7910	0.1712
USD/CHF	2.8257	0.0664	-6.8776	0.0063
USD/CZK	8.8514	0.0030	-1.3880	0.2593
USD/DKK	4.1808	0.0249	-2.1080	0.1256
USD/HKD	-0.8835	0.4420	-3.2288	0.0483
USD/HUF	-4.5300	0.0201	-1.2126	0.3121
USD/ILS	1.5616	0.2163	-10.9304	0.0016
USD/INR	0.2750	0.8011	6.8202	0.0064
USD/JPY	2.0267	0.1358	-2.6927	0.0742
USD/KRW	2.0683	0.1305	3.8599	0.0307
USD/MXN	-1.7112	0.1856	3.9655	0.0287
USD/NOK	-6.6105	0.0070	0.1307	0.9043
USD/PHP	-2.1860	0.1167	-3.8508	0.0309
USD/PLN	-0.0307	0.9775	-0.6764	0.5473
USD/SEK	0.4123	0.7078	-5.5526	0.0115
USD/SGD	-5.9437	0.0095	3.2506	0.0475
USD/TRY	-1.3530	0.2690	-0.1895	0.8618
USD/TWD	-0.7673	0.4988	4.4544	0.0211
USD/ZAR	-1.3339	0.2745	-1.3216	0.2781

Table 6.73: Ttest for payout/premium for ATMF puts, 06/01/1995–09/07/2018, 1 week tenor, by trading Monday, Tuesday or Wednesday.

FX rate	Tstat Mon	p-value Mon	Tstat Tue	p-value Tue	Tstat Wed	p-value Wed
AUD/USD	-4.2542	0.0238	3.7702	0.0327	1.3650	0.2656
EUR/AUD	-4.1463	0.0255	0.2373	0.8277	1.8333	0.1641
EUR/CAD	-0.6685	0.5517	-1.1271	0.3417	1.3720	0.2637
EUR/CZK	-1.4260	0.2491	-3.9711	0.0285	-0.0311	0.9771
EUR/GBP	-0.3868	0.7247	-0.2695	0.8050	2.3919	0.0966
EUR/HUF	-9.1324	0.0028	0.9848	0.3973	0.7989	0.4828
EUR/JPY	-4.0491	0.0271	2.4233	0.0939	0.7295	0.5185
EUR/NOK	3.6816	0.0347	-0.2322	0.8313	0.9163	0.4271
EUR/PLN	-7.1657	0.0056	2.4127	0.0948	1.6469	0.1981
EUR/SEK	-3.3230	0.0450	0.2310	0.8322	1.9826	0.1417
EUR/USD	-1.3788	0.2618	-1.9483	0.1465	2.6438	0.0774
GBP/USD	-1.3946	0.2575	-0.8925	0.4379	3.0698	0.0546
USD/CAD	0.1130	0.9172	-2.4460	0.0920	-2.6154	0.0793
USD/CHF	0.1685	0.8769	-1.0123	0.3860	2.0755	0.1296
USD/CZK	-2.2909	0.1059	-1.3834	0.2605	1.5610	0.2165
USD/DKK	-1.0757	0.3609	-1.2532	0.2989	3.3120	0.0453
USD/HKD	-4.7641	0.0176	-0.2165	0.8425	1.4763	0.2363
USD/HUF	2.0777	0.1293	0.4700	0.6704	2.4398	0.0925
USD/ILS	1.5234	0.2251	1.3911	0.2584	-0.2137	0.8444
USD/INR	1.2205	0.3095	0.5258	0.6354	-4.0846	0.0265
USD/JPY	-2.6660	0.0759	0.5770	0.6044	2.9108	0.0620
USD/KRW	-2.5625	0.0830	-2.4469	0.0919	-0.2324	0.8312
USD/MXN	-3.1561	0.0510	0.4934	0.6556	-2.3357	0.1016
USD/NOK	-1.3867	0.2596	1.7976	0.1701	2.8145	0.0670
USD/PHP	-0.1130	0.9172	1.8790	0.1569	3.4632	0.0405
USD/PLN	-2.9816	0.0585	-0.9489	0.4127	5.7010	0.0107
USD/SEK	-1.5554	0.2177	-4.1951	0.0247	2.5528	0.0837
USD/SGD	-0.3297	0.7633	0.6859	0.5420	-0.4537	0.6809
USD/TRY	-1.1534	0.3323	9.1703	0.0027	0.2074	0.8490
USD/TWD	-5.1144	0.0145	0.3374	0.7581	-0.5205	0.6387
USD/ZAR	-10.5087	0.0018	0.7704	0.4972	2.2835	0.1066

Table 6.74: Ttest for payout/premium for ATMF puts, 06/01/1995–09/07/2018, 1 week tenor, by trading Thursday or Friday.

FX rate	Tstat Thu	p-value Thu	Tstat Fri	p-value Fri
AUD/USD	0.1301	0.9047	-1.3267	0.2766
EUR/AUD	3.0674	0.0547	-1.5866	0.2108
EUR/CAD	4.7286	0.0179	-3.3846	0.0429
EUR/CZK	3.6584	0.0353	1.6046	0.2069
EUR/GBP	2.1819	0.1171	-6.1842	0.0085
EUR/HUF	2.5099	0.0869	-0.2782	0.7989
EUR/JPY	1.9927	0.1403	-1.9537	0.1457
EUR/NOK	-6.1890	0.0085	-0.0451	0.9668
EUR/PLN	0.4908	0.6572	-0.6522	0.5608
EUR/SEK	3.0463	0.0556	-2.1322	0.1228
EUR/USD	3.3585	0.0438	-1.8665	0.1588
GBP/USD	2.6284	0.0784	-3.0553	0.0552
USD/CAD	4.2296	0.0242	1.3398	0.2727
USD/CHF	2.5450	0.0843	-5.3899	0.0125
USD/CZK	5.0863	0.0147	-1.3260	0.2768
USD/DKK	2.4625	0.0907	-2.9893	0.0582
USD/HKD	3.6687	0.0350	-0.8407	0.4622
USD/HUF	-4.8212	0.0170	-1.4311	0.2478
USD/ILS	1.2326	0.3055	-12.0767	0.0012
USD/INR	-1.6397	0.1996	3.5961	0.0369
USD/JPY	1.8129	0.1675	-2.9433	0.0603
USD/KRW	2.7833	0.0688	2.6330	0.0781
USD/MXN	1.4888	0.2333	3.4297	0.0415
USD/NOK	-4.7693	0.0175	0.4070	0.7113
USD/PHP	-1.6889	0.1898	-3.5354	0.0385
USD/PLN	1.0945	0.3537	-1.0049	0.3890
USD/SEK	2.3359	0.1016	0.1575	0.8849
USD/SGD	-4.5393	0.0200	4.9486	0.0158
USD/TRY	-2.5110	0.0869	-0.5686	0.6094
USD/TWD	0.3118	0.7756	4.5770	0.0196
USD/ZAR	-0.1310	0.9041	1.0823	0.3584

TABLE 6.75: Ttest for payout/premium for ATMF straddles, 06/01/1995–09/07/2018, 1 week tenor, by trading Monday, Tuesday or Wednesday.

FX rate	Tstat Mon	p-value Mon	Tstat Tue	p-value Tue	Tstat Wed	p-value Wed
AUD/USD	-5.5198	0.0117	2.9536	0.0599	1.5654	0.2155
EUR/AUD	-4.0790	0.0266	0.2200	0.8400	1.2469	0.3009
EUR/CAD	-0.7396	0.5132	-0.8137	0.4754	0.8875	0.4402
EUR/CZK	-1.9170	0.1511	-3.3313	0.0447	0.3540	0.7467
EUR/GBP	-0.5584	0.6155	-0.0860	0.9369	2.6069	0.0799
EUR/HUF	-7.0327	0.0059	2.0767	0.1294	1.0681	0.3638
EUR/JPY	-4.1733	0.0251	2.1259	0.1235	0.9930	0.3939
EUR/NOK	4.1818	0.0249	0.0231	0.9831	0.7693	0.4977
EUR/PLN	-7.9603	0.0041	2.8280	0.0663	1.0604	0.3668
EUR/SEK	-3.1354	0.0518	0.3116	0.7758	1.9424	0.1474
EUR/USD	-1.1986	0.3167	-1.6918	0.1893	3.1016	0.0532
GBP/USD	-1.0272	0.3799	-1.2011	0.3159	3.3846	0.0429
USD/CAD	0.2388	0.8266	-1.2516	0.2994	-4.7670	0.0175
USD/CHF	0.4403	0.6895	-0.8624	0.4519	1.6044	0.2070
USD/CZK	-2.3005	0.1049	-1.1248	0.3425	1.1347	0.3390
USD/DKK	-1.1983	0.3168	-1.4559	0.2414	2.7177	0.0727
USD/HKD	-3.2542	0.0473	0.3002	0.7837	3.2447	0.0477
USD/HUF	2.5471	0.0842	1.1396	0.3372	1.2603	0.2967
USD/ILS	1.4570	0.2412	1.3304	0.2755	-0.2859	0.7936
USD/INR	0.9748	0.4016	-0.4088	0.7101	-4.0934	0.0264
USD/JPY	-2.6582	0.0765	0.4047	0.7128	3.0257	0.0565
USD/KRW	-2.5386	0.0848	-2.2562	0.1093	-0.4365	0.6920
USD/MXN	-2.0735	0.1298	1.5046	0.2295	-2.6992	0.0738
USD/NOK	-0.9345	0.4190	2.2248	0.1125	2.2557	0.1094
USD/PHP	0.4343	0.6934	2.3746	0.0981	2.3750	0.0981
USD/PLN	-3.8435	0.0311	-0.1422	0.8960	5.6927	0.0107
USD/SEK	-1.8169	0.1668	-3.2692	0.0468	3.0573	0.0551
USD/SGD	-0.0665	0.9511	1.0757	0.3609	-0.5657	0.6112
USD/TRY	-2.3039	0.1046	7.6550	0.0046	0.4874	0.6594
USD/TWD	-5.2344	0.0136	0.6766	0.5472	-0.3479	0.7509
USD/ZAR	-5.6523	0.0110	2.8616	0.0645	1.7588	0.1769

Table 6.76: Ttest for payout/premium for ATMF straddles, 06/01/1995–09/07/2018, 1 week tenor, by trading Thursday or Friday.

FX rate	Tstat Thu	p-value Thu	Tstat Fri	p-value Fri
AUD/USD	0.3494	0.7499	-1.0101	0.3868
EUR/AUD	3.9143	0.0296	-1.4415	0.2451
EUR/CAD	5.7480	0.0105	-3.3976	0.0425
EUR/CZK	4.2883	0.0233	1.0538	0.3693
EUR/GBP	1.9587	0.1450	-6.1146	0.0088
EUR/HUF	1.5336	0.2227	-0.9179	0.4264
EUR/JPY	2.0049	0.1387	-1.9858	0.1413
EUR/NOK	-5.3795	0.0126	-0.4796	0.6643
EUR/PLN	0.5065	0.6474	-0.3275	0.7648
EUR/SEK	3.0346	0.0561	-2.3333	0.1018
EUR/USD	2.8102	0.0673	-2.3358	0.1016
GBP/USD	2.3631	0.0991	-3.1115	0.0528
USD/CAD	3.1181	0.0525	1.6651	0.1945
USD/CHF	2.6843	0.0748	-6.1958	0.0085
USD/CZK	6.1745	0.0086	-1.3941	0.2576
USD/DKK	3.1481	0.0513	-2.6023	0.0802
USD/HKD	1.7788	0.1733	-2.1978	0.1154
USD/HUF	-5.4885	0.0119	-1.3270	0.2765
USD/ILS	1.4174	0.2514	-11.4250	0.0014
USD/INR	-0.7737	0.4955	4.8783	0.0165
USD/JPY	1.8820	0.1564	-2.8355	0.0659
USD/KRW	2.3843	0.0972	3.2201	0.0486
USD/MXN	-0.2702	0.8045	4.4080	0.0217
USD/NOK	-5.7720	0.0103	0.2466	0.8211
USD/PHP	-2.0837	0.1285	-3.6225	0.0362
USD/PLN	0.5385	0.6276	-0.8877	0.4401
USD/SEK	2.3281	0.1023	-0.2525	0.8170
USD/SGD	-5.3837	0.0126	3.8593	0.0307
USD/TRY	-1.7373	0.1807	-0.3759	0.7320
USD/TWD	-0.1184	0.9132	4.4160	0.0216
USD/ZAR	-0.8368	0.4641	0.1100	0.9193

6.9 Experiment 9: validation of option strategies

These strategies are also described in [167]. The results are shown in Tables 6.9, 6.9, 6.9, 6.80 in terms of cumulative and annualised returns, annualised volatility and Sharpe ratio. The Sharpe Ratio measures the performance of investment; it is obtained from the ratio of the excess return of the portfolio, relative to the risk-free rate, and the standard deviation of the portfolio's excess returns.

TABLE 6.77: Results of selling calls on the first five G10 currency pairs.

	EUR/USD	USD/JPY	GBP/USD	USD/CHF	AUD/USD
Cumulative return	3.75%	3.55%	3.08%	2.57%	3.65%
Annualised return	0.19%	0.15%	0.15%	0.13%	0.15%
Annualised volatility	0.12%	0.13%	0.11%	0.13%	0.14%
Sharpe ratio	1.58	1.13	1.41	1.02	1.13

TABLE 6.78: Results of selling calls on the other four G10 currency pairs.

	USD/CAD	USD/SEK	USD/NOK	USD/DKK
Cumulative return	4.15%	4.57%	3.40%	2.22%
Annualised return	0.17%	0.22%	0.21%	0.43%
Annualised volatility	0.11%	0.15%	0.16%	0.11%
Sharpe ratio	1.64	1.48	1.33	3.87

TABLE 6.79: Results of carry trading on the first five G10 currency pairs.

	EUR/USD	USD/JPY	GBP/USD	USD/CHF	AUD/USD
Cumulative return	0.32%	-0.08%	-0.40%	0.11%	1.72%
Annualised return	0.02%	0.00%	-0.02%	0.01%	0.07%
Annualised volatility	0.11%	0.13%	0.10%	0.12%	0.14%
Sharpe ratio	0.14	-0.02	-0.20	0.05	0.52

Short dated options are too expensive. On average the payout is only 83% of their premium. This appears to be universal: it is applicable to all the currency pairs and option type that we tested and every possible choice of trading day. Buying or selling options on a specific day in fact produces slightly different payouts only for a few cases. Option trading strategies are influenced by the length of the tenor too. Selling call options for short dated options provide positive payout as they expire worthless most of the time so selling them would allow to pocket the premium. The results in tables 6.9, 6.9 indeed show that the returns are always positive: all the calls are profitable to sell. The short tenor is also limiting the positive influence of

Table 6.80: Results of carry trading on the other four G10 currency pairs.

	USD/CAD	USD/SEK	USD/NOK	USD/DKK
Cumulative return	-1.36%	0.65%	-2.54%	1.30%
Annualised return	-0.06%	0.03%	-0.16%	0.25%
Annualised volatility	0.11%	0.15%	0.12%	0.05%
Sharpe ratio	-0.55	0.21	-1.35	4.96

the carry trade. We recall that in for FX options, calls pay out for depreciation of the quote currency, whist puts pay out for its appreciation. In this context, when the forward price is away from the spot, in correspondence to significant divergence between the base and the quote interest rates, the forward price is a biased estimator of the future spot price. For example, this should determine that call options lose money and put options make a profit, if the base has the lower interest rate. This carry effect is subdued for short tenor options as the bias implied by forward price for the future spot is likely to be small compared to longer tenors like three, six or 12 months even during periods in which the base and quote interest rates systematically e.g. AUD/USD or USD/JPY diverge as described by [167].

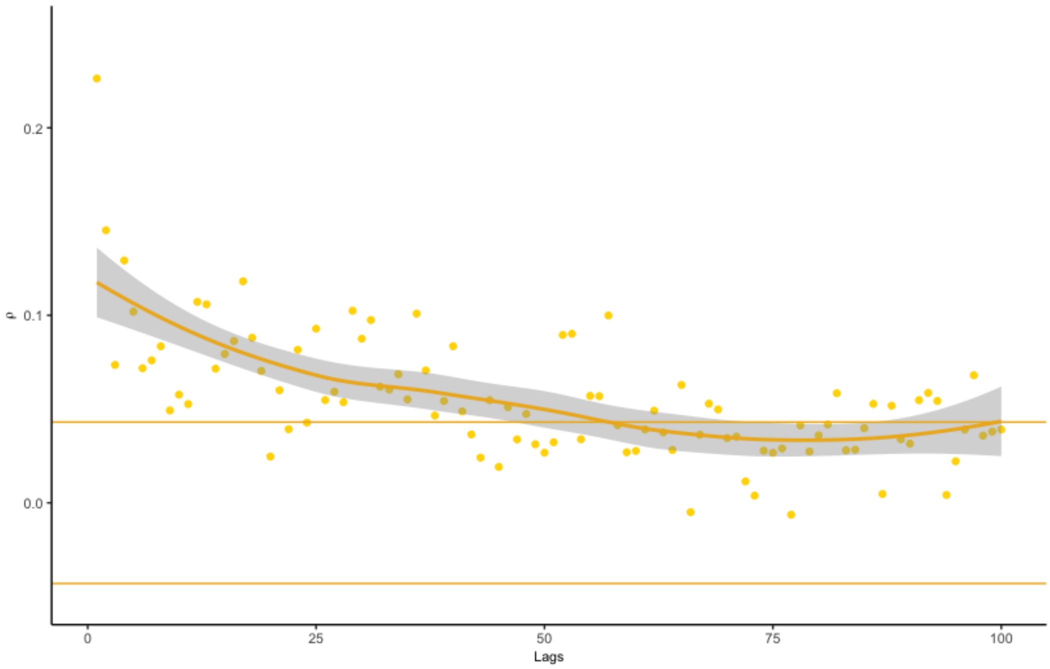


FIG. 6.36: Autocorrelation of returns, ρ, at various lags of time for EUR/USD. The figure displays the autocorrelation at various lags (blue points) and the interpolation line (yellow line) along with the area defined by the 95% bounds around the zero (yellow straight lines). The length of the blocks is chosen in correspondence of the lags for which the autocorrelation is significantly greater than zero. As an example, blocks long not more than 21 lags have higher correlation than those longer more than 21 lags for which the autocorrelation values are included in the 95% bounds area.

6.10 Experiment 10: validation of High-frequency momentum and mean-reverting strategies

Among the trading strategies, the most successful ones result to be the directional and trend-following. Also the mean reverting strategy on average produces a positive Sharpe ratio. The simplified version of the trend following strategy does not improve the results. Adding the Bollinger band improves only the simplified trend following algorithm. On average the highest Sharpe ratios are obtained for AUD/USD, EUR/USD and NZD/USD. USD/SEK and USD/ZAR are associated with the worst results.Tables that follow display the results of the various trading algorithms for all the currency pairs. The stochastic algorithm does not produce meaningful results on any currency pair of our dataset, which are therefore not displayed below.

Figure 6.36 shows an example of the autocorrelation function of EUR/USD calculated from the historical time series:

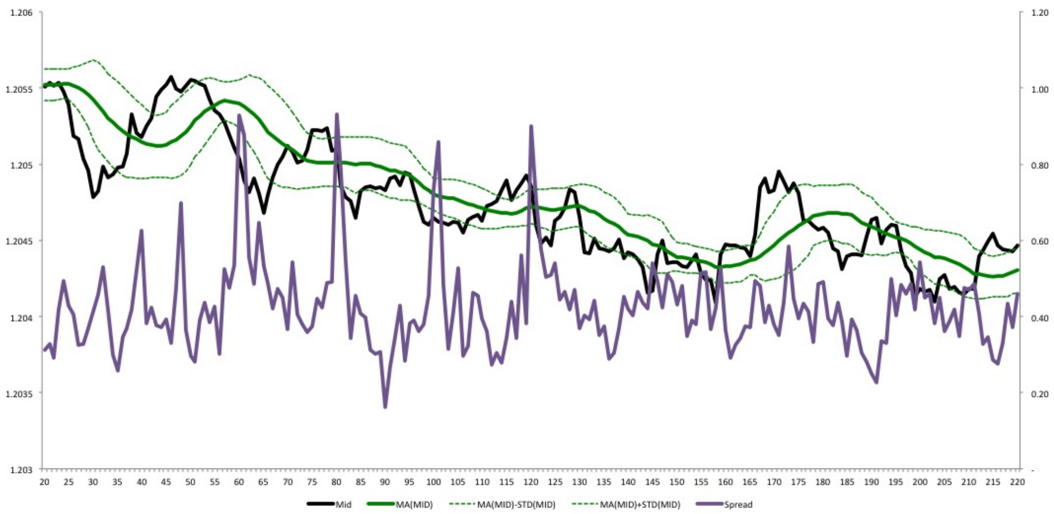


FIG. 6.37: Mid value of tick quotes relative to EUR/USD, 21-tick moving average, the Bollinger bands and the spread.

Figure 6.37 shows an example of the tick quotes relative to EUR/USD, along with our calculations for the 21−tick moving average, Bollinger band and the correspondent bid-ask spread. The figure illustrates the patterns of the mid quotes, their moving averages and the Bollinger bands along with the bid-ask spread.

Table 6.81 shows the Hurst exponent estimated from the data for each currency pair. It can be seen that the value is always above the 0.5 threshold.

TABLE 6.81: Average and standard deviation of the Hurst exponent by currency pair.

FX	μ	σ
EUR/USD	0.55	0.02
USD/JPY	0.55	0.03
GBP/USD	0.55	0.02
USD/CHF	0.56	0.02
AUD/USD	0.55	0.03
NZD/USD	0.55	0.03
USD/CAD	0.55	0.03
USD/SEK	0.52	0.02
USD/NOK	0.52	0.03
USD/DKK	0.53	0.12
USD/MXN	0.58	0.03
USD/RUB	0.52	0.08
USD/ZAR	0.59	0.03
USD/TRY	0.55	0.04

Figure 6.38 shows the EUR/USD tick prices as of 01-02-2015 in terms of the 15-second mid price, 15-second price simulated by the Ornestein−Uhlenbeck process and 30-minute moving average of the 15-second mid price. The yellow lines define

buy and sell values which correspond to extreme moves of the the simulated prices.

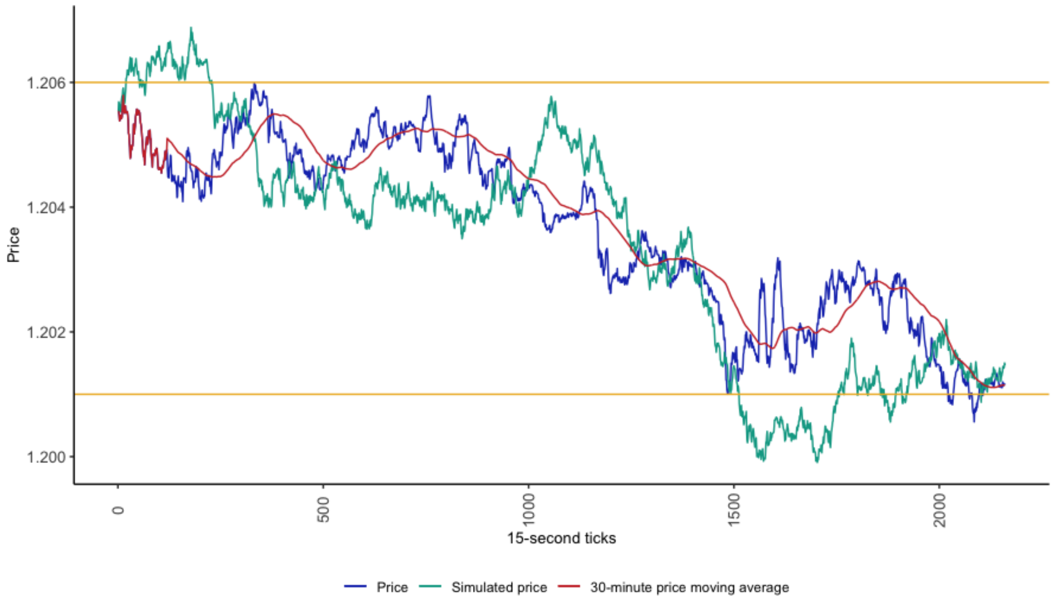


FIG. 6.38: EUR/USD 01-02-2015 tick prices: 15-second mid price, 15-second price simulated by the Ornestein Uhlenbeck process and 30-minute moving average of the 15-second mid price.

TABLE 6.82: Sharpe ratio relative to HFT strategies for some G10 currency pairs.

Strategy	EUR/USD	USD/JPY	GBP/USD	USD/CHF
Directional	4.12	2.62	3.87	1.70
Trend follow	2.29	2.02	2.86	1.73
Trend follow Bollinger	1.52	0.67	1.15	-1.44
Trend follow simplified	1.62	1.07	1.33	-0.42
Trend follow simplified Bollinger	1.99	1.71	2.10	0.79
Mean reverting	3.70	2.44	3.46	1.23

TABLE 6.83: Sharpe ratio relative to HFT strategies for some G10 currency pairs.

Strategy	AUD/USD	NZD/USD	USD/CAD	USD/SEK
Directional	4.39	3.09	3.72	-0.43
Trend follow	2.46	2.74	2.20	0.94
Trend follow Bollinger	1.37	-0.26	0.33	-2.50
Trend follow simplified	1.46	0.40	0.72	-2.07
Trend follow simplified Bollinger	2.21	1.56	1.53	-0.53
Mean reverting	3.78	2.53	2.99	-0.49

Table 6.84: Sharpe ratio relative to HFT strategies for some G10 and EM currency pairs.

Strategy	USD/NOK	USD/DKK	USD/MXN	USD/RUB
Directional	-0.16	1.89	1.99	-4.79
Trend follow	1.25	1.87	2.18	-1.23
Trend follow Bollinger	-2.67	0.50	-2.62	-5.74
Trend follow simplified	-2.26	1.10	-1.17	-6.52
Trend follow simplified Bollinger	-0.54	1.70	0.60	-3.67
Mean reverting	-0.10	1.83	1.49	-3.57

Table 6.85: Sharpe ratio relative to HFT strategies for some EM currency pairs.

Strategy	USD/ZAR	USD/TRY	Average
Directional	1.51	1.84	1.40
Trend follow	2.22	1.68	1.62
Trend follow Bollinger	-3.41	-1.80	-1.08
Trend follow simplified	-1.11	-0.68	-0.66
Trend follow simplified Bollinger	0.63	0.83	0.59
Mean reverting	0.93	1.49	1.31

Table 6.86: Results for the pairs trading strategy relative to EUR/USD and GBP/USD, USD/CAD and USD/JPY, AUD/USD and NZD/USD, EUR/USD and USD/CHF in terms of average and standard deviations of returns, annualised returns, annualised volatility and Sharpe Ratio.

Strategy	EUR/GBP	CAD/JPY	AUD/NZD	EUR/CHF
MeanRet	0.26%	0.09%	0.15%	0.04%
StdRet	0.19%	0.14%	0.18%	0.19%
AnnualRet	0.69%	0.24%	0.40%	0.11%
AnnualVol	0.26%	0.19%	0.25%	0.27%
Sharpe	2.67	1.30	1.64	0.41

6.11 Experiment 11: validation of High-frequency forecasting with RNNs

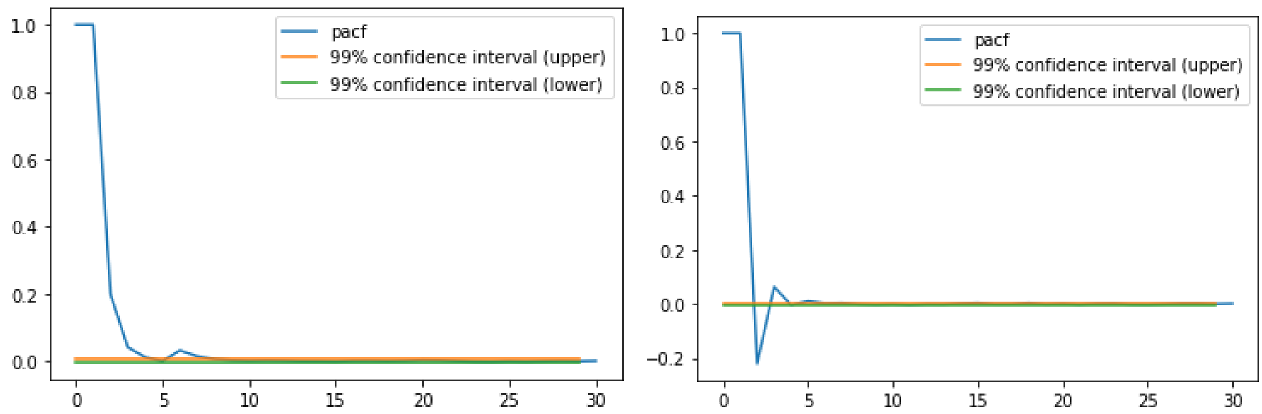
The α-RNN model is tested on a subset of the high-frequency data illustrated in section 5.4. The input of this experiment consists of the January 2015 tick quotes. The other datasets are not included as the algorithm takes a several hours to process only a month of tick data. The model appears to be suitable for this type of data as the dataset is a chronologically ordered time series. Firstly, we determine if the time series is stationary, which implies that the auto-covariance is independent of time. This is tested through the augmented Dickey-Fuller test, which assumes that the time series has a constant bias but does not show a trend. If the stationarity test fails a solution could be taking the differences of time series. The null hypothesis of the test is that there is a unit root, with the alternative that there is no unit root. Table 6.87 displays the result of the ADF test and the number of steps estimated from the PACF. The number of lags used by the RNN is estimated through the partial auto-correlation function (PACF). The analysis of the partial autocorrelations allows to determine the number of steps. With the exclusion of GBP/USD the time series

Table 6.87: ADF stationarity test and number of steps estimated from the PACF for the time series.

FX	test	p-value	steps
EUR/USD	-1.11038	0.71091	4
USD/JPY	-0.49424	0.89314	5
GBP/USD	-3.71251	0.00394	2
USD/CHF	-0.55459	0.88092	2
AUD/USD	-2.01070	0.28190	2
NZD/USD	-0.13917	0.94539	2
USD/CAD	-0.74522	0.83469	4
USD/SEK	-1.98268	0.29422	3
USD/NOK	-2.20803	0.20335	3
USD/DKK	-1.10332	0.71375	6
USD/MXN	-0.84352	0.80600	2
USD/RUB	-1.65478	0.45455	14
USD/ZAR	-1.75515	0.40295	3
USD/TRY	0.07057	0.96399	4
NZD/USD interpolated	-0.15714	0.94344	8

are non-stationary as the ADF test is not rejected at the 99% confidence level. A minimum of 4 lags appears satisfactory for most of the cases. Only USD/RUB and NZD/USD appear to require many more lags.

The model is trained on the first 80% of the time series and tested on the remaining 20%. This means that the training set generally includes the first 27 days, while the test set contains tick quotes from the last 3 days of the month. The data is standardized to avoid scaling difficulties in the fitting of the model. The training set is standardized using the mean and standard deviation of the training set and



(a) EUR/USD

(b) USD/JPY

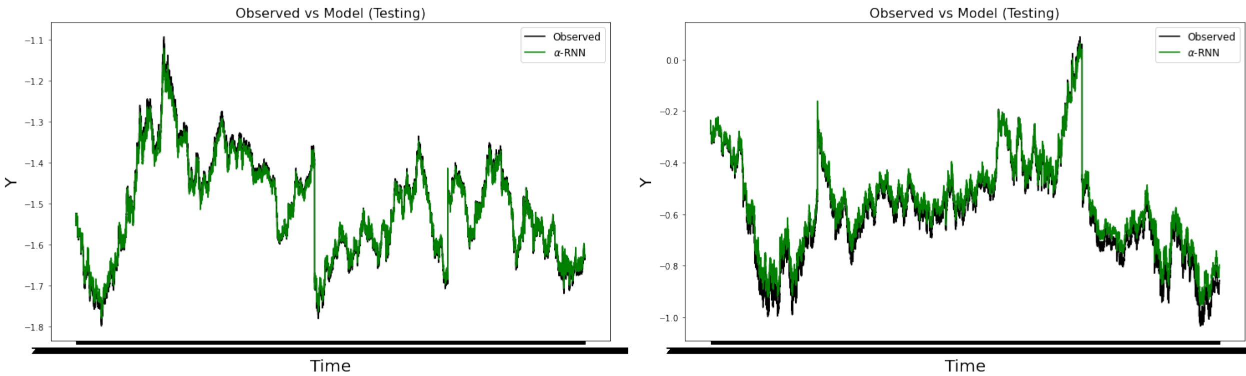
FIG. 6.39: Partial autocorrelation function (PACF) relative to EUR/USD and USD/JPY calculated using January 2015 high-frequency data.

the same normalization is used for the test set - the mean and standard deviation of the training set are used to normalize the test set. We study the presence of outliers and intra-day seasonality looking at the returns distribution. Outliers are identified at extreme values of the tails. This allows to identify jumps in the quote prices between close price and opening prices of particular days. Such intra-day seasonality bias is not present in all the time series and not over all the trading days. For example, jumps in the time series are found for NZD/USD, USD/CAD and USD/TRY. Jumps can be treated by interpolating the data included in a jump. This approach can be done using linear or polynomial interpolation: the interpolated data replaces the jumps from the observed time series. This approach is tested on NZD/USD which presents five jumps overall at 05/01/2015 08:00, 08/01/2015 08:00, 16/01/2015 08:00, 23/01/2015 08:00, 29/01/2015 08:00. The data are replaced by linear interpolation.

Once the data is prepared for the α-RNN model, the models are trained on the training set and validated on the test set, separately. We can then informally assess the extent of over-fitting. From the trained model we derive the forecast for each time series. The output is shown in figures 6.40a– 6.47b. The in-sample prediction is reliable with the exception of the time series that present jumps like NZD/USD, USD/CAD and USD/TRY. From figures 6.43a and 6.43b it is possible to note that the forecast related to the interpolated NZD/USD time series is much more accurate than that built on the raw data.

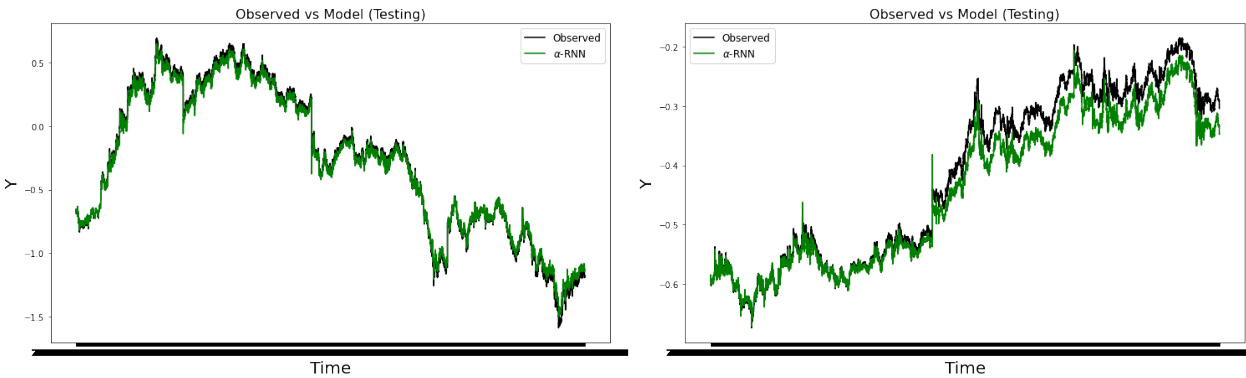
By looking at the figures related to the MSE of the forecast, 6.48a– 6.55b, we see that most of the out-of-sample prediction is also accurate.

The fitting of the model is assessed by looking at the model residuals. This requires checking if the model residuals are a white noise or instead auto-correlated. Auto-correlated residuals would suggest that more lags could be used to specify the structure of RNN model. The null hypothesis holds that $\rho_1 = \ldots \rho_m = 0$, where ρ_i are the sample autocorrelations on the residuals. This is verified by the Ljung-Box



(a) EUR/USD (b) USD/JPY

FIG. 6.40: Observed and modelled prices relative to EUR/USD and USD/JPY calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



(a) GBP/USD (b) USD/CHF

FIG. 6.41: Observed and modelled prices relative to GBP/USD and USD/CHF calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

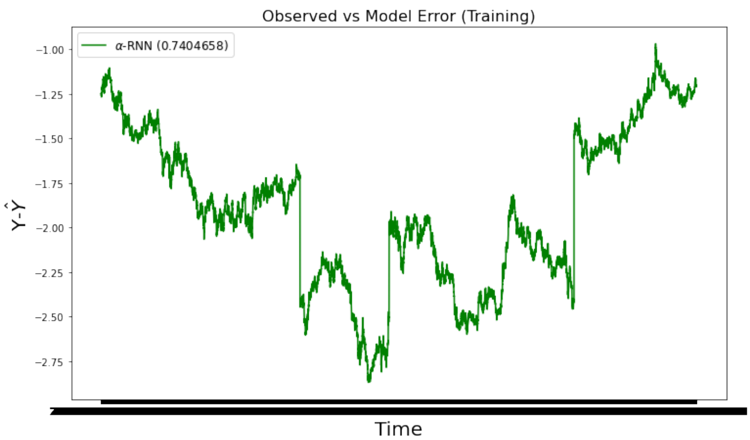
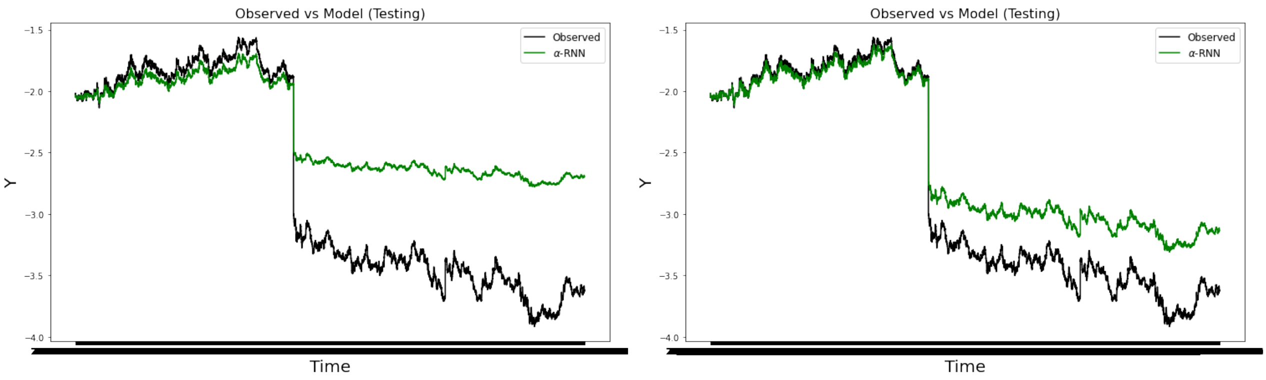
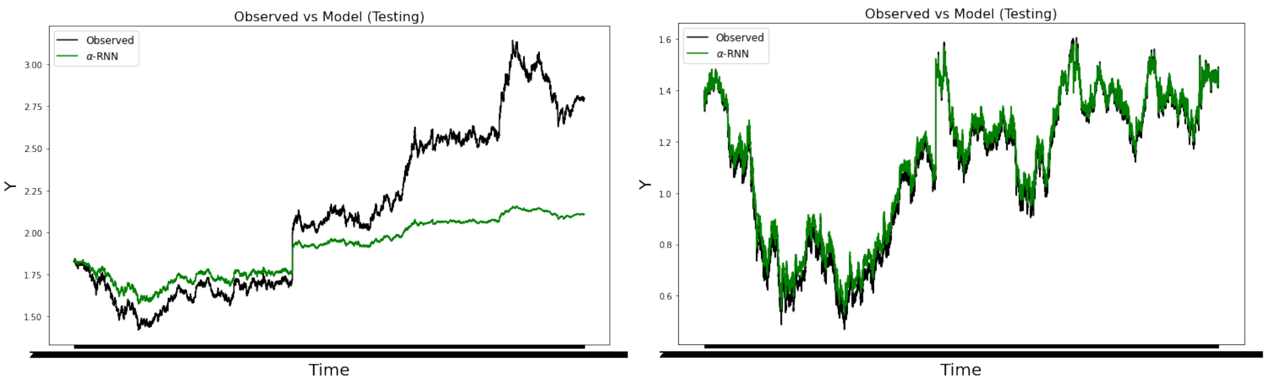


FIG. 6.42: Observed and modelled prices relative to AUD/USD calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



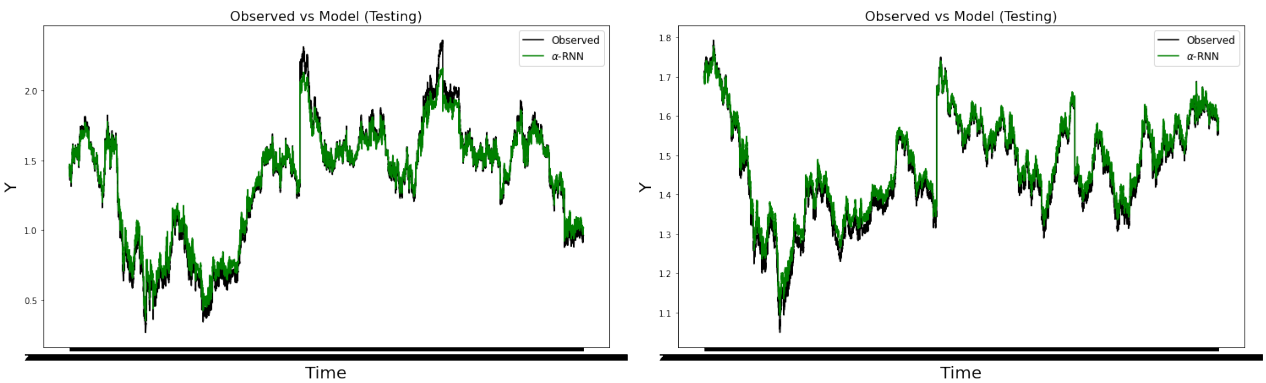
(a) NZD/USD (b) NZD/USD interploated

FIG. 6.43: Observed and modelled prices relative to NZD/USD calculated using the raw and the interpolated high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



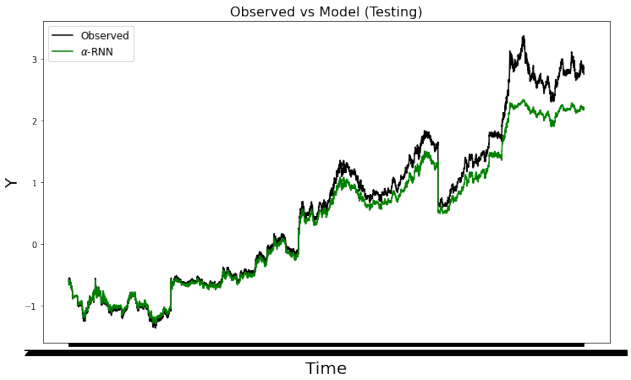
(a) USD/CAD (b) USD/SEK

FIG. 6.44: Observed and modelled prices relative to USD/CAD and USD/SEK calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

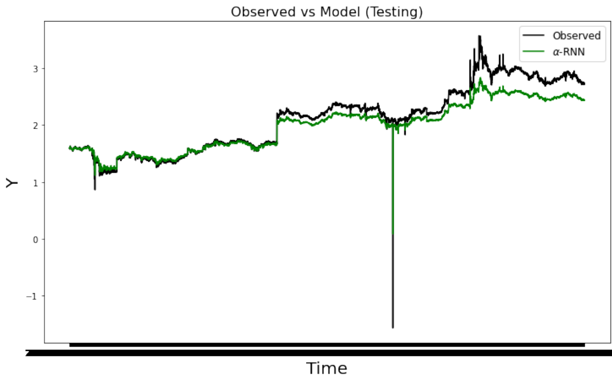


(a) USD/NOK (b) USD/DKK

FIG. 6.45: Observed and modelled prices relative to USD/NOK and USD/DKK calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

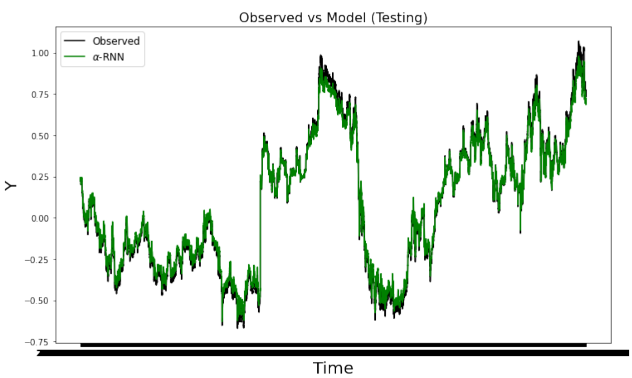


(a) USD/MXN

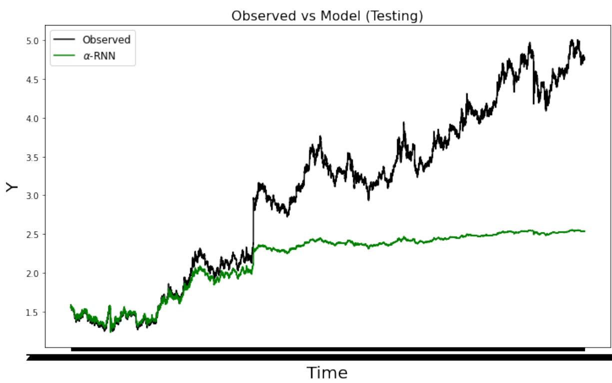


(b) USD/RUB

Fig. 6.46: Observed and modelled prices relative to USD/MXN and USD/RUB calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



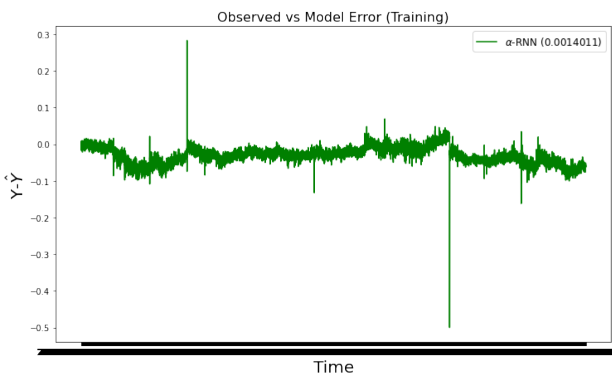
(a) USD/ZAR



(b) USD/TRY

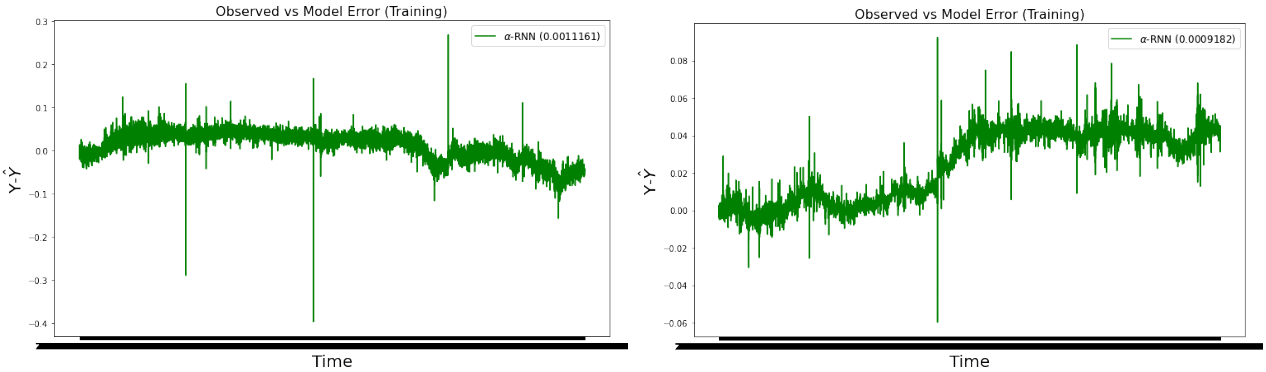
Fig. 6.47: Observed and modelled prices relative to USD/ZAR and USD/TRY calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

(a) EUR/USD



(b) USD/JPY

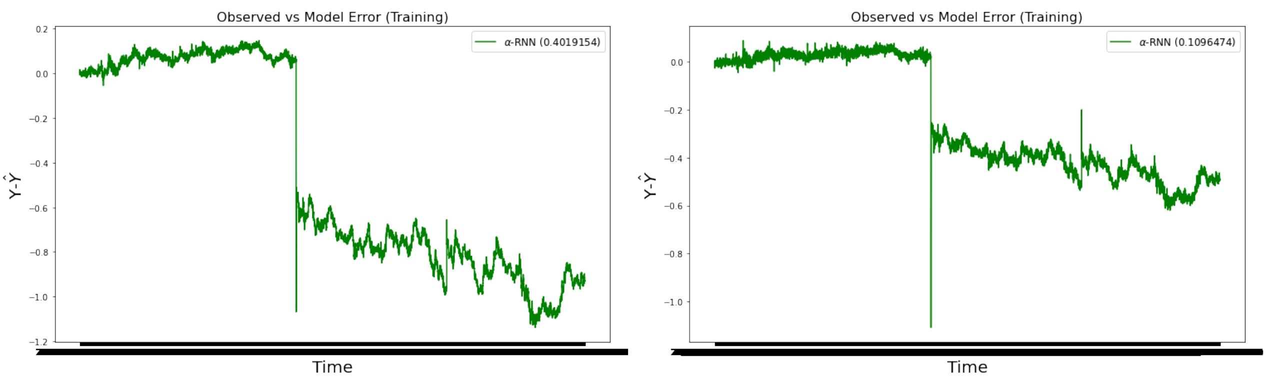
Fig. 6.48: Mean square error of the observed and modelled prices relative to EUR/USD and USD/JPY calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



(a) GBP/USD (b) USD/CHF

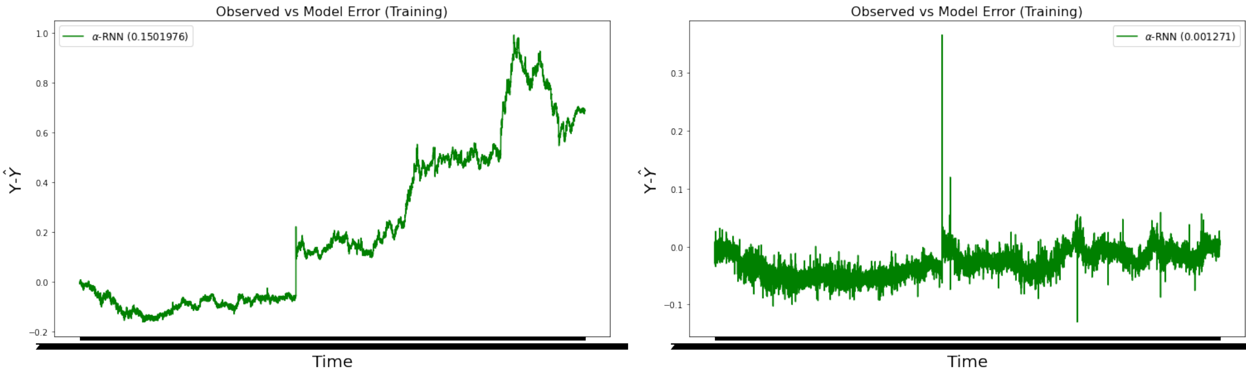
FIG. 6.49: Mean square error of the observed and modelled prices relative to GBP/USD and USD/CHF calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

FIG. 6.50: Mean square error of the observed and modelled prices relative to AUD/USD calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



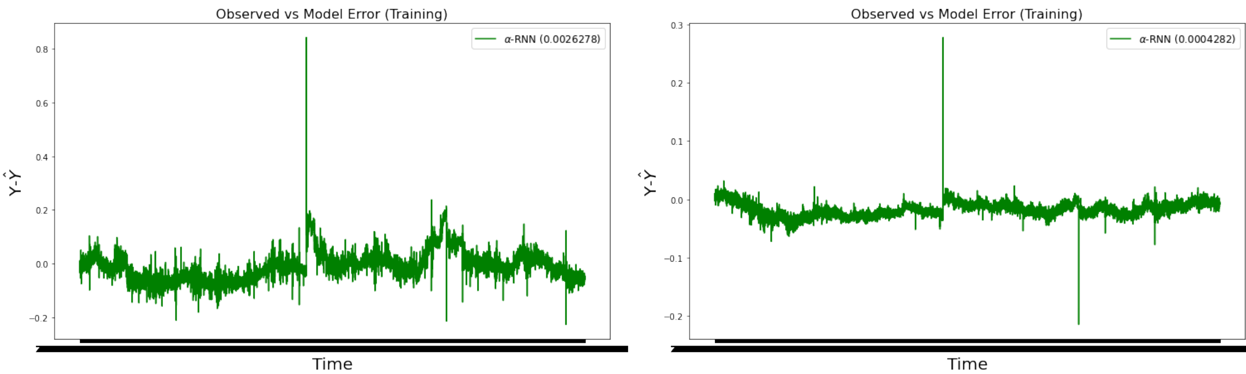
(a) NZD/USD (b) NZD/USD interpolated

FIG. 6.51: Mean square error of the observed and modelled prices relative to NZD/USD calculated using the raw and the interpolated high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



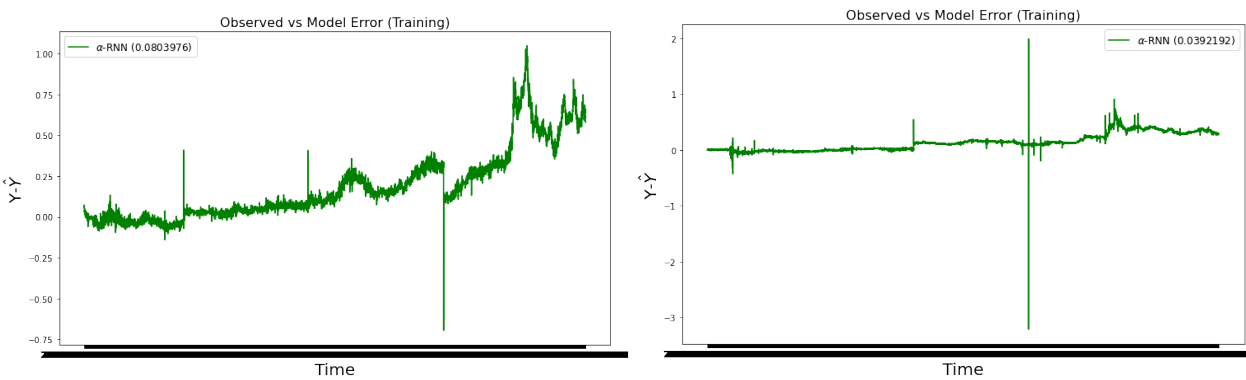
(a) USD/CAD (b) USD/SEK

FIG. 6.52: Mean square error of the observed and modelled prices relative to USD/CAD and USD/SEK calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



(a) USD/NOK (b) USD/DKK

FIG. 6.53: Mean square error of the observed and modelled prices relative to USD/NOK and USD/DKK calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



(a) USD/MXN (b) USD/RUB

FIG. 6.54: Mean square error of the observed and modelled prices relative to USD/MXN and USD/RUB calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

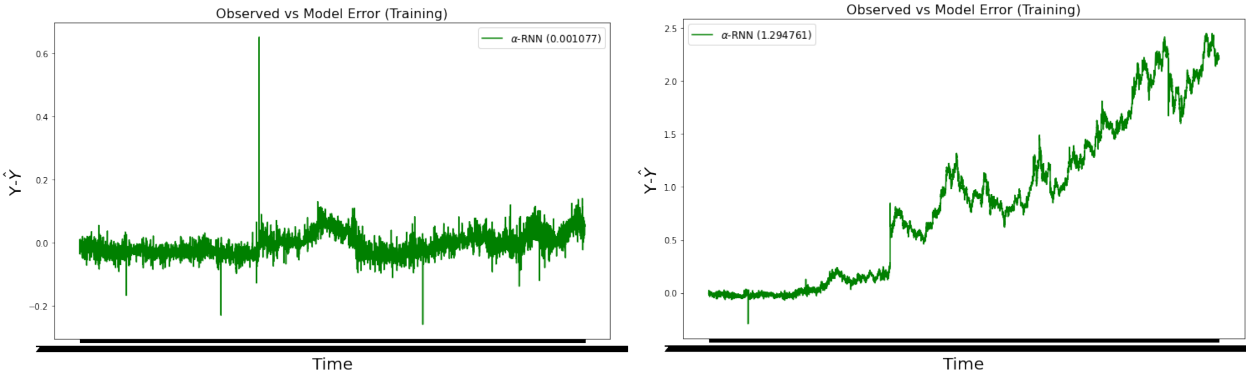
TABLE 6.88: Alpha parameter estimated from January 2015 data by currency pair.

FX	α
EURUSD	0.371777
USDJPY	0.461827
GBPUSD	0.636913
USDCHF	0.456411
AUDUSD	0.387215
NZDUSD	0.294864
USDCAD	0.339870
USDSEK	0.492189
USDNOK	0.401675
USDDKK	0.445720
USDMXN	0.288862
USDRUB	0.462897
USDZAR	0.403841
USDTRY	0.396320
USDCAD no outliers	0.355461
NZDUSD interpolated	0.319236

test

$$Q(m) = T(T+2)\sum_{j=1}^{m}\frac{\hat{\tau}_j^2}{T-j}. \tag{6.6}$$

This statistic also follows an asymptotically chi-squared distribution with m degrees of freedom. For all the time series the p-values are all smaller than 0.01, indicating that we can reject the null at the 99% confidence level for any lag. This is strong evidence that the model is under-fitting and more lags are needed in our model.



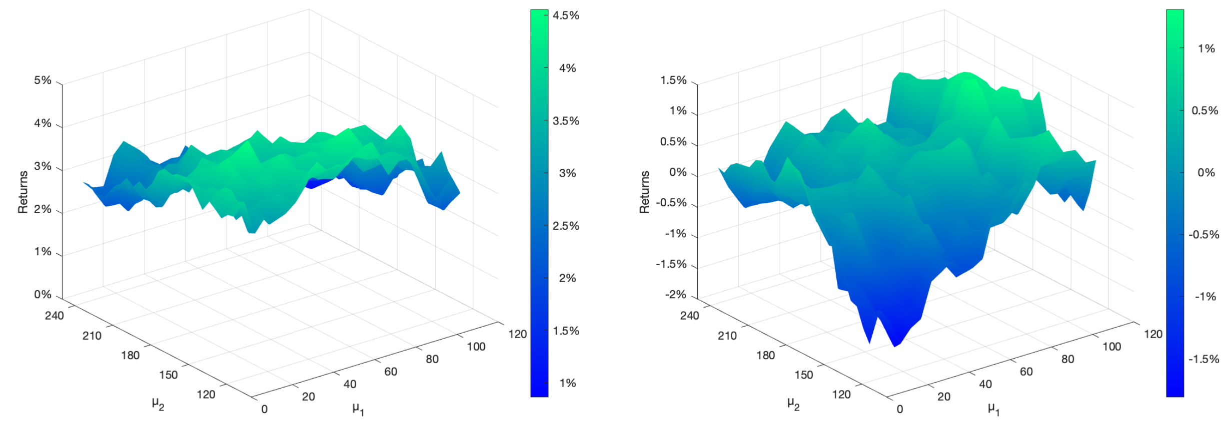
(a) USD/ZAR (b) USD/TRY

FIG. 6.55: Mean square error of the observed and modelled prices relative to USD/ZAR and USD/TRY calculated using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

Finally, once the forecast of the time series is made available by the α-RNN model, a trading strategy can be tested to profit from such a prediction of the future values. Many different trading strategies could be built. In this context, we choose one of the simplest: the moving average crossover which is defined by the algorithm 3.1.1. We choose the combination of short and long-term moving averages that produce the highest returns. For that we observe the surface of daily returns implied by the two moving averages as displayed by figures 6.56a, 6.56b, 6.57a, 6.57b, 6.58a, 6.58b, 6.59a, 6.59b, 6.60a, 6.60b, 6.61a, 6.61b, 6.62a, 6.62b. The buy/sell signal is derived from the RNN forecast and the performance is assessed from the returns of the observed prices. The strategy is only applied on the test dataset of the RNN forecast. The results of the strategy are shown in terms of average daily returns, their standard deviation and Sharpe ratio. They are contained in tables 6.89, 6.90, 6.91, 6.92. The strongest performance is obtained for EUR/USD, USD/CAD and USD/TRY among the group of currency pairs.

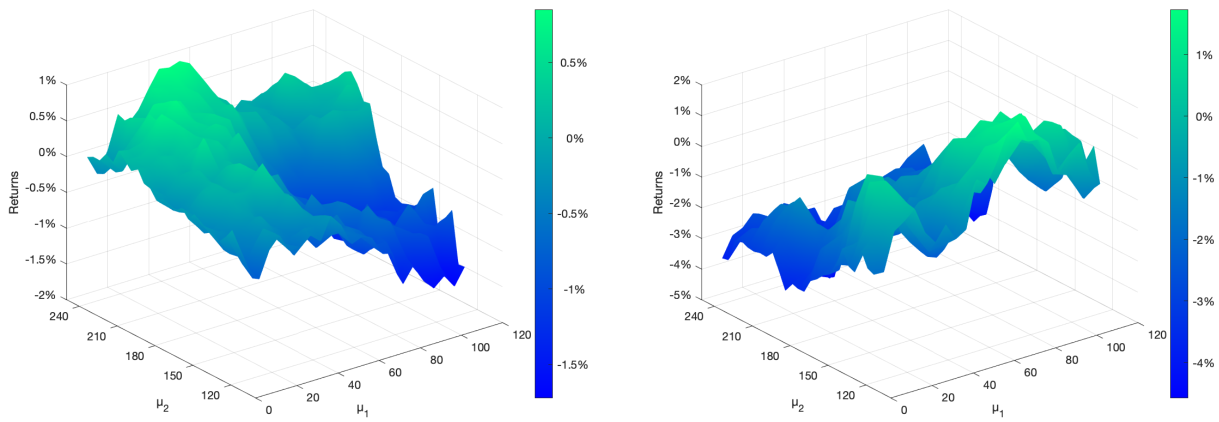
TABLE 6.89: Mean, standard deviation and Sharpe ratio of returns calculated using moving averages crossovers on the alpha-RNN forecast using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

Strategy	EUR/USD	USD/JPY	GBP/USD	USD/CHF
MeanRet	0.01	0.00	0.00	0.00
StdRet	0.00	0.00	0.00	0.01
Sharpe	1.91	0.12	-0.71	-0.60



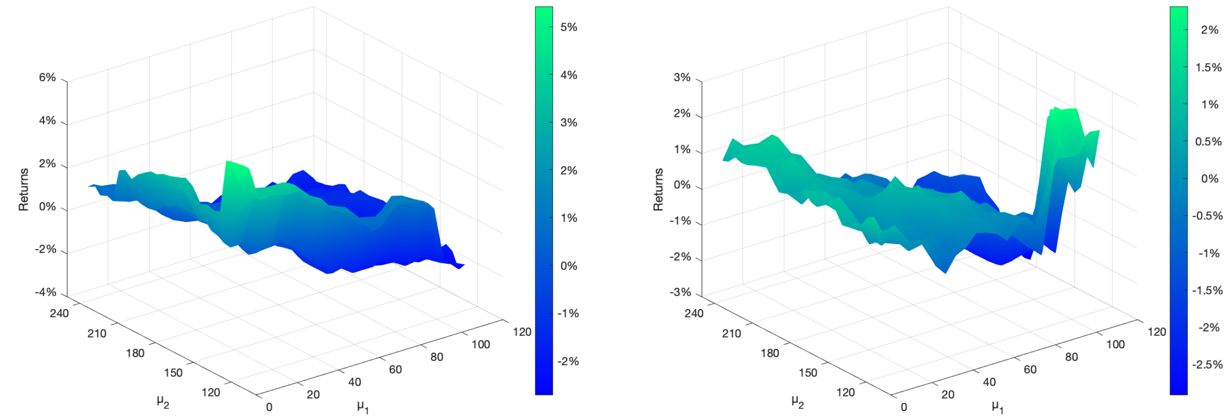
(a) EUR/USD (b) USD/JPY

FIG. 6.56: Daily returns relative to EUR/USD and USD/JPY calculated using moving averages crossovers on the alpha-RNN forecast using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



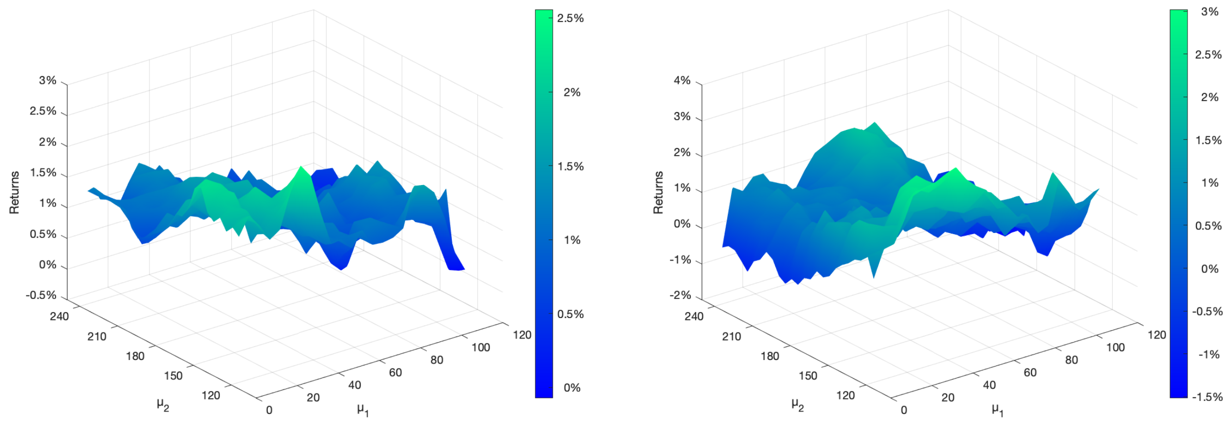
(a) GBP/USD (b) USD/CHF

FIG. 6.57: Daily returns relative to GBP/USD and USD/CHF calculated using moving averages crossovers on the alpha-RNN forecast using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



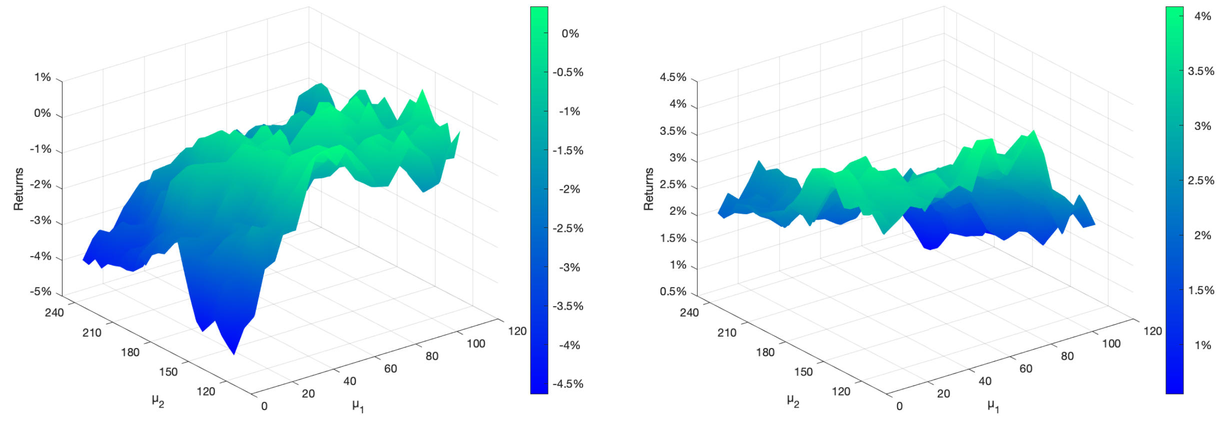
(a) AUD/USD (b) NZD/USD

Fig. 6.58: Daily returns relative to AUD/USD and NZD/CHF calculated using moving averages crossovers on the alpha-RNN forecast using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



(a) USD/CAD (b) USD/SEK

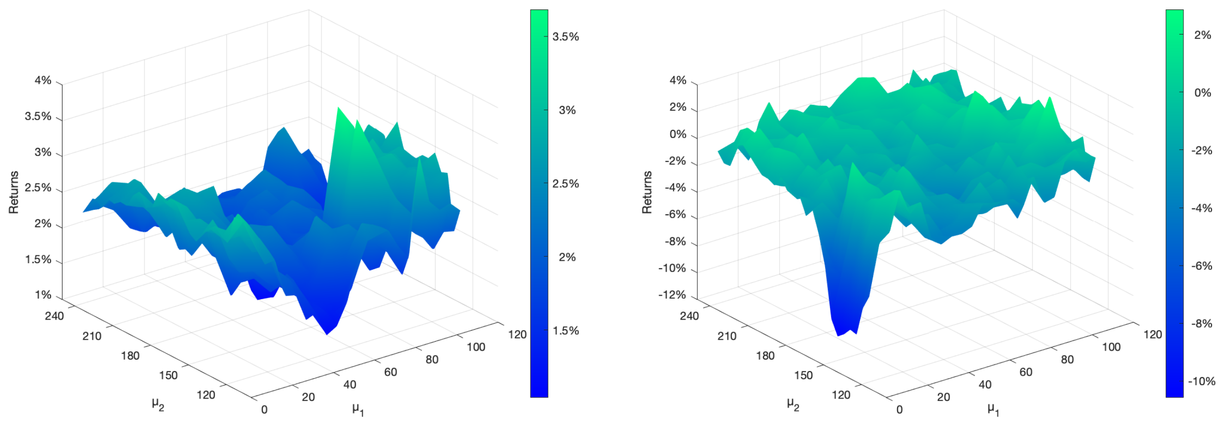
Fig. 6.59: Daily returns relative to USD/CAD and USD/SEK calculated using moving averages crossovers on the alpha-RNN forecast using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



(a) USD/NOK

(b) USD/DKK

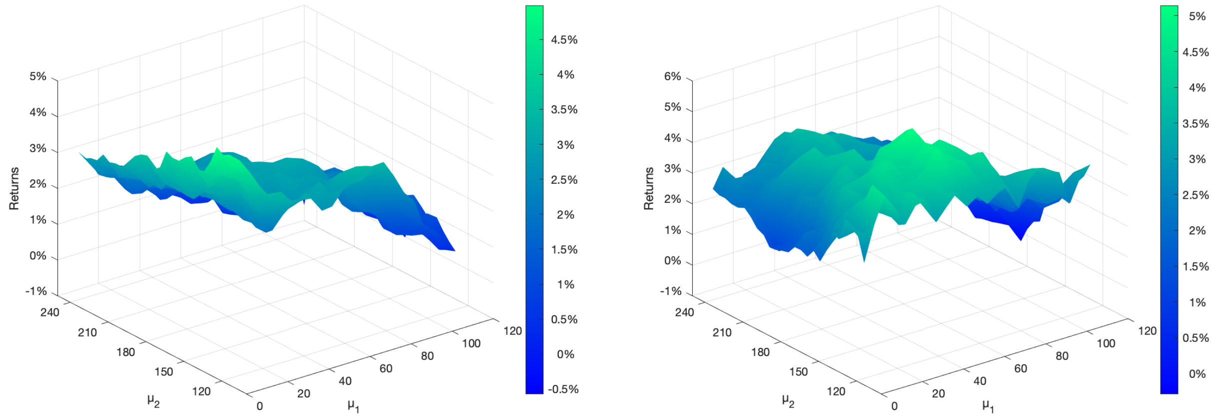
FIG. 6.60: Daily returns relative to USD/NOK and USD/DKK calculated using moving averages crossovers on the alpha-RNN forecast using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



(a) USD/MXN

(b) USD/RUB

FIG. 6.61: Daily returns relative to USD/MXN and USD/RUB calculated using moving averages crossovers on the alpha-RNN forecast using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.



(a) USD/ZAR (b) USD/TRY

Fig. 6.62: Daily returns relative to USD/ZAR and USD/TRY calculated using moving averages crossovers on the alpha-RNN forecast using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

Table 6.90: Mean, standard deviation and Sharpe ratio of returns calculated using moving averages crossovers on the alpha-RNN forecast using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

Strategy	AUD/USD	NZD/USD	USD/CAD	USD/SEK
MeanRet	0.00	0.00	0.00	-0.01
StdRet	0.01	0.00	0.00	0.01
Sharpe	0.43	0.26	1.37	-1.04

Table 6.91: Mean, standard deviation and Sharpe ratio of returns calculated using moving averages crossovers on the alpha-RNN forecast using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

Strategy	USD/NOK	USD/DKK	USD/MXN	USD/RUB
MeanRet	-0.03	0.00	0.00	-0.08
StdRet	0.01	0.00	0.01	0.02
Sharpe	-3.21	0.41	0.30	-5.13

Table 6.92: Mean, standard deviation and Sharpe ratio of returns calculated using moving averages crossovers on the alpha-RNN forecast using the high-frequency data from the first 27 days of January 2015 and tested on the last 3 days of the month.

Strategy	USD/ZAR	USD/TRY	NZD/USD interpolated
MeanRet	0.00	0.01	0.01
StdRet	0.01	0.00	0.02
Sharpe	0.49	4.10	0.42

Chapter 7

Final conclusions

This research is devoted to the validation of some trading strategies in the foreign exchange.

Seeking alpha in FX through trend-following strategy has proved to be very much different compared to 20 or 30 years ago. As interest rates diverge much less than in the past and economies tend to be less asynchronous than before, the strategy appears to be strongly influenced by the *U.S.* monetary and trade policies. In this research I have investigated the impact of various investment styles applied to different trading approach. As an example, trend-following and momentum is tested on daily data to assess systematic strategies that are commonly adopted by CTA and hedge funds and also as a HFT strategy. I looked at carry trade as can be adopted within the systematic trading and in the context of option trading. Finally I define various implementations for the mean reversion in particular for HFT.

Trend-following strategies produced exceptional results in the distant past (e.g. 20 years ago). Their performance appears to be subdued when we look at their results on the recent data. During cycles of strong dollar (e.g 2014–2015) and during those of (very) weak dollar (2019) trends may appear in FX. In between those cycles, FX prices tend to follow ranging patterns rather than trends. As prices move in a short range, the short-term volatility is too high and trends cannot emerge. Furthermore, the rising volatility that stormed the markets after the most recent global pandemic crisis has further increased the short-term volatility and as such reduced the chances for trend followers to make money in FX. Is this the death of trend in FX? Currently yes. Lack of a consistent USD direction has meant that trends are now both unlikely and short term. It is likely that if, in the future trend-friendly conditions like long term asynchronous in large economies return, trends that is worth trading may come back. But currently trend strategies lack evidence to support their sustainability. Carry trade and value investing bring more positive results on the most recent years compared to trend-following/momentum in particular for the emerging market currency pairs (EM). Momentum, carry and value can be combined together into a risk premia index, which has positive returns until early 2018. The combined strategies appear to struggle during the 2018 and the first month of the 2019.

Short dated options are too expensive. On average the payout is only 83% of their premium. This appears to be universal: it is applicable to all the currency pairs and option type that we tested and every possible choice of trading day. Buying or selling options on a specific day in fact produces slightly different payouts only for a few cases. Option trading strategies are influenced by the length of the tenor too. Selling call options for short dated options provide positive payout as they expire worthless most of the time so selling them would allow to pocket the premium. The results indeed show that the returns are always positive: all the calls are profitable to sell. The short tenor is also limiting the positive influence of the carry trade as the bias of the forward price with respect to the future spot price tend to be small over the weekly tenor. For long tenor options the divergence between forward and future spot prices can be amplified by a significant divergence between the base and the quote interest rates, and so opening more trading opportunities for carry trade. Thus, the carry effect for weekly options is small compared to longer tenors like three, six or 12 months even during periods in which the base and quote interest rates systematically e.g. AUD/USD or USD/JPY diverge.

Directional and mean reverting strategies applied to high-frequency data produce positive results also when trading costs are taken into consideration. Mean reverting appears to be a successful investment approach when applied to pairs trading if the currency pairs are carefully selected. This investment style bring positive results for currencies like EUR/USD and GBP/USD, EUR/USD and USD/CHF, and AUD/USD and NZD/USD.

Deep learning models proved to adequately forecast high-frequency prices. From that forecast a range of trading strategies can be adopted to profit from future moves of the price. Exponentially smoothed RNN models can be trained in few hours also on very large dataset. They resulted to be robust when the price time series is not affected by steep jumps in the data.

In conclusion, this research has investigated a wide range of methodologies and approaches for FX trading strategies. A future development in this line of research is possible. For example, it could be interesting studying exponentially smoothed RNN models to find more robust models against price jumps and more complex models in terms of memory management and look-back steps. Another possible continuation of this research could lead to study quantitative methods that also take into consideration FX order book and volumes of trades. This would allow to extend the focus of the research to market makers and automated exchanges.

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Appendix A

Trend-following results relative to the G20 currency group

We show the results relative to the G10 currencies relative to each year from 2007 to 2017.

Table A.1: Table of results of the trend-following strategy for EUR/USD relative to period $2007 - 2011$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/USD	2007	2008	2009	2010	2011
Cumulative Returns	10.9%	2.8%	−0.8%	−6.8%	3.5%
Annualised Returns	10.9%	2.8%	−0.8%	−6.9%	3.6%
Annualised Volatility	6.3%	14.3%	12.9%	12.0%	11.9%
Sharpe Ratio	1.74	0.19	-0.06	-0.57	0.30
Max DD	−3.8%	−14.1%	−13.3%	−17.2%	−8.7%

Table A.2: Table of results of the trend-following strategy for EUR/USD relative to period $2012 - 2017$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/USD	2012	2013	2014	2015	2016	2017
Cumulative Returns	−2.5%	−3.0%	11.1%	8.6%	−0.2%	4.3%
Annualised Returns	−2.6%	−3.0%	11.1%	8.6%	−0.2%	4.4%
Annualised Volatility	8.4%	7.5%	6.2%	12.3%	8.3%	7.4%
Sharpe Ratio	-0.30	-0.40	1.79	0.70	-0.03	0.59
Max DD	−9.0%	−10.5%	−2.9%	−9.1%	−8.1%	−5.6%

TABLE A.3: Table of results of the trend-following strategy for USD/JPY relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/JPY	2007	2008	2009	2010	2011
Cumulative Returns	−4.9%	3.2%	−6.1%	5.3%	2.0%
Annualised Returns	−5.0%	3.2%	−6.2%	5.3%	2.0%
Annualised Volatility	9.9%	16.9%	13.1%	10.6%	9.4%
Sharpe Ratio	-0.50	0.19	-0.47	0.50	0.22
Max DD	−11.6%	−17.3%	−13.4%	−10.0%	−8.7%

TABLE A.4: Table of results of the trend-following strategy for USD/JPY relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/JPY	2012	2013	2014	2015	2016	2017
Cumulative Returns	4.0%	13.8%	10.8%	−3.6%	17.0%	−10.9%
Annualised Returns	4.0%	13.9%	10.9%	−3.6%	17.2%	−11.0%
Annualised Volatility	7.5%	12.3%	8.0%	8.2%	12.5%	8.6%
Sharpe Ratio	0.54	1.12	1.36	-0.44	1.38	-1.29
Max DD	−7.5%	−8.8%	−4.1%	−7.5%	−6.7%	−12.1%

TABLE A.5: Table of results of the trend-following strategy for GBP/USD relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

GBP/USD	2007	2008	2009	2010	2011
Cumulative Returns	1.8%	30.5%	−5.8%	−0.3%	10.9%
Annualised Returns	1.8%	30.6%	−5.8%	−0.3%	11.0%
Annualised Volatility	6.9%	14.3%	14.5%	10.3%	8.5%
Sharpe Ratio	0.25%	2.14%	−0.40%	−0.03%	1.29%
Max DD	−6.2%	−6.8%	−17.5%	−10.6%	−4.9%

TABLE A.6: Table of results of the trend-following strategy for GBP/USD relative to period 2012 − 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

GBP/USD	2012	2013	2014	2015	2016	2017
Cumulative Returns	−4.5%	7.6%	4.7%	−1.8%	−7.8%	0.7%
Annualised Returns	−4.5%	7.6%	4.7%	−1.8%	−7.9%	0.8%
Annualised Volatility	6.3%	7.8%	5.7%	8.5%	14.1%	8.5%
Sharpe Ratio	-0.71	0.98	0.82	-0.21	-0.56	0.09
Max DD	−9.2%	−5.3%	−6.2%	−10.9%	−19.8%	−6.4%

TABLE A.7: Table of results of the trend-following strategy for USD/CHF relative to period 2007 − 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/CHF	2007	2008	2009	2010	2011
Cumulative Returns	13.1%	5.3%	7.1%	−5.1%	3.1%
Annualised Returns	13.2%	5.3%	7.1%	−5.2%	3.1%
Annualised Volatility	7.1%	14.8%	13.1%	10.6%	17.4%
Sharpe Ratio	1.86	0.36	0.54	-0.49	0.18
Max DD	−5.4%	−13.6%	−8.9%	−14.1%	−23.2%

We show the results relative to the G20 currencies for relative to each year from 2007 to 2017.

Table A.8: Table of results of the trend-following strategy for USD/CHF relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/CHF	2012	2013	2014	2015	2016	2017
Cumulative Returns	−5.5%	1.5%	10.5%	4.5%	−6.5%	−6.7%
Annualised Returns	−5.6%	1.5%	10.5%	4.5%	−6.6%	−6.7%
Annualised Volatility	8.3%	8.8%	6.8%	20.8%	7.9%	7.1%
Sharpe Ratio	-0.67	0.17	1.55	0.22	-0.83	-0.95
Max DD	−12.5%	−6.3%	−3.2%	−15.9%	−12.9%	−8.0%

Table A.9: Table of results of the trend-following strategy for AUD/USD relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

AUD/USD.	2007	2008	2009	2010	2011
Cumulative Returns	10.7%	−3.5%	30.8%	0.6%	0.5%
Annualised Returns	10.8%	−3.5%	31.0%	0.6%	0.5%
Annualised Volatility	12.6%	28.5%	19.5%	14.9%	14.6%
Sharpe Ratio	0.85	-0.12	1.59	0.04	0.03
Max DD	−10.2%	−22.6%	−11.4%	−17.6%	−11.6%

Table A.10: Table of results of the trend-following strategy for AUD/USD relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

AUD/USD.	2012	2013	2014	2015	2016	2017
Cumulative Returns	−16.5%	7.8%	−6.1%	9.6%	−2.9%	−15.8%
Annualised Returns	−16.6%	7.9%	−6.1%	9.7%	−2.9%	−16.0%
Annualised Volatility	8.9%	10.1%	8.5%	11.7%	11.4%	7.7%
Sharpe Ratio	-1.86	0.78	-0.72	0.83	-0.26	-2.10
Max DD	−18.7%	−8.5%	−14.6%	−6.7%	−10.0%	−15.8%

Table A.11: Table of results of the trend-following strategy for NZD/USD relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

NZD/USD	2007	2008	2009	2010	2011
Cumulative Returns	4.1%	20.4%	−0.3%	−1.8%	−5.6%
Annualised Returns	4.2%	20.5%	−0.3%	−1.9%	−5.7%
Annualised Volatility	14.5%	21.6%	20.5%	14.5%	15.3%
Sharpe Ratio	0.29	0.95	-0.01	-0.13	-0.37
Max DD	−14.7%	−12.5%	−26.6%	−11.9%	−17.0%

Table A.12: Table of results of the trend-following strategy for NZD/USD relative to period 2012 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

NZD/USD	2012	2013	2014	2015	2016	2017
Cumulative Returns	−9.8%	−12.2%	−5.4%	10.9%	0.6%	−11.7%
Annualised Returns	−9.8%	−12.3%	−5.4%	10.9%	0.7%	−11.9%
Annualised Volatility	9.8%	10.6%	9.3%	13.2%	12.2%	8.6%
Sharpe Ratio	-1.00	-1.16	-0.58	0.83	0.05	-1.37
Max DD	−12.9%	−16.0%	−14.1%	−9.0%	−9.2%	−18.7%

Table A.13: Table of results of the trend-following strategy for USD/CAD relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/CAD	2007	2008	2009	2010	2011
Cumulative Returns	4.0%	16.4%	−2.6%	−9.0%	2.4%
Annualised Returns	4.0%	16.4%	−2.7%	−9.1%	2.4%
Annualised Volatility	9.7%	15.8%	14.6%	11.1%	9.8%
Sharpe Ratio	0.41	1.04	-0.18	-0.82	0.24
Max DD	−9.9%	−11.2%	−17.3%	−15.5%	−6.5%

Table A.14: Table of results of the trend-following strategy for USD/CAD relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/CAD	2012	2013	2014	2015	2016	2017
Cumulative Returns	−7.7%	0.0%	5.8%	17.4%	−7.7%	−6.5%
Annualised Returns	−7.7%	0.0%	5.8%	17.6%	−7.8%	−6.6%
Annualised Volatility	6.4%	6.1%	6.3%	9.1%	9.5%	7.3%
Sharpe Ratio	-1.21	0.00	0.93	1.92	-0.82	-0.90
Max DD	−10.2%	−5.8%	−7.1%	−6.5%	−13.7%	−9.2%

Table A.15: Table of results of the trend-following strategy for USD/SEK relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/SEK	2007	2008	2009	2010	2011
Cumulative Returns	5.3%	12.0%	9.6%	−10.7%	11.5%
Annualised Returns	5.3%	12.0%	9.7%	−10.8%	11.7%
Annualised Volatility	8.8%	18.3%	21.2%	14.4%	16.0%
Sharpe Ratio	0.61	0.66	0.46	-0.75	0.73
Max DD	−5.7%	−14.8%	−20.3%	−22.6%	−9.5%

TABLE A.16: Table of results of the trend-following strategy for USD/SEK relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/SEK	2012	2013	2014	2015	2016	2017
Cumulative Returns	2.0%	−8.1%	20.4%	6.6%	−0.2%	1.9%
Annualised Returns	2.0%	−8.1%	20.5%	6.6%	−0.2%	2.0%
Annualised Volatility	10.0%	10.4%	8.4%	11.6%	10.0%	8.3%
Sharpe Ratio	0.20	-0.78	2.44	0.57	-0.02	0.24
Max DD	−8.2%	−13.6%	−3.1%	−8.1%	−11.4%	−7.1%

TABLE A.17: Table of results of the trend-following strategy for USD/NOK relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/NOK	2007	2008	2009	2010	2011
Cumulative Returns	9.9%	11.6%	2.6%	−8.6%	1.3%
Annualised Returns	10.0%	11.6%	2.7%	−8.6%	1.3%
Annualised Volatility	9.6%	19.7%	18.6%	13.9%	14.6%
Sharpe Ratio	1.05	0.59	0.14	-0.62	0.09
Max DD	−6.9%	−17.9%	−12.8%	−17.9%	−17.4%

TABLE A.18: Table of results of the trend-following strategy for USD/NOK relative to period 2007 – 2018. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/NOK	2012	2013	2014	2015	2016	2017
Cumulative Returns	−6.4%	−0.3%	10.6%	16.5%	−1.7%	−4.5%
Annualised Returns	−6.5%	−0.3%	10.6%	16.6%	−1.7%	−4.5%
Annualised Volatility	9.7%	10.9%	8.8%	14.3%	11.2%	8.5%
Sharpe Ratio	-0.67	-0.03	1.22	1.16	-0.15	-0.53
Max DD	−12.2%	−7.9%	−11.4%	−12.1%	−12.2%	−13.6%

TABLE A.19: Table of results of the trend-following strategy for USD/DKK relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/DKK	2007	2008	2009	2010	2011
Cumulative Returns	10.4%	1.2%	0.9%	−10.4%	7.5%
Annualised Returns	10.5%	1.2%	0.9%	−10.5%	7.6%
Annualised Volatility	6.3%	14.3%	12.9%	12.1%	12.0%
Sharpe Ratio	1.67	0.08	0.07	-0.87	0.63
Max DD	−3.9%	−13.5%	−11.9%	−19.2%	−11.2%

TABLE A.20: Table of results of the trend-following strategy for USD/DKK relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/DKK	2012	2013	2014	2015	2016	2017
Cumulative Returns	5.1%	−4.8%	11.0%	3.8%	1.6%	5.3%
Annualised Returns	5.2%	−4.8%	11.1%	3.8%	1.6%	5.4%
Annualised Volatility	8.4%	7.4%	6.2%	12.1%	8.2%	7.3%
Sharpe Ratio	0.62	-0.65	1.78	0.31	0.19	0.74
Max DD	−8.0%	−12.0%	−2.9%	−12.2%	−9.5%	−5.4%

TABLE A.21: Table of results of the trend-following strategy for USD/ARS relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/ARS	2007	2008	2009	2010	2011
Cumulative Returns	4.7%	−13.9%	9.9%	4.7%	8.4%
Annualised Returns	4.7%	−14.0%	10.0%	4.7%	8.5%
Annualised Volatility	3.0%	5.3%	3.5%	1.9%	1.8%
Sharpe Ratio	1.59	-2.63	2.88	2.53	4.74
Max DD	−1.9%	−16.4%	−1.7%	−0.6%	−0.5%

TABLE A.22: Table of results of the trend-following strategy for USD/ARS relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/ARS	2012	2013	2014	2015	2016	2017
Cumulative Returns	14.3%	32.4%	30.7%	51.3%	20.3%	16.8%
Annualised Returns	14.4%	32.6%	30.8%	51.6%	20.6%	17.0%
Annualised Volatility	1.9%	2.6%	13.6%	31.0%	13.4%	9.9%
Sharpe Ratio	7.53	12.64	2.27	1.67	1.53	1.71
Max DD	−0.6%	−0.2%	−3.2%	−3.9%	−13.2%	−5.7%

TABLE A.23: Table of results of the trend-following strategy for USD/BRL relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/BRL	2007	2008	2009	2010	2011
Cumulative Returns	18.0%	12.7%	16.4%	−11.7%	3.5%
Annualised Returns	18.1%	12.8%	16.5%	−11.8%	3.5%
Annualised Volatility	14.7%	29.7%	19.1%	13.7%	16.3%
Sharpe Ratio	1.24	0.43	0.87	-0.86	0.22
Max DD	−12.6%	−21.5%	−12.8%	−19.6%	−12.8%

TABLE A.24: Table of results of the trend-following strategy for USD/BRL relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/BRL	2012	2013	2014	2015	2016	2017
Cumulative Returns	−2.6%	1.7%	4.3%	47.0%	−11.0%	−12.7%
Annualised Returns	−2.6%	1.7%	4.4%	47.3%	−11.1%	−12.9%
Annualised Volatility	11.1%	13.3%	13.6%	21.2%	18.1%	14.2%
Sharpe Ratio	-0.24	0.13	0.32	2.23	-0.61	-0.91
Max DD	−14.4%	−12.2%	−12.4%	−11.4%	−14.6%	−15.3%

TABLE A.25: Table of results of the trend-following strategy for USD/CNY relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/CNY	2007	2008	2009	2010	2011
Cumulative Returns	7.0%	5.2%	−0.3%	2.6%	4.7%
Annualised Returns	7.0%	5.3%	−0.3%	2.6%	4.7%
Annualised Volatility	1.6%	2.3%	0.6%	1.7%	2.2%
Sharpe Ratio	4.33	2.33	-0.48	1.57	2.19
Max DD	−0.6%	−1.7%	−0.5%	−0.8%	−0.7%

TABLE A.26: Table of results of the trend-following strategy for USD/CNY relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/CNY	2012	2013	2014	2015	2016	2017
Cumulative Returns	0.4%	2.9%	−0.8%	−1.2%	4.9%	4.4%
Annualised Returns	0.4%	2.9%	−0.8%	−1.2%	5.0%	4.5%
Annualised Volatility	1.5%	1.0%	1.9%	2.8%	3.1%	3.3%
Sharpe Ratio	0.25	2.81	-0.43	-0.43	1.58	1.37
Max DD	−1.2%	−0.5%	−2.2%	−4.9%	−2.6%	−2.8%

TABLE A.27: Table of results of the trend-following strategy for USD/INR relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/INR	2007	2008	2009	2010	2011
Cumulative Returns	11.9%	18.9%	3.5%	−4.3%	3.0%
Annualised Returns	12.0%	19.0%	3.5%	−4.3%	3.0%
Annualised Volatility	6.0%	10.3%	9.7%	7.7%	7.9%
Sharpe Ratio	1.99	1.85	0.36	-0.56	0.38
Max DD	−2.6%	−6.8%	−10.0%	−11.9%	−8.9%

TABLE A.28: Table of results of the trend-following strategy for USD/INR relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/INR	2012	2013	2014	2015	2016	2017
Cumulative Returns	1.2%	11.9%	3.7%	4.6%	2.3%	−9.6%
Annualised Returns	1.2%	12.0%	3.7%	4.6%	2.3%	−9.7%
Annualised Volatility	9.8%	12.2%	5.9%	5.7%	5.0%	4.1%
Sharpe Ratio	0.12	0.98	0.63	0.81	0.46	-2.38
Max DD	−9.4%	−11.3%	−6.0%	−3.5%	−3.9%	−10.3%

TABLE A.29: Table of results of the trend-following strategy for USD/IDR relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/IDR	2007	2008	2009	2010	2011
Cumulative Returns	1.2%	21.1%	2.1%	3.5%	4.0%
Annualised Returns	1.2%	21.1%	2.1%	3.5%	4.1%
Annualised Volatility	6.8%	13.2%	9.6%	4.8%	5.9%
Sharpe Ratio	0.17	1.60	0.22	0.74	0.69
Max DD	−8.6%	−10.7%	−15.6%	−3.9%	−6.8%

TABLE A.30: Table of results of the trend-following strategy for USD/IDR relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/IDR	2012	2013	2014	2015	2016	2017
Cumulative Returns	5.5%	26.1%	−0.7%	9.9%	−4.3%	−0.5%
Annualised Returns	5.5%	26.3%	−0.7%	10.0%	−4.3%	−0.5%
Annualised Volatility	4.5%	6.2%	7.1%	8.1%	6.0%	2.6%
Sharpe Ratio	1.22	4.25	-0.09	1.23	-0.72	-0.21
Max DD	−3.1%	−4.9%	−8.7%	−8.8%	−5.3%	−2.8%

TABLE A.31: Table of results of the trend-following strategy for USD/KRW relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/KRW	2007	2008	2009	2010	2011
Cumulative Returns	−1.3%	33.2%	6.9%	−9.4%	3.2%
Annualised Returns	−1.3%	33.3%	6.9%	−9.5%	3.2%
Annualised Volatility	4.7%	27.3%	16.2%	13.0%	10.4%
Sharpe Ratio	-0.27	1.22	0.43	-0.73	0.31
Max DD	−4.6%	−16.7%	−21.5%	−15.5%	−12.8%

TABLE A.32: Table of results of the trend-following strategy for USD/KRW relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/KRW	2012	2013	2014	2015	2016	2017
Cumulative Returns	5.9%	−9.1%	−7.3%	6.2%	−10.2%	0.5%
Annualised Returns	5.9%	−9.2%	−7.3%	6.3%	−10.3%	0.5%
Annualised Volatility	5.7%	6.5%	6.9%	8.9%	10.7%	8.0%
Sharpe Ratio	1.04	-1.41	-1.07	0.71	-0.96	0.06
Max DD	−5.6%	−11.6%	−11.9%	−6.5%	−14.4%	−7.0%

TABLE A.33: Table of results of the trend-following strategy for USD/MXN relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/MXN	2007	2008	2009	2010	2011
Cumulative Returns	−12.0%	6.1%	−3.1%	−6.7%	8.3%
Annualised Returns	−12.1%	6.1%	−3.1%	−6.8%	8.4%
Annualised Volatility	6.4%	20.9%	16.0%	11.6%	14.9%
Sharpe Ratio	-1.88	0.29	-0.19	-0.58	0.57
Max DD	−12.8%	−17.0%	−18.7%	−12.8%	−10.3%

TABLE A.34: Table of results of the trend-following strategy for USD/MXN relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/MXN	2012	2013	2014	2015	2016	2017
Cumulative Returns	−7.4%	−1.3%	7.8%	15.8%	19.8%	−10.8%
Annualised Returns	−7.4%	−1.4%	7.8%	15.9%	20.0%	−11.0%
Annualised Volatility	10.7%	10.7%	7.4%	10.9%	17.1%	12.0%
Sharpe Ratio	-0.69	-0.13	1.06	1.46	1.17	-0.91
Max DD	−11.3%	−11.2%	−7.7%	−4.8%	−10.3%	−19.1%

TABLE A.35: Table of results of the trend-following strategy for USD/RUB relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/RUB	2007	2008	2009	2010	2011
Cumulative Returns	6.9%	14.7%	7.1%	10.1%	−1.3%
Annualised Returns	7.0%	14.7%	7.1%	10.2%	−1.3%
Annualised Volatility	3.3%	9.7%	15.4%	9.0%	11.8%
Sharpe Ratio	2.13	1.52	0.46	1.13	-0.11
Max DD	−2.0%	−10.9%	−18.6%	−6.6%	−18.3%

Table A.36: Table of results of the trend-following strategy for USD/RUB relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/RUB	2012	2013	2014	2015	2016	2017
Cumulative Returns	−19.9%	−4.4%	27.6%	−19.1%	−5.4%	5.2%
Annualised Returns	−20.0%	−4.4%	27.8%	−19.2%	−5.5%	5.3%
Annualised Volatility	10.6%	7.8%	29.0%	26.7%	19.0%	11.0%
Sharpe Ratio	-1.88	-0.56	0.96	-0.72	-0.29	0.48
Max DD	−22.5%	−8.9%	−21.9%	−42.5%	−23.1%	−8.6%

TABLE A.37: Table of results of the trend-following strategy for USD/TRY relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/TRY	2007	2008	2009	2010	2011
Cumulative Returns	17.9%	−0.6%	−5.4%	−19.4%	15.1%
Annualised Returns	18.1%	−0.6%	−5.5%	−19.6%	15.3%
Annualised Volatility	15.4%	23.8%	15.8%	11.7%	13.1%
Sharpe Ratio	1.18	-0.02	-0.35	-1.68	1.17
Max DD	−11.8%	−22.7%	−21.1%	−21.1%	−8.4%

TABLE A.38: Table of results of the trend-following strategy for USD/TRY relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/TRY	2012	2013	2014	2015	2016	2017
Cumulative Returns	−4.6%	11.5%	7.5%	24.5%	−2.9%	−7.1%
Annualised Returns	−4.6%	11.6%	7.6%	24.6%	−2.9%	−7.2%
Annualised Volatility	7.3%	9.1%	10.8%	13.1%	13.0%	12.8%
Sharpe Ratio	-0.63	1.27	0.70	1.89	-0.22	-0.56
Max DD	−7.3%	−6.9%	−11.3%	−7.7%	−21.8%	−18.6%

TABLE A.39: Table of results of the trend-following strategy for USD/ZAR relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/ZAR	2007	2008	2009	2010	2011
Cumulative Returns	3.9%	−10.5%	1.6%	3.0%	0.6%
Annualised Returns	4.0%	−10.5%	1.6%	3.0%	0.7%
Annualised Volatility	14.9%	31.9%	20.8%	12.7%	19.4%
Sharpe Ratio	0.26	-0.33	0.08	0.24	0.03
Max DD	−8.8%	−19.7%	−22.9%	−9.5%	−12.1%

Table A.40: Table of results of the trend-following strategy for USD/ZAR relative to period $2012 - 2017$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/ZAR	2012	2013	2014	2015	2016	2017
Cumulative Returns	-14.2%	23.7%	0.3%	32.2%	1.0%	-4.0%
Annualised Returns	-14.3%	23.8%	0.3%	32.5%	1.0%	-4.1%
Annualised Volatility	14.1%	13.7%	11.3%	15.6%	21.5%	15.7%
Sharpe Ratio	-1.01	1.74	0.02	2.08	0.05	-0.26
Max DD	-19.4%	-7.7%	-11.3%	-7.2%	-15.5%	-15.3%

Appendix B

Trend-following results relative to the EM currency group

We show the results relative to the EM currencies for relative to each year from 2007 to 2017.

TABLE B.1: Table of results of the trend-following strategy for USD/CLP relative to period $2007-2011$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/CLP	2007	2008	2009	2010	2011
Cumulative Returns	11.3%	14.5%	−3.0%	−13.7%	−8.7%
Annualised Returns	11.4%	14.5%	−3.0%	−13.8%	−8.7%
Annualised Volatility	5.8%	17.2%	12.7%	10.2%	12.6%
Sharpe Ratio	1.99	0.84	-0.24	-1.35	-0.69
Max DD	−4.4%	−20.1%	−13.0%	−20.9%	−15.0%

TABLE B.2: Table of results of the trend-following strategy for USD/CLP relative to period $2012-2017$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/CLP	2012	2013	2014	2015	2016	2017
Cumulative Returns	−1.4%	−0.6%	14.6%	15.5%	−0.1%	−0.5%
Annualised Returns	−1.4%	−0.6%	14.7%	15.6%	−0.1%	−0.5%
Annualised Volatility	8.7%	8.1%	8.4%	9.5%	10.7%	8.2%
Sharpe Ratio	-0.16	-0.08	1.76	1.63	-0.01	-0.06
Max DD	−8.8%	−8.1%	−5.3%	−7.3%	−10.1%	−11.5%

Table B.3: Table of results of the trend-following strategy for USD/CNH relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/CNH	2011	2012	2013	2014	2015	2016	2017
Cumulative Returns	−0.9%	2.4%	−3.8%	5.5%	5.2%	1.6%	
Annualised Returns	−0.9%	2.5%	−3.8%	5.5%	5.3%	1.6%	
Annualised Volatility	1.5%	1.4%	2.3%	4.5%	3.8%	4.3%	
Sharpe Ratio	1.90	-0.56	1.70	-1.64	1.22	1.38	0.38
Max DD	−2.7%	−0.9%	−4.3%	−2.9%	−3.6%	−3.4%	

Table B.4: Table of results of the trend-following strategy for USD/COP relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/COP	2007	2008	2009	2010	2011
Cumulative Returns	−10.8%	25.8%	12.1%	−8.0%	−7.0%
Annualised Returns	−10.9%	25.9%	12.2%	−8.1%	−7.1%
Annualised Volatility	12.8%	19.9%	16.5%	11.5%	8.6%
Sharpe Ratio	-0.85	1.30	0.74	-0.70	-0.82
Max DD	−25.4%	−14.1%	−12.7%	−11.0%	−11.7%

Table B.5: Table of results of the trend-following strategy for USD/COP relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/COP	2012	2013	2014	2015	2016	2017
Cumulative Returns	−5.1%	−0.2%	14.2%	33.6%	−4.4%	−17.0%
Annualised Returns	−5.2%	−0.2%	14.3%	33.8%	−4.5%	−17.2%
Annualised Volatility	6.2%	6.0%	9.4%	17.4%	17.8%	9.2%
Sharpe Ratio	-0.83	-0.03	1.52	1.95	-0.25	-1.87
Max DD	−7.1%	−7.2%	−10.9%	−14.2%	−15.8%	−18.0%

Table B.6: Table of results of the trend-following strategy for USD/CZK relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/CZK	2007	2008	2009	2010	2011
Cumulative Returns	14.2%	−13.5%	−11.1%	−20.9%	2.5%
Annualised Returns	14.4%	−13.6%	−11.1%	−21.1%	2.5%
Annualised Volatility	8.0%	20.8%	19.3%	14.9%	15.9%
Sharpe Ratio	1.80	-0.65	-0.58	-1.42	0.16
Max DD	−4.4%	−33.0%	−26.7%	−29.3%	−15.7%

TABLE B.7: Table of results of the trend-following strategy for USD/CZK relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/CZK	2012	2013	2014	2015	2016	2017
Cumulative Returns	−3.9%	−7.5%	13.1%	−0.7%	4.9%	0.6%
Annualised Returns	−3.9%	−7.5%	13.2%	−0.7%	5.0%	0.6%
Annualised Volatility	13.0%	10.4%	6.8%	12.4%	8.3%	8.2%
Sharpe Ratio	-0.30	-0.72	1.94	-0.06	0.60	0.07
Max DD	−12.4%	−12.9%	−3.2%	−14.3%	−8.5%	−10.2%

TABLE B.8: Table of results of the trend-following strategy for USD/HUF relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/HUF	2007	2008	2009	2010	2011
Cumulative Returns	9.3%	−21.7%	8.6%	−12.1%	12.4%
Annualised Returns	9.4%	−21.7%	8.6%	−12.2%	12.5%
Annualised Volatility	10.8%	23.5%	24.0%	19.3%	20.9%
Sharpe Ratio	0.86	-0.93	0.36	-0.63	0.60
Max DD	−8.8%	−35.8%	−22.3%	−25.0%	−17.8%

TABLE B.9: Table of results of the trend-following strategy for USD/HUF relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/HUF	2012	2013	2014	2015	2016	2017
Cumulative Returns	−21.5%	−11.0%	11.4%	9.7%	−10.1%	−2.0%
Annualised Returns	−21.6%	−11.1%	11.5%	9.7%	−10.3%	−2.1%
Annualised Volatility	15.8%	11.3%	9.3%	13.4%	9.9%	8.7%
Sharpe Ratio	-1.37	-0.98	1.24	0.72	-1.04	-0.24
Max DD	−24.8%	−18.4%	−6.7%	−8.1%	−11.6%	−8.3%

TABLE B.10: Table of results of the trend-following strategy for USD/ILS relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/ILS	2007	2008	2009	2010	2011
Cumulative Returns	−5.8%	−0.7%	3.1%	−4.9%	0.1%
Annualised Returns	−5.9%	−0.7%	3.2%	−5.0%	0.1%
Annualised Volatility	7.6%	15.4%	10.7%	6.3%	9.0%
Sharpe Ratio	-0.78	-0.05	0.30	-0.79	0.01
Max DD	−15.2%	−17.9%	−10.6%	−10.8%	−10.2%

TABLE B.11: Table of results of the trend-following strategy for USD/ILS relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/ILS	2012	2013	2014	2015	2016	2017
Cumulative Returns	0.0%	6.8%	3.0%	−5.7%	−4.6%	4.3%
Annualised Returns	0.0%	6.8%	3.0%	−5.7%	−4.7%	4.3%
Annualised Volatility	6.7%	6.7%	5.4%	8.6%	5.9%	5.2%
Sharpe Ratio	0.00	1.03	0.57	-0.66	-0.80	0.83
Max DD	−7.5%	−4.2%	−6.2%	−10.6%	−9.0%	−4.0%

TABLE B.12: Table of results of the trend-following strategy for USD/PHP relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/PHP	2007	2008	2009	2010	2011
Cumulative Returns	17.9%	−2.1%	−5.0%	1.2%	5.3%
Annualised Returns	18.0%	−2.1%	−5.0%	1.3%	5.4%
Annualised Volatility	7.4%	8.9%	8.3%	7.4%	5.9%
Sharpe Ratio	2.45	-0.24	-0.61	0.17	0.92
Max DD	−5.9%	−11.7%	−10.4%	−7.4%	−4.5%

TABLE B.13: Table of results of the trend-following strategy for USD/PHP relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/PHP	2012	2013	2014	2015	2016	2017
Cumulative Returns	1.6%	1.3%	−4.5%	0.1%	−4.0%	0.4%
Annualised Returns	1.6%	1.4%	−4.5%	0.1%	−4.0%	0.4%
Annualised Volatility	5.4%	5.8%	4.3%	4.3%	5.5%	4.3%
Sharpe Ratio	0.30	0.23	-1.05	0.03	-0.73	0.10
Max DD	−5.4%	−5.3%	−7.2%	−4.7%	−8.9%	−3.9%

TABLE B.14: Table of results of the trend-following strategy for USD/PLN relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/PLN	2007	2008	2009	2010	2011
Cumulative Returns	17.0%	5.2%	8.2%	−8.8%	−0.5%
Annualised Returns	17.1%	5.2%	8.2%	−8.9%	−0.5%
Annualised Volatility	9.5%	22.6%	24.9%	19.5%	20.1%
Sharpe Ratio	1.81	0.23	0.33	-0.46	-0.02
Max DD	−5.1%	−25.1%	−21.3%	−29.9%	−21.3%

TABLE B.15: Table of results of the trend-following strategy for USD/PLN relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/PLN	2012	2013	2014	2015	2016	2017
Cumulative Returns	−18.5%	−3.8%	9.8%	9.4%	−0.8%	−0.1%
Annualised Returns	−18.6%	−3.8%	9.9%	9.5%	−0.8%	−0.1%
Annualised Volatility	14.9%	10.5%	8.2%	12.6%	11.7%	9.2%
Sharpe Ratio	-1.25	-0.37	1.21	0.76	-0.07	-0.01
Max DD	−25.8%	−9.4%	−4.4%	−10.7%	−10.1%	−10.1%

TABLE B.16: Table of results of the trend-following strategy for USD/SGD relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/SGD	2007	2008	2009	2010	2011
Cumulative Returns	4.5%	3.0%	3.5%	6.2%	−1.5%
Annualised Returns	4.5%	3.0%	3.5%	6.3%	−1.5%
Annualised Volatility	3.7%	7.6%	6.1%	5.9%	8.5%
Sharpe Ratio	1.23	0.40	0.58	1.07	-0.18
Max DD	−3.3%	−6.4%	−7.1%	−5.1%	−11.7%

TABLE B.17: Table of results of the trend-following strategy for USD/SGD relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/SGD	2012	2013	2014	2015	2016	2017
Cumulative Returns	−5.5%	−3.6%	2.9%	6.5%	2.2%	−1.0%
Annualised Returns	−5.5%	−3.6%	2.9%	6.5%	2.2%	−1.1%
Annualised Volatility	4.8%	4.6%	3.9%	6.6%	6.5%	4.6%
Sharpe Ratio	-1.14	-0.79	0.74	0.99	0.34	-0.23
Max DD	−9.6%	−4.5%	−3.3%	−5.4%	−4.7%	−4.8%

TABLE B.18: Table of results of the trend-following strategy for USD/TWD relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/TWD	2007	2008	2009	2010	2011
Cumulative Returns	−0.4%	6.5%	−1.1%	4.4%	−2.0%
Annualised Returns	−0.4%	6.5%	−1.1%	4.5%	−2.0%
Annualised Volatility	2.4%	5.8%	6.1%	4.9%	5.1%
Sharpe Ratio	-0.17	1.13	-0.18	0.92	-0.39
Max DD	−4.1%	−5.2%	−11.0%	−6.0%	−5.2%

TABLE B.19: Table of results of the trend-following strategy for USD/TWD relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

USD/TWD	2012	2013	2014	2015	2016	2017
Cumulative Returns	−2.7%	−6.2%	3.1%	0.7%	−5.2%	2.7%
Annualised Returns	−2.7%	−6.3%	3.1%	0.7%	−5.3%	2.8%
Annualised Volatility	3.2%	3.6%	2.8%	6.7%	6.2%	4.7%
Sharpe Ratio	-0.85	-1.73	1.09	0.11	-0.85	0.59
Max DD	−4.4%	−6.5%	−4.2%	−6.2%	−7.1%	−3.7%

Appendix C

Trend-following results relative to the EUR G10 currency group

We show the results relative to the EUR G10 currencies for relative to each year from 2007 to 2017.

TABLE C.1: Table of results of the trend-following strategy for EUR/CHF relative to period $2007 - 2011$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/CHF	2007	2008	2009	2010	2011
Cumulative Returns	2.4%	−5.1%	1.2%	17.9%	−3.6%
Annualised Returns	2.5%	−5.1%	1.2%	18.1%	−3.7%
Annualised Volatility	4.1%	9.5%	6.5%	9.0%	16.1%
Sharpe Ratio	0.60	-0.53	0.19	2.00	-0.23
Max DD	−2.9%	−13.7%	−5.2%	−7.1%	−19.5%

TABLE C.2: Table of results of the trend-following strategy for EUR/CHF relative to period $2012 - 2017$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/CHF	2012	2013	2014	2015	2016	2017
Cumulative Returns	−1.9%	1.7%	2.1%	4.5%	0.8%	4.9%
Annualised Returns	−1.9%	1.7%	2.1%	4.5%	0.8%	5.0%
Annualised Volatility	1.7%	4.5%	2.0%	18.2%	4.5%	5.0%
Sharpe Ratio	-1.10	0.39	1.09	0.25	0.19	1.00
Max DD	−2.6%	−2.7%	−0.9%	−12.3%	−4.1%	−3.3%

Table C.3: Table of results of the trend-following strategy for EUR/GBP relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/GBP	2007	2008	2009	2010	2011
Cumulative Returns	7.7%	28.7%	−13.9%	−7.3%	5.0%
Annualised Returns	7.7%	28.8%	−14.0%	−7.4%	5.0%
Annualised Volatility	5.3%	11.7%	12.5%	9.3%	8.8%
Sharpe Ratio	1.46	2.46	-1.12	-0.79	0.57
Max DD	−4.9%	−5.2%	−15.9%	−12.0%	−5.9%

Table C.4: Table of results of the trend-following strategy for EUR/GBP relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/GBP	2012	2013	2014	2015	2016	2017
Cumulative Returns	2.4%	−6.3%	6.7%	5.2%	15.7%	−9.2%
Annualised Returns	2.4%	−6.3%	6.7%	5.2%	15.9%	−9.3%
Annualised Volatility	6.1%	7.1%	5.9%	9.7%	11.9%	8.1%
Sharpe Ratio	0.39	-0.89	1.15	0.54	1.33	-1.15
Max DD	−5.5%	−8.2%	−2.9%	−7.2%	−8.2%	−13.5%

Table C.5: Table of results of the trend-following strategy for EUR/JPY relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/JPY	2007	2008	2009	2010	2011
Cumulative Returns	2.5%	−16.0%	−4.6%	12.5%	−11.3%
Annualised Returns	2.5%	−16.0%	−4.6%	12.7%	−11.4%
Annualised Volatility	11.1%	22.0%	16.7%	15.3%	13.6%
Sharpe Ratio	0.22	-0.73	-0.28	0.83	-0.84
Max DD	−9.1%	−28.6%	−15.9%	−8.5%	−19.8%

Table C.6: Table of results of the trend-following strategy for EUR/JPY relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/JPY	2012	2013	2014	2015	2016	2017
Cumulative Returns	−3.1%	25.7%	−11.5%	−20.7%	3.5%	−0.3%
Annualised Returns	−3.1%	25.9%	−11.5%	−20.8%	3.5%	−0.3%
Annualised Volatility	11.1%	13.2%	7.5%	10.6%	12.2%	8.1%
Sharpe Ratio	-0.28	1.96	-1.54	-1.96	0.29	-0.04
Max DD	−14.2%	−6.0%	−11.5%	−22.8%	−10.4%	−7.8%

TABLE C.7: Table of results of the trend-following strategy for EUR/SEK relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/SEK	2007	2008	2009	2010	2011
Cumulative Returns	1.4%	12.7%	−4.7%	10.8%	−2.9%
Annualised Returns	1.4%	12.7%	−4.7%	11.0%	−2.9%
Annualised Volatility	5.0%	9.8%	12.8%	7.7%	8.3%
Sharpe Ratio	0.28	1.30	-0.37	1.43	-0.35
Max DD	−3.7%	−5.2%	−14.6%	−4.0%	−6.4%

TABLE C.8: Table of results of the trend-following strategy for EUR/SEK relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/SEK	2012	2013	2014	2015	2016	2017
Cumulative Returns	−2.6%	−6.4%	8.1%	−5.7%	3.5%	−1.7%
Annualised Returns	−2.6%	−6.4%	8.1%	−5.8%	3.5%	−1.7%
Annualised Volatility	7.0%	6.9%	6.2%	7.9%	5.7%	5.3%
Sharpe Ratio	-0.37	-0.92	1.31	-0.73	0.61	-0.32
Max DD	−9.0%	−10.6%	−2.5%	−7.1%	−4.0%	−4.7%

TABLE C.9: Table of results of the trend-following strategy for EUR/NOK relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/NOK	2007	2008	2009	2010	2011
Cumulative Returns	0.2%	19.4%	−1.4%	−1.8%	3.0%
Annualised Returns	0.2%	19.4%	−1.4%	−1.8%	3.1%
Annualised Volatility	5.9%	11.4%	11.4%	7.9%	7.7%
Sharpe Ratio	0.03	1.71	-0.12	-0.23	0.40
Max DD	−6.0%	−8.2%	−10.8%	−7.9%	−4.9%

TABLE C.10: Table of results of the trend-following strategy for EUR/NOK relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/NOK	2012	2013	2014	2015	2016	2017
Cumulative Returns	4.7%	7.3%	−0.8%	−0.3%	−2.0%	0.6%
Annualised Returns	4.7%	7.3%	−0.8%	−0.3%	−2.1%	0.6%
Annualised Volatility	6.0%	8.3%	7.7%	11.4%	7.7%	6.4%
Sharpe Ratio	0.79	0.88	-0.10	-0.03	-0.27	0.09
Max DD	−3.3%	−4.6%	−10.0%	−9.5%	−6.9%	−7.7%

Appendix D

Trend-following results relative to the EUR G20 currency group

We show the results relative to the EUR G20 currencies for relative to each year from 2007 to 2017.

TABLE D.1: Table of results of the trend-following strategy for EUR/RUB relative to period $2007-2011$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/RUB	2007	2008	2009	2010	2011
Cumulative Returns	3.6%	−15.1%	−2.8%	−2.1%	−4.6%
Annualised Returns	3.6%	−15.1%	−2.8%	−2.1%	−4.7%
Annualised Volatility	3.4%	8.5%	13.5%	10.1%	9.3%
Sharpe Ratio	1.06	-1.77	-0.21	-0.21	-0.50
Max DD	−1.8%	−18.1%	−11.8%	−17.7%	−7.3%

TABLE D.2: Table of results of the trend-following strategy for EUR/RUB relative to period $2012-2017$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/RUB	2012	2013	2014	2015	2016	2017
Cumulative Returns	−11.8%	9.6%	27.8%	−28.5%	−1.7%	−13.3%
Annualised Returns	−11.8%	9.6%	28.0%	−28.6%	−1.8%	−13.5%
Annualised Volatility	8.2%	7.8%	29.2%	28.7%	19.4%	12.3%
Sharpe Ratio	-1.44	1.24	0.96	-1.00	-0.09	-1.10
Max DD	−13.5%	−4.9%	−23.8%	−44.7%	−25.1%	−20.5%

TABLE D.3: Table of results of the trend-following strategy for EUR/TRY relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/TRY	2007	2008	2009	2010	2011
Cumulative Returns	4.6%	5.3%	3.2%	6.1%	17.5%
Annualised Returns	4.7%	5.3%	3.3%	6.2%	17.8%
Annualised Volatility	13.7%	20.7%	14.1%	9.4%	11.5%
Sharpe Ratio	0.34	0.26	0.23	0.65	1.54
Max DD	−9.7%	−23.2%	−11.6%	−5.6%	−6.1%

TABLE D.4: Table of results of the trend-following strategy for EUR/TRY relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/TRY	2012	2013	2014	2015	2016	2017
Cumulative Returns	3.8%	13.3%	−4.7%	14.5%	13.2%	9.4%
Annualised Returns	3.8%	13.4%	−4.7%	14.6%	13.3%	9.5%
Annualised Volatility	8.0%	9.4%	11.1%	15.6%	11.1%	12.5%
Sharpe Ratio	0.47	1.42	-0.42	0.93	1.20	0.76
Max DD	−9.8%	−8.2%	−15.3%	−12.9%	−5.4%	−11.9%

TABLE D.5: Table of results of the trend-following strategy for EUR/ZAR relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/ZAR	2007	2008	2009	2010	2011
Cumulative Returns	24.3%	−20.1%	−5.2%	2.0%	−11.7%
Annualised Returns	24.5%	−20.2%	−5.3%	2.0%	−11.8%
Annualised Volatility	12.9%	25.9%	16.7%	11.7%	14.5%
Sharpe Ratio	1.91	-0.78	-0.31	0.17	-0.81
Max DD	−5.4%	−37.2%	−18.3%	−10.7%	−18.2%

TABLE D.6: Table of results of the trend-following strategy for EUR/ZAR relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/ZAR	2012	2013	2014	2015	2016	2017
Cumulative Returns	6.9%	28.9%	3.0%	19.4%	7.9%	−9.2%
Annualised Returns	6.9%	29.1%	3.1%	19.5%	8.0%	−9.3%
Annualised Volatility	11.4%	13.3%	11.3%	17.0%	19.9%	15.1%
Sharpe Ratio	0.60	2.19	0.27	1.15	0.40	-0.62
Max DD	−8.6%	−6.8%	−9.2%	−11.1%	−12.5%	−16.4%

Appendix E

Trend-following results relative to the EUR EM currency group

We show the results relative to the EUR EM currencies for relative to each year from 2007 to 2017.

Table E.1: Table of results of the trend-following strategy for EUR/CZK relative to period $2007 - 2011$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/CZK	2007	2008	2009	2010	2011
Cumulative Returns	−5.2%	1.1%	−7.7%	7.6%	3.1%
Annualised Returns	−5.2%	1.1%	−7.7%	7.7%	3.1%
Annualised Volatility	5.0%	11.9%	11.8%	6.3%	6.8%
Sharpe Ratio	-1.05	0.09	-0.66	1.23	0.46
Max DD	−7.6%	−14.0%	−16.7%	−4.5%	−4.4%

Table E.2: Table of results of the trend-following strategy for EUR/CZK relative to period $2012 - 2017$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/CZK	2012	2013	2014	2015	2016	2017
Cumulative Returns	2.1%	4.8%	0.5%	0.6%	0.0%	5.7%
Annualised Returns	2.1%	4.9%	0.5%	0.6%	0.0%	5.8%
Annualised Volatility	6.6%	6.4%	2.3%	3.3%	0.7%	3.5%
Sharpe Ratio	0.32	0.76	0.24	0.18	-0.02	1.66
Max DD	−5.5%	−3.3%	−1.7%	−3.9%	−0.5%	−1.9%

TABLE E.3: Table of results of the trend-following strategy for EUR/HUF relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/HUF	2007	2008	2009	2010	2011
Cumulative Returns	−5.2%	2.5%	15.2%	−6.6%	16.3%
Annualised Returns	−5.3%	2.5%	15.3%	−6.7%	16.5%
Annualised Volatility	7.8%	15.9%	16.0%	11.0%	11.9%
Sharpe Ratio	-0.67	0.16	0.96	-0.61	1.38
Max DD	−9.1%	−14.1%	−12.8%	−11.0%	−5.9%

TABLE E.4: Table of results of the trend-following strategy for EUR/HUF relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/HUF	2012	2013	2014	2015	2016	2017
Cumulative Returns	−9.3%	−10.3%	−2.8%	−5.9%	−5.6%	−3.3%
Annualised Returns	−9.3%	−10.4%	−2.9%	−5.9%	−5.6%	−3.3%
Annualised Volatility	10.1%	7.8%	6.7%	7.3%	4.9%	3.5%
Sharpe Ratio	-0.92	-1.34	-0.43	-0.81	-1.14	-0.94
Max DD	−14.4%	−15.3%	−8.1%	−10.0%	−7.0%	−5.3%

TABLE E.5: Table of results of the trend-following strategy for EUR/PLN relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/PLN	2007	2008	2009	2010	2011
Cumulative Returns	5.6%	0.2%	−1.2%	−7.5%	7.0%
Annualised Returns	5.6%	0.2%	−1.2%	−7.6%	7.1%
Annualised Volatility	6.3%	14.1%	17.9%	11.1%	11.1%
Sharpe Ratio	0.89	0.01	-0.07	-0.68	0.64
Max DD	−3.0%	−23.8%	−19.6%	−15.5%	−7.3%

TABLE E.6: Table of results of the trend-following strategy for EUR/PLN relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/PLN	2012	2013	2014	2015	2016	2017
Cumulative Returns	−8.1%	0.6%	0.5%	−5.0%	−1.1%	−5.1%
Annualised Returns	−8.1%	0.6%	0.5%	−5.0%	−1.2%	−5.1%
Annualised Volatility	8.7%	6.1%	5.2%	7.1%	7.4%	4.6%
Sharpe Ratio	-0.94	0.09	0.10	-0.71	-0.15	-1.11
Max DD	−15.2%	−4.2%	−3.3%	−8.2%	−6.1%	−5.8%

TABLE E.7: Table of results of the trend-following strategy for EUR/CNH relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/CNH	2013	2014	2015	2016	2017
Cumulative Returns	0.1%	10.1%	14.9%	−1.0%	5.3%
Annualised Returns	0.1%	10.1%	15.0%	−1.0%	5.4%
Annualised Volatility	7.5%	6.1%	11.6%	7.9%	6.3%
Sharpe Ratio	0.01	1.66	1.29	-0.12	0.86
Max DD	−6.7%	−4.7%	−8.5%	−5.9%	−3.9%

TABLE E.8: Table of results of the trend-following strategy for EUR/CNY relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

EUR/CNY	2013	2014	2015	2016	2017
Cumulative Returns	0.9%	9.6%	14.0%	2.3%	0.9%
Annualised Returns	0.9%	9.6%	14.1%	2.3%	1.0%
Annualised Volatility	6.9%	6.0%	12.2%	7.2%	6.2%
Sharpe Ratio	0.14	1.59	1.15	0.32	0.15
Max DD	−6.6%	−5.0%	−10.1%	−3.8%	−4.4%

Appendix F

Trend-following results relative to the cross-currencies group

We show the results relative to the cross-currencies for relative to each year from 2007 to 2017.

Table F.1: Table of results of the trend-following strategy for CHF/JPY relative to period $2007-2011$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

CHF/JPY	2007	2008	2009	2010	2011
Cumulative Returns	−5.3%	8.4%	−8.6%	−9.4%	6.6%
Annualised Returns	−5.4%	8.4%	−8.6%	−9.5%	6.7%
Annualised Volatility	8.7%	16.8%	15.8%	12.9%	16.0%
Sharpe Ratio	-0.62	0.50	-0.54	-0.74	0.42
Max DD	−12.2%	−11.2%	−17.2%	−16.6%	−19.4%

Table F.2: Table of results of the trend-following strategy for CHF/JPY relative to period $2012-2017$. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

CHF/JPY	2012	2013	2014	2015	2016	2017
Cumulative Returns	−8.8%	24.0%	−8.4%	11.9%	12.0%	−9.0%
Annualised Returns	−8.9%	24.2%	−8.5%	12.0%	12.1%	−9.1%
Annualised Volatility	11.0%	11.6%	7.2%	17.2%	11.1%	6.8%
Sharpe Ratio	-0.81	2.09	-1.17	0.69	1.09	-1.34
Max DD	−21.0%	−4.6%	−10.9%	−12.2%	−7.2%	−10.1%

TABLE F.3: Table of results of the trend-following strategy for AUD/NZD relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

AUD/NZD	2007	2008	2009	2010	2011
Cumulative Returns	−7.9%	−9.3%	−1.9%	−5.9%	−6.6%
Annualised Returns	−8.0%	−9.4%	−1.9%	−6.0%	−6.7%
Annualised Volatility	8.2%	11.9%	9.3%	7.4%	7.9%
Sharpe Ratio	-0.97	-0.79	-0.21	-0.80	-0.85
Max DD	−11.8%	−19.6%	−8.4%	−9.0%	−11.4%

TABLE F.4: Table of results of the trend-following strategy for AUD/NZD relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

AUD/NZD	2012	2013	2014	2015	2016	2017
Cumulative Returns	10.3%	15.6%	−5.9%	−8.4%	−5.7%	−7.4%
Annualised Returns	10.4%	15.7%	−5.9%	−8.4%	−5.8%	−7.5%
Annualised Volatility	5.0%	6.9%	6.5%	10.0%	8.2%	6.8%
Sharpe Ratio	2.09	2.27	-0.91	-0.84	-0.71	-1.11
Max DD	−3.5%	−3.6%	−9.0%	−12.1%	−9.1%	−9.6%

TABLE F.5: Table of results of the trend-following strategy for AUD/JPY relative to period 2007 – 2011. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

AUD/JPY	2007	2008	2009	2010	2011
Cumulative Returns	23.6%	−7.9%	12.7%	−17.7%	1.8%
Annualised Returns	23.8%	−7.9%	12.8%	−17.9%	1.9%
Annualised Volatility	18.9%	39.4%	25.2%	20.1%	16.5%
Sharpe Ratio	1.26	-0.20	0.51	-0.89	0.11
Max DD	−15.6%	−28.4%	−24.4%	−24.5%	−12.6%

TABLE F.6: Table of results of the trend-following strategy for AUD/JPY relative to period 2012 – 2017. Results are expressed in terms of cumulative and annualised returns, annualised volatility, Sharpe ratio and maximum drawdown.

AUD/JPY	2012	2013	2014	2015	2016	2017
Cumulative Returns	5.3%	−6.8%	−2.6%	−21.1%	6.7%	−8.1%
Annualised Returns	5.3%	−6.8%	−2.6%	−21.2%	6.7%	−8.2%
Annualised Volatility	11.0%	14.0%	9.2%	13.0%	15.6%	8.8%
Sharpe Ratio	0.48	-0.48	-0.29	-1.63	0.43	-0.94
Max DD	−15.4%	−21.6%	−7.6%	−23.4%	−9.9%	−11.4%

Appendix G

List of Bloomberg tickers used for FX risk premia

TABLE G.1: G10 currency pairs data, Bloomberg ticker and description.

Ticker	description
EURUSD	spot rate
EUR1M	EURUSD 1 Month forward outright
EURI1M	EURUSD 1 Month forward implied yield
EUDRA	EUR 1 Month currency deposit rate
USDJPY	spot rate
JPY1M	USDJPY 1 Month forward outright
JPYI1M	USDJPY 1 Month forward implied yield
JYDRA	JPY 1 Month currency deposit rate
GBPUSD	spot rate
GBP1M	GBPUSD 1 Month forward outright
GBPI1M	GBPUSD 1 Month forward implied yield
BPDRA	GBP 1 Month currency deposit rate
USDCHF	spot rate
CHF1M	USDCHF 1 Month forward outright
CHFI1M	USDCHF 1 Month forward implied yield
SFDRA	CHF 1 Month currency deposit rate
AUDUSD	spot rate
AUD1M	AUDUSD 1 Month forward outright
AUDI1M	AUDUSD 1 Month forward implied yield
ADDRA	AUD 1 Month currency deposit rate
NZDUSD	spot rate
NZD1M	NZDUSD 1 Month forward outright
NZDI1M	NZDUSD 1 Month forward implied yield
NDDRA	NZD 1 Month currency deposit rate
USDCAD	spot rate
CAD1M	USDCAD 1 Month forward outright
CADI1M	USDCAD 1 Month forward implied yield
CDDRA	CAD 1 Month currency deposit rate
USDRA	USD 1 Month currency deposit rate
USDSEK	spot rate
SEK1M	USDSEK 1 Month forward outright
SEKI1M	USDSEK 1 Month forward implied yield
SKDRA	SEK 1 Month currency deposit rate
USDNOK	spot rate
NOK1M	USDNOK 1 Month forward outright
NOKI1M	USDNOK 1 Month forward implied yield
NKDRA	NOK 1 Month currency deposit rate
USDDKK	spot rate
DKK1M	USDDKK 1 Month forward outright
DKKI1M	USDDKK 1 Month forward implied yield
DKDRA	DKK 1 Month currency deposit rate

Table G.2: G20 currency pairs data, Bloomberg ticker and description.

Ticker	description
USDARS	spot rate
APN1M	USDARS 1 Month forward outright
APNI1M	USDARS 1 Month forward implied yield
APDRA	ARS1 Month currency deposit rate
USDBRL	spot rate
BCN1M	USDBRL 1 Month forward outright
BCNI1M	USDBRL 1 Month forward implied yield
BCDRA	BRL1 Month currency deposit rate
USDCNY	spot rate
CCN+1M	USDCNY 1 Month forward outright
CCNI1M	USDCNY 1 Month forward implied yield
SHIF1M	CNY 1 Month currency deposit rate
USDCNH	spot rate
CNH1M	USDCNH 1 Month forward outright
CNHI1M	USDCNH 1 Month forward implied yield
CGDRA	CNH 1 Month currency deposit rate
USDINR	spot rate
IRN+1M	USDINR 1 Month forward points
IRNI1M	USDINR 1 Month forward implied yield
IRSWOA	INR 1 Month currency deposit rate
USDIDR	spot rate
IHN+1M	USDIDR 1 Month forward points
IHNI1M	USDIDR 1 Month forward implied yield
IHDRA	IDR 1 Month currency deposit rate
USDKRW	spot rate
KWN+1M	USDKRW 1 Month forward outright
KWNI1M	USDKRW 1 Month forward implied yield
USDMXN	spot rate
MXN1M	USDMXN 1 Month forward outright
MXNI1M	USDMXN 1 Month forward implied yield
MXIBTIIE	MXN 1 Month currency deposit rate
USDRUB	spot rate
RUB1M	USDRUB 1 Month forward outright
RUBI1M	USDRUB 1 Month forward implied yield
RRDRA	RUB 1 Month currency deposit rate
USDZAR	spot rate
ZAR1M	USDZAR 1 Month forward outright
ZARI1M	USDZAR 1 Month forward implied yield
SADRA	ZAR 1 Month currency deposit rate
TRY	USDTRY spot rate
TRY1M	USDTRY 1 Month forward outright
TRYI1M	USDTRY 1 Month forward implied yield
TYDRA	TRY 1 Month currency deposit rate

TABLE G.3: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description
SBWGC	lndex Citi World Government Bond Index (Hedged USD)
SBWGU	lndex Citi World Government Bond Index (Unhedged)
SBGIMS	lndex Citi EM Government Bond Index (USD Terms)
SPX Index	SP 500 Index
DXY Curncy	Dollar index
CVIX lndex	DB Currency Volatility Index
BTOP FX Index	
BUSG	BBG US Gov
BUSY	BBG US Treasury
BUSY10	BBG US Treasury 10+
BUSY110	BBG US Treasury 1-10
BUSY13	BBG US Treasury 1-3
BUSY15	BBG US Treasury 1-5
BUSY510	BBG US Treasury 5-10
BUSY710	BBG US Treasury 7-10
BAGY	BBG US Agency
BGRL	BBG USD Gov Rel
BNSO	BBG USD xUS Sov
BDEV	BBG USD Gov Dev Bk
BRGL	BBG Gov Reg/Loc
BEM	BBG USD EM Comp
BEMS	BBG USD EM Sov
BEIS	BBG USD IG EM Sov
BEHS	BBG USD HY EM Sov
BEMS10	BBG USD EM Sov 10+
BEMS110	BBG USD EM Sov 1-10
BEMS13	BBG USD EM Sov 1-3
BEMS15	BBG USD EM Sov 1-5
BEMS510	BBG USD EM Sov 5-10
BEMSEMA	BBD USD EM Sov EMEA

Table G.4: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description
BEMSLAM	BBD USD EM Sov LatAm
BEMSAM	BBD USD EM Sov Armenia
BEMSAR	BBD USD EM Sov Argentina
BEMSAW	BBD USD EM Sov Aruba
BEMSBB	BBD USD EM Sov Barbados
BEMSBM	BBD USD EM Sov Bermuda
BEMSBO	BBD USD EM Sov Bolivia
BEMSBR	BBD USD EM Sov Brazil
BEMSBS	BBD USD EM Sov Bahamas
BEMSCL	BBD USD EM Sov Chile
BEMSCO	BBD USD EM Sov Colombia
BEMSCR	BBD USD EM Sov CostaRica
BEMSDO	BBD USD EM Sov Dorn Rep
BEMSEC	BBD USD EM Sov Ecuador
BEMSEG	BBD USD EM Sov Egypt
BEMSGA	BBD USD EM Sov Gabon
BEMSGE	BBD USD EM Sov Georgia
BEMSGH	BBD USD EM Sov Ghana
BEMSGT	BBD USD EM Sov Guatemala
BEMSHN	BBD USD EM Sov Honduras
BEMSHR	BBD USD EM Sov Croatia
BEMSHU	BBD USD EM Sov Hungary
BEMSID	BBD USD EM Sov Indonesia
BEMSIL	BBD USD EM Sov Israel
BEMSJM	BBD USD EM Sov Jamaica
BEMSJO	BBD USD EM Sov Jordan
BEMSKR	BBD USD EM Sov S Korea
BEMSLB	BBD USD EM Sov Lebanon
BEMSLK	BBD USD EM Sov Sri Lanka

TABLE G.5: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description
BEMSLT	BBD USD EM Sov Lithuania
BEMSLV	BBD USD EM Sov Latvia
BEMSMA	BBD USD EM Sov Morocco
BEMSMN	BBD USD EM Sov Mongolia
BEMSMX	BBD USD EM Sov Mexico
BEMSNG	BBD USD EM Sov Nigeria
BEMSPA	BBD USD EM Sov Panama
BEMSPE	BBD USD EM Sov Peru
BEMSPH	BBD USD EM Sov Phlpn
BEMSPK	BBD USD EM Sov Pakistan
BEMSPL	BBD USD EM Sov Poland
BEMSPY	BBD USD EM Sov Paraguay
BEMSQA	BBD USD EM Sov Qatar
BEMSRO	BBD USD EM Sov Romania
BEMSRS	BBD USD EM Sov Serbia
BEMSRU	BBD USD EM Sov Russia
BEMSRW	BBD USD EM Sov Rwanda
BEMSSN	BBD USD EM Sov Senegal
BEMSTR	BBD USD EM Sov Turkey
BEMSTT	BBD USD EM Sov Trinidad
BEMSUA	BBD USD EM Sov Ukraine
BEMSUY	BBD USD EM Sov Uruguay
BEMSVE	BBD USD EM Sov Venezuela
BEMSVN	BBD USD EM Sov Vietnam
BEMSZA	BBD USD EM Sov S Africa
BEMSZM	BBD USD EM Sov Zambia

Table G.6: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description
BEMC	BBG USD EM Corp
BIEM	BBG USD IG EM Corp
BiEM10	BBG USD IG EM Corp 10+
BIEM110	BBG USD IG EM Corp 1-10
BIEM13	BBG USD IG EM Corp 1-3
BIEM15	BBG USD IG EM Corp 1-5
BIEM510	BBG USD IG EM Corp 5-10
BEAC	BBG USD HY EM Corp
BEMC10	BBG USD EM Corp 10+
BEMC110	BBG USD EM Corp 1-10
BEMC13	BBG USD EM Corp 1-3
BEMC15	BBG USD EM Corp 1-5
BEMC510	BBG USD EM Corp 5-10
BEMI	BBG USD IG EM
BEMH	BBG USD HY EM
BEMTY10	BBG USD EM Comp 10+
BEMTY110	BBG USD EM Comp 1-10
BEMTY13	BBG USD EM Comp 1-3
BEMTY15	BBG USD EM Comp 1-5
BEMTY510	BBG USD EM Comp 5-10
BCOR	BBG Glob IG Corp
BUSC	BBG USD Corp
BUSC10	BBG USD Corp 10+
BUSC110	BBG USD Corp 1-10
BUSC13	BBG USD Corp 1-3
BUSC15	BBG USD Corp 1-5
BUSC510	BBG USD Corp 5-10
BUSCCD	BBG USD Corp Disc
BUSCCO	BBG USD Corp Comm
BUSCCS	BBG USD Corp Stpl
BUSCEN	BBG USD Corp Energy
BUSCFI	BBG USD Corp Fin
BUSCHC	BBG USD Corp Hlth
BUSCIN	BBG USD Corp Ind
BUSCMA	BBG USD Corp Matv
BUSCTE	BBG USD Corp Techv
BUSCUT	BBG USD Corp Util
BUSCAA	BBG USD Corp AA
BUSCA	BBG USD Corp A

Table G.7: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description	
BECO	BBG Eurp IG Corp	
BGBP	BBG GBP IG Corp	
BGBP10	BBG GBP IG Corp 10+v BGBP110	BBG GBP IG Corp 1-10
BGBP13	BBG GBP IG Corp 1-3	
BGBP15	BBG GBP IG Corp 1-5v BGBP510	BBG GBP IG Corp 5-10
BERC	BBG EUR IG Corp	
BERC10	BBG EUR IG Corp 10+	
BERC110	BBG EUR IG Corp 1-10	
BERC13	BBG EUR IG Corp 1-3	
BERC15	BBG EUR IG Corp 1-5	
BERC510	BBG EUR IG Corp 5-10	
BERCCD	BBG EUR IG Corp Discv BERCCO	BBG EUR IG Corp Comm
BERCCS	BBG EUR IG Corp Stpl	
BERCEN	BBG EUR IG Corp Enrgy	
BERCFI	BBG EUR IG Corp Fin	
BERCHC	BBG EUR IG Corp Hlth	
BERCIN	BBG EUR IG Corp Ind	
BERCMA	BBG EUR IG Corp Mat	
BERCTE	BBG EUR IG Corp Tech	
BERCUT	BBG EUR IG Corp Util	
BSCA	BBG Scan IG Corp	
BNOK	BBG NOK IG Corp	
BSEK	BBG SEK IG Corp	
BCHS	BBG CHF IG Corpv	

TABLE G.8: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description
BCHS10	BBG CHF IG Corp 10+
BCHS110	BBG CHF IG Corp 1-10
BCHS13	BBG CHF IG Corp 1-3
BCHS15	BBG CHF IG Corp 1-5
BCHS510	BBG CHF IG Corp 5-10
BECO10	BBG Eurp IG Corp 10+
BECO110	BBG Eurp IG Corp 1-10
BEC013	BBG Eurp IG Corp 1-3
BEC015	BBG Eurp IG Corp 1-5
BECO510	BBG Eurp IG Corp 5-10
BAUD	BBG AUD IG Corp
BCAD	BBG CAD IG Corp
BCAD10	BBG CAD IG Corp 10+
BCAD110	BBG CAD IG Corp 1-10
BCAD13	BBG CAD IG Corp 1-3
BCAD15	BBG CAD IG Corp 1-5
BCAD510	BBG CAD IG Corp 5-10
BJPY	BBG JPY IG Corp
BJPY10	BBG JPY IG Corp 10+
BJPY110	BBG JPY IG Corp 1-10
BJPY15	BBG JPY IG Corp 1-5
BJPY510	BBG JPY IG Corp 5-10
BCOR10	BBG Glob IG Corp 10+
BCOR110	BBG Glob IG Corp 1-10
BCOR13	BBG Glob IG Corp 1-3
BCOR15	BBG Glob IG Corp 1-5
BCOR510	BBG Glob IG Corp 5-10
BHYC	BBG Glob HY Corp
BUHY	BBG USD HY Corp

Table G.9: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description	
BUHY10	BBG USD HY Corp 10+	
BUHY110	BBG USD HY Corp 1-10	
BUHY13	BBG USD HY Corp 1-3	
BUHY15	BBG USD HY Corp 1-5v BUHY510	BBG USD HY Corp 5-10
BUHYCD	BBG USD HY Corp Disc	
BUHYCO	BBG USD HY Corp Commv BUHYCS	BBG USD HY Corp Stpl
BUHYEN	BBG USD HY Corp Enrgy	
BUHYFI	BBG USD HY Corp Finv	
BUHYHC	BBG USD HY Corp Hlth	
BUHYIN	BBG USD HY Corp Ind	
BUHYMA	BBG USD HY Corp Mat	
BUHYTE	BBG USD HY Corp Tech	
BUHYUT	BBG USD HY Corp Util	
BNHY	BBG xUSD HY Corp	
BCAH	BBG CAD HY Corp	
BEUH	BBG EUR HY Corp	
BEUH10	BBG EUR HY Corp 10+	
BEUH110	BBG EUR HY Corp 1-10	
BEUH13	BBG EUR HY Corp 1-3	
BEUH15	BBG EUR HY Corp 1-5	
BEUH510	BBG EUR HY Corp 5-10	
BGBH	BBG GBP HY Corp	
BHYC10	BBG Glob HY Corp 10+	
BHYC110	BBG Glob HY Corp 1-10	
BHYC13	BBG Glob HY Corp 1-3	
BHYC15	BBG Glob HY Corp 1-5v BHYC510	BBG Glob HY Corp 5-10
BGSV	BBG Glob Dev Sov	
BGSX	BBG Dev Sov xUS	
BCAN	BBG Canada Sov	
BEUR	BBG Eurozone Sov	
BAUR	BBG Austria Sov	
BBEL	BBG Belgium Sov	
BFIN	BBG Finland Sov	
BFRA	BBG France Sov	
BGER	BBG Germany Sov	

TABLE G.10: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description
BIRE	BBG Ireland Sov
BITA	BBG Italy Sov
BLUX	BBG Luxembourg Sov
BNET	BBG Netherlands Sov
BPOR	BBG Portugal Sov
BSLK	BBG Slovakia Sov
BSLN	BBG Slovenia Sov
BSPS	BBG Spain Sov
BEUR10	BBG Eurozone Sov 10+
BEUR110	BBG Eurozone Sov 1-10
BEUR13	BBG Eurozone Sov 1-3
BEUR15	BBG Eurozone Sov 1-5
BEUR510	BBG Eurozone Sov 5-10
BEURXGR	BBG Eurozone Sov xGreece
BEURXSS	BBG Eurozone Sov xSS
BEURXSSG	BBG Eurozone Sov xSSG
BEUX	BBG Other Eurp Sov
BDEN	BBG Denmark Sov
BNOR	BBG Norway Sov
BSWE	BBG Sweden Sov
BSWI	BBG Switzerland Sov
BRIT	BBG UK Sov
BPAC	BBG Pac Rim Sov
BAUS	BBG Australia Sov
BHON	BBG Hong Kong Sov
BJPN	BBG Japan Sov
BNEW	BBG New Zealand Sov
BSIN	BBG Singapore Sov

Table G.11: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description
BGSV10	BBG Glob Dev Sov 10+
BGSV110	BBG Glob Dev Sov 1-10
BGSV13	BBG Glob Dev Sov 1-3
BGSV15	BBG Glob Dev Sov 1-5
BGSV510	BBG Glob Dev Sov 5-10
BCORCD	BI Global IG Corp CD
BCORCO	BI Global IG Corp CO
BCORCS	BI Global IG Corp CS
BCOREN	BI Global IG Corp EN
BCORFI	BI Global IG Corp FI
BCORHC	BI Global IG Corp HC
BCORIN	BI Global IG Corp IN
BCORMA	BI Global IG Corp MA
BCORTE	BI Global IG Corp TE
BCORUT	BI Global IG Corp UT
BCOV10	BI Covered 10+
BCOV110	BI Covered 1-10
BCOV13	BI Covered 1-3
BCOV15	BI Covered 1-5
BEMCD	Bl USD EM Sov CD
BEMCO	BI USD EM Sov CO
BEMCS	BI USD EM Sov CS
BEMEN	BI USD EM Sov EN
BEMFN	B1 USD EM Sov FI
BEMHC	BI USD EM Sov HC
BEMIN	BI USD EM Sov IN
BEMMA	BI USD EM Sov MA
BEMTE	BI USD EM Sov TE
BEMUT	BI USD EM Sov UT

TABLE G.12: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description
BEUHCD	BI EUR HY Corp CD
BEUHCO	BI EUR HY Corp CO
BEUHCS	BI EUR HY Corp CS
BEUHEN	BI EUR HY Corp EN
BEUHFI	BI EUR HY Corp FI
BEUHHC	BI EUR HY Corp HC
BEUHIN	BI EUR HY Corp IN
BEUHMA	BI EUR HY Corp MA
BEUHTE	BI EUR HY Corp TE
BEUHUT	BI EUR HY Corp UT
BGRL10	BBG USD Gov Rel 10+
BGRL110	BBG USD Gov Rel 1-10
BGRL13	BBG USD Gov Rel 1-3
BGRL15	BBG USD Gov Rel 1-5
BGRL510	BBG USD Gov Rel 5-10
BGSV17	BI Global Dev Sov 1-7
BGSV310	BI Global Dev Sov 3-10
BGSV35	BI Global Dev Sov 3-5
BGSV37	BI Global Dev Sov 3-7
BGSV3	BI Global Dev Sov 3+
BGSV57	BI Global Dev Sov 5-7
BGSV5	BI Global Dev Sov 5+
BGSV710	BI Global Dev Sov 7-10
BGSV7	BI Global Dev Sov 7+
BHYCCD	BI Global HY Corp CD
BHYCCO	BI Global HY Corp CO
BHYCCS	BI Global HY Corp CS
BHYCEN	BI Global HY Corp EN
BHYCFNBI	Global HY Corp FI
BHYCHC	BI Global HY Corp HC

TABLE G.13: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description
BHYCIN	BI Global HY Corp IN
BHYCMA	BI Global HY Corp MA
BHYCTE	BI Global HY Corp TE
BHYCUT	BI Global HY Corp UT
BUSG10	BBG US Gov 10+
BUSG110	BBG US Gov 1-10
BUSG13	BBG US Gov 1-3
BUSG510	BBG US Gov 5-10
BG7SOV	BBG G7 Sov
BEUIGHY	BBG EUR Corp IG HY
BEUIGSC	BBG Eurp Sov IG Corp
BEUISCC	BBG Eurp Sov IG Corp Cov
BEUC	BBG EUR Covered
BSTIGSC	BBG GBP Sov IG Corp
BSTISCC	BBG GBP Sov IG Corp Cov
BGBC	BBG GBP Covered
BNIGSC	BBG Norway Sov IG Corp
BCIGSC	BBG Canada Sov IG Corp
BSZIGSC	BBG Switz Sov IG Corp
BLCSV	BBG EM Local Sov
BEMEA	BBG EM Local Sov EMEA
BTUR	BBG Turkey Local Sov
BCZE	BBG Czech Rep Local Sov
BHUF	BBG Hungary Local Sov
BILGO	BBG Israel Local Sov
BRUSS	BBG Russia Local Sov
BPOL	BBG Poland Local Sov
BSAFR	BBG S Africa Local Sov
BROMA	BBG Romania Local Sov
BSERB	BBG Serbia Local Sov
BLITH	BBG Lithuania Local Sov
BNGRI	BBG Nigeria Local Sov
BBUL	BBG Bulgaria Local Sov
BCROA	BBG Croatia Local Sov
BEGYP	BBG Egypt Local Sov
BKEN	BBG Kenya Local Sov
BLATV	BBG Latvia Local Sov
BASIA	BBG EM Local Sov APAC

TABLE G.14: Indexes and benchmark, Bloomberg ticker and description.

Ticker	description
BTHB	BBG Thailand Local Sov
BPHIL	BBG Philippine Local Sov
BINDO	BBG Indonesia Local Sov
BMYR	BBG Malaysia Local Sov
BKRW	BBG S Korea Local Sov
BCGB	BBG China Local Sov
BINDI	BBG India Local Sov
BTAIW	BBG Taiwan Local Sov
BLATAM	BBG EM Local Sov LATAM
BMXCO	BBG Mexico Local Sov
BPERU	BBG Peru Local Sov
BCHIL	BBG Chile Local Sov
BZIL	BBG Brazil Local Sov
BDOM	BBG Dominican Rep Local Sov
BJAMA	BBG Jamaica Local Sov
BCOLM	BBG Colombia Local Sov
BUSYFL	BBG US Treasury FRN

TABLE G.15: G10 data extracted to validate option trading strategies, Reuters ticker and description.

RIC	description
EUR	EURUSD spot rate
EURSWD	EUR 1 week currency deposit rate
EUR1MD	EUR 1 month currency deposit rate
EUR1M	EURUSD 1 month forward exchange rate (points)
EURSW	EURUSD 1 week Forward exchange rate (points)
EUR1MO	volatilities implied by one-month at-the-money EURUSD options
EUR1MO	volatilities implied by one-week at-the-money EURUSD options
JPYUSD	JPY spot rate
JPYSWD	JPY1 week currency deposit rate
JPY1MD	JPY 1 month currency deposit rate
JPY1M	USDJPY 1 month forward exchange rate (points)
JPYSW	USDJPY 1 week Forward exchange rate (points)
JPY1MO	volatilities implied by one-month at-the-money USDJPY options
JPY1MO	volatilities implied by one-week at-the-money USDJPY options
GBP	GBPUSD spot rate
GBPSWD	GBP 1 week currency deposit rate
GBP1MD	GBP 1 month currency deposit rate
GBP1M	GBPUSD 1 month forward exchange rate (points)
GBPSW	GBPUSD 1 week Forward exchange rate (points)
GBP1MO	volatilities implied by one-month at-the-money GBPUSD options
GBP1MO	volatilities implied by one-week at-the-money GBPUSD options
CHF	USDCHF spot rate
CHFSWD	CHF 1 week currency deposit rate
CHF1MD	CHF 1 month currency deposit rate
CHF1M	USDCHF 1 month forward exchange rate (points)
CHFSW	USDCHF 1 week Forward exchange rate (points)
CHF1MO	volatilities implied by one-month at-the-money USDCHF options
CHF1MO	volatilities implied by one-week at-the-money USDCHF options
AUD	AUDUSD spot rate
AUDSWD	AUD 1 week currency deposit rate
AUD1MD	AUD 1 month currency deposit rate
AUD1M	AUD 1 month forward exchange rate
AUDSW	AUDUSD 1 week Forward exchange rate (points)
AUD1MO	volatilities implied by one-month at-the-money AUDUSD options
AUD1MO	volatilities implied by one-week at-the-money AUDUSD options

TABLE G.16: G10 data extracted to validate option trading strategies, Reuters ticker and description.

RIC	description
NZD	NZDUSD spot rate
NZDSWD	NZD 1 week currency deposit rate
NZD1MD	NZD 1 month currency deposit rate
NZD1M	NZDUSD 1 month forward exchange rate (points)
NZDSW	NZDUSD 1 week Forward exchange rate (points)
NZD1MO	volatilities implied by one-month at-the-money NZDUSD options
NZD1MO	volatilities implied by one-week at-the-money NZDUSD options
CAD	USDCAD spot rate
CADSWD	CAD 1 week currency deposit rate
CAD1MD	CAD 1 month currency deposit rate
CAD1M	USDCAD 1 month forward exchange rate (points)
CADSW	USDCAD 1 week Forward exchange rate (points)
CAD1MO	volatilities implied by one-month at-the-money USDCAD options
CAD1MO	volatilities implied by one-week at-the-money USDCAD options
SEK	USDSEK spot rate
SEKSWD	SEK 1 week currency deposit rate
SEK1MD	SEK 1 month currency deposit rate
SEK1M	USDSEK 1 month forward exchange rate (points)
SEKSW	USDSEK 1 week Forward exchange rate (points)
SEK1MO	volatilities implied by one-month at-the-money USDSEK options
SEK1MO	volatilities implied by one-week at-the-money USDSEK options
NOK	USDNOK spot rate
NOKSWD	NOK 1 week currency deposit rate
NOK1MD	NOK 1 month currency deposit rate
NOK1M	USDNOK 1 month forward exchange rate (points)
NOKSW	USDNOK 1 week Forward exchange rate (points)
NOK1MO	volatilities implied by one-month at-the-money USDNOK options
NOK1MO	volatilities implied by one-week at-the-money USDNOK options
DKK	USDDKK spot rate
DKKSWD	DKK 1 week currency deposit rate
DKK1MD	DKK 1 month currency deposit rate
DKK1M	USDDKK 1 month forward exchange rate (points)
DKKSW	USDDKK 1 week Forward exchange rate (points)
DKK1MO	volatilities implied by one-month at-the-money USDDKK options
DKK1MO	volatilities implied by one-week at-the-money USDDKK options

Appendix H

Trend-following HFT strategies simplified versions

We test alternative versions of the trend-following algorithms. For example, the algorithm H.0.1 follows the same logic of the strategy 3.6.1 but it compares one moving average with the observed price only at one point instead of at their second crossing, while the algorithm H.0.2 is consistent with the strategy 3.6.2.

ALGORITHM H.0.1. Trend-following version2 algorithm.

Calculate the moving average of the price: $\mu_{s,n}$ based on lookback parameter n'.
if $S_n > \mu_{s,n}$ **then**
    Ψ_n= 1.
end
if $S_n < \mu_{s,n}$ **then**
    Ψ_n= -1.
end

ALGORITHM H.0.2. Trend-following version 2 and Bollinger bands algorithm.

Calculate the moving average of the price: $\mu_{s,n}$ and the moving volatility $\sigma_{s,n}$ based on lookback parameter n'.
Calculate the Bollinger bands as:
$\mathcal{B}_n^+ = \mu_{s,n} + \sigma_{s,n}$
$\mathcal{B}_n^- = \mu_{s,n}$ - $\sigma_{s,n}$
if $S_n > \mathcal{B}_n^+$ **then**
    Ψ_n= 1.
end
if $S_n < \mathcal{B}_n^-$ **then**
    Ψ_n= -1.
end