The cross-sectional profitability of anomaly trading in the FX market

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1. Introduction

First, Jegadeesh & Titman (1993) shed light on the fact, that buying assets with high recent returns and selling the ones with low is a very profitable investment. As of today, we can be sure that this Momentum anomaly in stock markets withstood the test of time. However, efficient market people are confused by this phenomenon, and still have no explicit clue why it is possible. In one reasoning, they conclude that Momentum captures risk aversion, therefore the premium is caused by taking bigger risks: there is no free lunch. The other side argues that Momentum is an observable proof of non rational economic behaviour. Despite the tons of researches that have been made for resolving this, the literature does not seem to have settled on a generally accepted explanation.

In this paper, I study foreign exchange (FX) markets as a natural laboratory for the analysis of momentum returns. My study heavily relies on the precious work of Menkhoff *et al.* (2012). Generally speaking, one could say that the FX market is more liquid than the stock market, albeit it is more fixed as well. The price of an arbitrary currency depends on the demand-supply dynamics, but there are levels when the government needs to intervene in order to prevent high inflation for example. Moreover, in the FX market, there are way less tradable assets than in the stock equivalent. Together, these facts yield that the question "Does Momentum exist in FX Market?" is accurate. If so, then financial institutions may have the chance to diversificate their exposure, which is highly beneficial regarding risk management. In my study, I answer this question carefully.

The significance of Momentum both in the stock and the FX market is worth considering. The simplest buy and hold strategy would be profitable when applied to stocks, as stocks have a positive trend in the long run. In spite of the fact that the same does not hold for currencies, an additional factor can increase the excess return of the latter. Currency return is indeed decomposable into two parts, interest rate differentials and spot rate changes, respectively.

Additionaly, one could think of the interest rate differentials as the main driver of currency excess returns. So many people believes in this, that it has a name: the so-called Carry trade, where investors go long in high interest rate currencies, and short in low interest rate currencies. While the uncovered interest rate parity (UIP) hypothesizes that the Carry gain due to the interest rate differential is offset by a commensurate depreciation of the investment currency, empirically the reverse holds, namely, the investment currency appreciates a little on average. An important question is to what extent momentum strategies simply capture the same information as the carry trade strategy. I also examine thorougly the carry-based trading strategy, and conclude its returns.

Han *et al.* (2013) show how to apply technical trading rules in cross-sectional trading strategies. According to them, I also apply the famous Moving Average trading rule to the Momentum, Carry factor portfolios extended with the Volatility-sorted portfolio. This is because FX volatility is a simple proxy of information uncertainty. Brown & Jennings (1989) show that rational investors can gain from forming expectations based on historical prices, and this gain is an increasing function of the volatility of the asset. Empirically, I show that the average return of using market timing is slightly less than without timing. One should check the Sharpe-ratios accordingly, that tell us that moving average portfolios might be less riskier. I also conclude, if we calculate with transactions costs, than market timing is a crucial feature of the trading.

In his extensive analysis of many anomalies published by various studies, Schwert (2003) finds that momentum appears to be the only one that is persistent and has survived since its publication. However, I provide evidence that besides Momentum, Carry is a still existing phenomena, that needs to be taken into account.

Investing into the Momentum, Carry and Volatility portfolios might have other advantages. The famous Markowitz-portfolio theory, for example, works quite good in theory, but not in practice. For estimating the optimal portfolio of different assets, one should estimate also the covariance matrix of them. However, the estimation of the latter is just asymptotically unbiased, and the convergence is very slow. On the other hand, if we invest into factor-portfolios, we can reduce the noise very efficiently. We can conclude therefore, that the factors are more stable. Furthermore, Patton & Ramadorai (2013) show in a general universe of hedge funds that there is significant exposure to Carry trade and Momentum-type returns and that this exposure is time-varying. Pojarliev & Levich (2010) also show via style regressions that currency fund managers engage in both Carry trade and momentum-type strategies.

The remainder of this paper proceeds as follows. In Section 2, I detail my data and portfolio formation procedure. I also present the market timing portfolio investment based on the idea of Han *et al.* (2013). In the following Section, I present the theoretical basis of the momentum anomaly. After selectively discussing the earlier literature, I also describe momentum returns in all approach. Section 4 and Section 5 are very similar to Section 3, I show there the efficiency of Carry trading, and Volatility-based trading. After exploring the results, Section 6 explores the link among the different strategies. In Section 7, I define a more sophisticated strategy, namely the one based on double sorting. After all, Section 8 concludes. All of the codes, figures, tables and the data are avaialable on my GitHub profile (https://github.com/kujbika/Anomaly-trading-in-FX-market).

2. Data and Portfolio construction

2.1. **Data** The data for daily spot exchange rates and daily annualized interest rates for several maturities[1] cover the sample period from January 2005 to January 2018. The sample contains

[1] 1 week, 2 weeks, 1 month, 2 months, 3 months, 6 months, 1 year, 2, 3, 4, 5, 6, ,7 8, 9, 10 years

all the relevant information for the G10 countries, and barely has missing values. These countries are: Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom, United States. All of the currencies are quoted against the U.S. dollar.

2.2. **Currency excess returns** Monthly excess returns to a US investor for holding foreign currency k are given by

$$r_{t+1}^{k} = i_t^k - i_t + \Delta y_S \tag{2.1}$$

, where i_t^k denotes the interest rate in country k, i_t denotes the U.S interest rate and Δy_S stands for the (log) spot rate change of the currency. Consider equation 2.2:

$$\mathbb{E}r_{t+1} = \mathbb{E}i_t^k - \mathbb{E}i_t + \mathbb{E}\Delta y_S \tag{2.2}$$

The equation yields, that if no arbitrage can happen in the market, the expected interest rate differential has to equal the the negative of the logreturn. That is, if in the foreign country k the interest rate is bigger than in the U.S, the spot rate of k has to decrease, so that the two opposite impact eliminate each other.

In the following analysis, I carefully compute the daily return of any currency based on formula 2.1.

2.3. **Portfolio construction - basic approach** The basic portfolio construction method is the same for the factors Momentum(1) and Volatility (2), and a little bit different for the Carry factor (3). Both of them are based on Menkhoff *et al.* (2012).

(1) I define a formation period $f = 1,\ 3,\ 6,\ 9,\ 12$ months. In case of the Momentum anomaly, I form three portfolios based on the currencies lagged excess returns over the previuos f months time period. Then, I go long into the first third ('High') portfolio, and go short into the last three currencies ('Low') dollar neutrally[2]. That means, I take loan from the 'Low' portfolio, and buys the 'High'[3]. Let us denote the outcoming portfolio by high-minus-low . The high-minus-low portfolio is then held for $h = 1,\ 3,\ 6,\ 9,\ 12$ months before reallocation. Hence, this procedure yields a time series of a currency momentum portfolio's excess return.
(2) The very same holds for Volatility-sorting. Based on the work of Han *et al.* (2013), I create three portfolios according to the volatility of the currencies. The highest variance currencies are denoted by 'High', whereas the most stable currencies are formed to portfolio 'Low'. From this point, the construction is the same.

[2]Since the dollar component cancels out when taking the difference between two portfolios.
[3]$\frac{1}{3}$weight is assigned to every elements of 'High', and $-\frac{1}{3}$ goes for the currencies in 'Low'.

(3) Constructing the Carry portfolios is similar in general, but for this we do not need any formation period. We decide about what to long and short from the interest rate as of date. The three currencies with highest interest rates will be in the long side, and analogously the three currencies with the lowest ones are going to be in the short side.

However, since interest rate differentials contribute a significant share of the excess return of any currency, I also track the pure spot rate changes of of the portfolios themselves and report them separately in many tables. In this way, we can figure out the dependency of each portfolio allocation strategy on spot rate changes. I conjecture that Momentum portfolios are sensible for spot rate changes, and Carry portfolios are mostly interest rate differential dependent.

Finally, the portfolios are denoted by $MOM_{f,h}$, $VOL_{f,h}$ and C_h, for formation period f and holding period h.

2.4. **Portofolio construction - market timing** At this part, I document an application of a moving average timing strategy of technical analysis to portfolios sorted by Momentum, Carry and Volatility.

For a given portfolio, the MA investment timing strategy is to buy or continue to hold the portfolio today when yesterday's price is above the 10-day moving average price. The nature of my investment strategy is dollar neutral, therefore whenever I long the 'High' portfolio, I short the 'Low', and the converse also holds. In particular, I form the 3 portfolios in every case according to the 2.3 subsection. After I decide about trading based on the portfolio-wise moving average rule for the 'High' portfolio. At days, when no investment happens, the wealth level remains the same.

2.4.1. *Possible reasons for the profitability of MA* In most of the mathematical models regarding price movements, we assume that the price dynamics follows a random walk, in which returns are unpredictable. Even more is true, the great model of financial markets, namely the efficient market hypothesis states that based on every available information, one could not configure a profitable investment strategy without taking risks, there is no free lunch. If we take these for granted, then the profitability of using technical analysis and the existence of any anomaly are ruled out by design. However later studies find evidence of on return predictability. They show, that efficiency can hold at most asymptotically, and little frictions can exist in the market that are therefore predictable.

Indeed, Brock *et al.* (1992) provide strong evidence on the profitability of using the MA signal to predict the Dow Jone Index. Neely *et al.* (2014) find in a complex work that technical analysis in forecasting the market risk premium is an added value.

In other markets, such as the FX markets, evidence of profitability of technical analysis is even stronger. LeBaron (1999) and Neely (2002) show that there are substantial gains with the use of the MA signal, and the gains are much larger than those for stock indices.

From a theoretical point of view, incomplete information on the fundamentals is a key for investors to use technical analysis. Blume *et al.* (1994) find that traders who use information contained in market statistics perform better than traders who do not. With incomplete information, the investors can face model uncertainty even if the stock returns are indeed predictable. Zhu & Zhou (2009) show that MA strategies can help investors to learn about predictability and thus can add value to asset allocation.

3. Momentum anomaly

3.1. **What is Momentum?** Briefly saying, Momentum is a trend following feature of any financial market. It claims, that whoever performed better recently will perform better in the following time period as well. The "winners" are going to win, the "losers" are going to lose. The empirical literature is highly influenced by Jegadeesh & Titman (1993), who show in a thorough analysis of the U.S. stock market that simple momentum strategies generate high returns, and are difficult to rationalize by standard asset pricing models.

Let me clarify now the differences between Momentum investing and the so-called Time Series Momentum (TSMOM) technical trading rule. According to Marshall *et al.* (2017), an investor who invests based on the TSMOM rule, has buying signals in the form of $\chi_{Pt>P_{t-n}}$. In other words, he/she takes a long position in an asset if it has positive return over a well-defined time period[4]. In contrast, Momentum investing is a *system* of buying different stocks or other securites based on their performance in the time period, i.e, rank all the assets by $r_t - r_{t-n}$, and go into a long position in the first several assets, and short the worst ones. Obviously, it can happen that the best asset has negative momentum (so do all the others), but we start the long position anyway. Therefore momentum investing works in the *cross-section* of the assets.

It is absolutely not a trivial question if momentum exists in the FX market, or not. Take the stock market as an example, where the majority of the assets have positive trend in its returns. That is captured by the famous buy-and-hold strategy, that claims that holding any asset is profitable in the long run. However, the best estimation for the trend of any currency is zero, and is is empirically observed as well. Therefore, it is very doubted that any trend following strategy could win in the FX market, despite it is a more or less commonly known fact that the stock market has this property.

[4]and shorts if it has negative

3.2. **Possible reasons for the existence of Momentum** According to Menkhoff *et al.* (2012), the major approaches to explain momentum can be classified into three categories:

(1) Risk-based and charachteristic-based explanations
(2) Explanations invoking cognitive biases or informational issues
(3) Explanations based on transaction costs or other forms of limits to arbitrage.

Studies have shown that momentum returns cannot be explained by covariance risk with standard financial factors (Fama & French (1996)). Moreover, momentum is barely rationalizable by macroeconomic risk. However, for example momentum appears to be stronger among smaller firms (Hong *et al.* (2000)), among firms with low credit rating (Avramov *et al.* (2007)), and among firms with high revenue growth volatility (Sagi & Seasholes (2007)). Also, according to Eisdorfer (2008), momentum returns appear to a large extent concentrated in firms with a high likelihoog to go bankrupt.

The second theory assumes that momentum investors are exploiting behavioral shortcomings in other investors, such as investor herding, investor over and underreaction, disposition effects and confirmation bias. Stressing how information is incorporated into prices, Chan *et al.* (1996) provide early evidence that analsts' earning forecasts respond gradually to news which can generate underreaction.

As Lesmond *et al.* (2004) show, reasonably high transaction costs could decrease the efficiency of momentum easily, which yields that momentum trading does not provide high excess returns. Menkhoff *et al.* (2012) find that momentum returns are indeed fairly sensitive to transaction costs. Adjusting returns for bid-ask spread lowers the profitability of momentum strategies signficantly since momentum portfolios are skewed towards currencies with high transaction costs. However, they argue that transaction costs are unable to completely account for currency momentum returns.

3.3. **Momentum in the FX market** Currency momentum studies generally do not analyize cross-section momentum, just single time series of exchange rates. In these papers these strategies are often framed as technical trading rules. The two most famous strategies are the Moving Average (MA), and the Time Series Momentum (TSMOM) rules, respectively. Marshall *et al.* (2017) deeply investigates the similarity and difference between those. In the following pages, I also conclude what happens with the cross section profitability if market timing strategies are getting applied.

One exception from the time-series focus is Okunev & White (2003) who analyze the cross-sectional profibality of Moving Average strategies. They allocate between 354 different strategies, assigning weights to them similarly as we assign weigths to momentum returns. This yields a return of about 6% p.a., which is independent of the base currency chosen and of the specific trading rule chosen. Thus, there is a clear indication that currency momentum strategies can be profitable and thus worthy a thorough examination.

More recently, Asness *et al.* (2013) have also investigated returns to a currency momentum strategy based on 10 currencies. The paper's primary objective is to explore the commonality of momentum across asset classes.

The main contribution for exploring this topic is definitely linked to Marshall *et al.* (2017). They show in an amazingly complex paper, that momentum strategies yield surpisingly high unconditional excess returns up to 10% p.a. They explain that momentum returns are almost uncorrelated from the more conventional technical trading rules returns. They also find that momentum portfolios in the FX market are significantly skewed towards minor currencies that have relatively high transaction costs, accounting for roughly 50% of momentum returns.

3.4. **Charachterizing currency momentum returns** At this part, I present my main empirical results regarding the profitability of momentum strategies.

Table1, Panel A, shows average annualized excess returns and spot rate changes for a number of high-minus-low momentum portfolios with formation and holding periods each varying between one and 12 months. Average excess returns in the left are calculated based on lagged excess returns, whereas the right side contains only pure spot rate changes, based on the same sorting. Table1, Panel B provides Sharpe-ratio metrics respectively, to measure the risk-based premium of each investment.

Turning to excess returns in the left panel first, I find that currency momentum strategies yield a substantial (and highly significant) excess returns in the level of 5-7% in one month holding period. As we can see, momentum is not confined to short holding periods, as $h = 12$ produces considerable annual returns. In the right side of Panel A, I also report the average logreturn of the spot price flow for the high-minus-low portfolio. Interestingly, the profitablity of currency momentum strategies is also clearly visible in spot rate changes themselves and is thus not mostly driven by interest rate differentials. In fact, there are sevaral cases (formation period is 9 and 12 months, holding period is one and three) when the strategies is completely driven by favorable spot rate changes and the interest rate differential reduces the excess return somewhat.

Table 1. Momentum returns and Sharpe ratios

This table shows annualized average returns for different currency momentum strategies / high-minus-low portfolios. The rows show formation periods (f), and the columns indicate holding periods (h) in months. The left side of Panel A contains excess returns (logreturns adjusted for interest rate differentials) based on lagged excess return sorting, whereas the right side tracks only the pure spot rate changes based on the same sorting. The returns of the strategies are highly autocorrelated, therefore I applied the Newey West test for caputre the significance of the returns. The nullhypothes is that the average return is zero, and the counter hypothesis claims that it is different from zero. *** means 1% signficance level ,** means 5% and * means 10%, respectively. Panel B shows annualized Sharpe ratios. The sample period is January 2005 - January 2018 for G10 currencies.

Panel A: Excess returns and spot range changes

	Excess returns						Spot rate changes				
	holding period h						holding period h				
f	**1**	**3**	**6**	**9**	**12**	**f**	**1**	**3**	**6**	**9**	**12**
1	6.44***	0.57	3.37*	1.15	3.39*	**1**	5**	0.79	4.26**	1.06	3.13
3	3.5*	-0.51	-0.9	0.81	1.79	**3**	4.35*	0.85	0.19	1.59	2.46
6	5.12**	-0.25	0.26	-1	3.34	**6**	4.21*	-0.82	-1.88	-1.95	3.9
9	6.77***	-1.61	-1	-1.8	0.5	**9**	7.45***	-1.17	-0.59	-2.72	-0.25
12	5.23**	1.18	2.8	3.53*	0.18	**12**	5.83**	2.99	0.71	2.84	-2.27

Panel B: Sharpe ratios

	Excess returns						Spot rate changes				
	holding period h						holding period h				
f	**1**	**3**	**6**	**9**	**12**	**f**	**1**	**3**	**6**	**9**	**12**
1	0.88	0.05	0.52	0.12	0.54	**1**	0.56	0.06	0.57	0.09	0.43
3	0.41	-0.11	-0.17	0.08	0.23	**3**	0.44	0.06	-0.02	0.15	0.28
6	0.66	-0.07	-0.01	-0.19	0.38	**6**	0.46	-0.14	-0.25	-0.31	0.39
9	0.91	-0.26	-0.18	-0.3	0.05	**9**	0.86	-0.18	-0.11	-0.38	-0.07
12	0.69	0.15	0.36	0.45	-0.01	**12**	0.66	0.35	0.04	0.3	-0.3

As a first and simple means of investigating a possible link between momentum returns and to provide a graphical exposition of momentum returns, figure 3.1 shows cumulative excess returns for the three benchmark strategies $MOM_{1,1}$, $MOM_{6,1}$ and $MOM_{12,1}$(upper figure). The bottom figure has the same properties, but it plots the P&L of the timed momentum strategies. The shaded area corresponds to the great recession. The three benchmark strategies show some comovement but are not perfectly correlated.

Figure 3.1. P&L of momentum strategies

Cumulative excess returns of momentum strategies. The two figure shows cumulative excess returns, which are not adjusted for transaction costs, accruing to three different momentum returns. The blue line corresponds for the $MOM_{1,1}$ strategy, the red for the $MOM_{6,1}$, and the black for the $MOM_{12,1}$ respectively. The shaded area corresponds to the great recession. 10-day moving average timing was applied to momentum strategies in the bottom figure, where the second argument stands for the formation period, and the third for the holding period. G10 currencies were used in the sample period of January 2005 - January 2018.

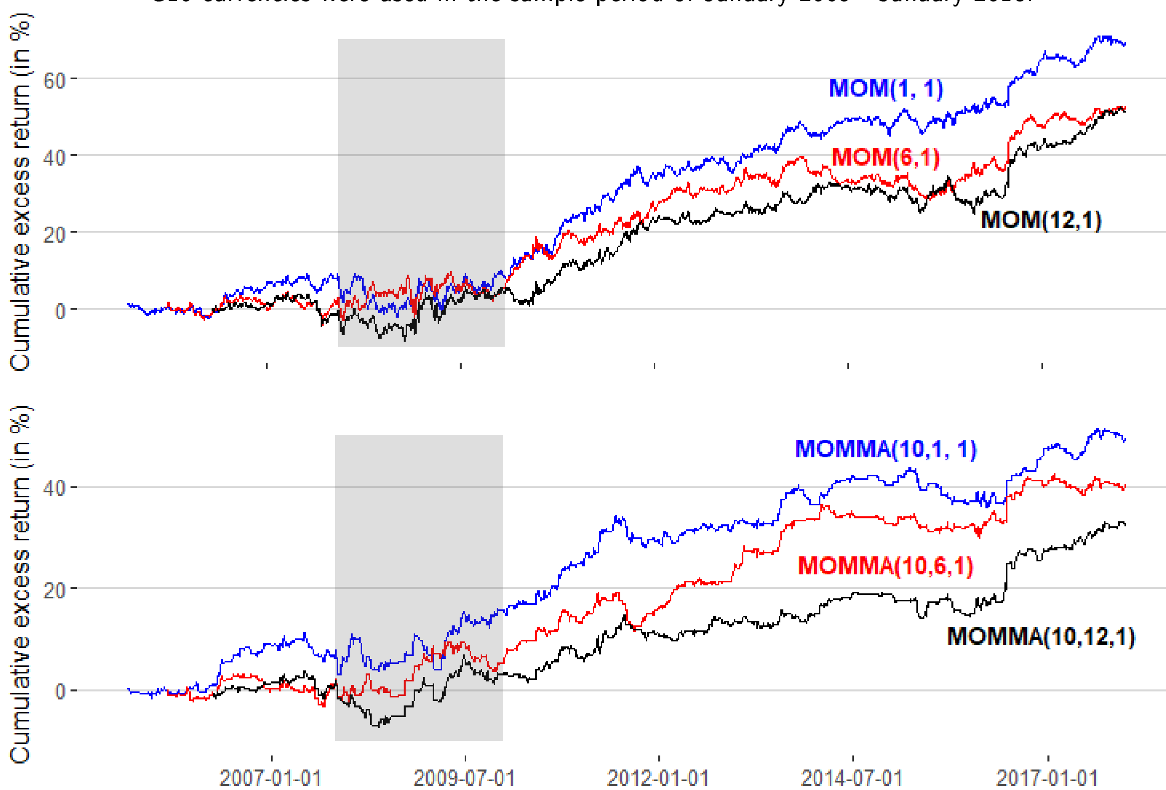


Table 2 contains the same information as Table1 does, but in this step I used moving average timing when investing, on a lag of 10 days. As it is seen in the left side of Panel A, the excess returns decreased compared to Table1. However, there is an interesting phenomena, namely the pure spot rate changes got substantially greater. This yields the conclusion, that MA timing is based on the spot rates, therefore it is only able to time the market regarding spot rate changes. Table 2 Panel B also shows that the MA strategies are less volatile than the simple equivalents, as the Sharpe-ratios are almost equal in Table 1 and Table 2.

Table 2. Momentum returns and Sharpe ratios based on MA timing

This table shows annualized average returns for different currency momentum strategies / high-minus-low portfolios based MA(10) timing. The lag for the moving average trading rule is 10 days. The rows show formation periods (f), and the columns indicate holding periods (h) in months. The left side of Panel A contains excess returns (logreturns adjusted for interest rate differentials) based lagges excess return sorting, whereas the right side tracks only the pure spot rate change based on the same sorting. The returns of the strategies are highly autocorrelated, therefore I applied the Newey West test for caputre the significance of the returns. The nullhypothes is that the average return is zero, and the counter hypothesis claims that it is different from zero. *** means 1% signficance level,** means 5% and * means 10%, respectively. Panel B shows annualized Sharpe ratios. The sample period is January 2005 - January 2018 for G10 currencies.

Panel A: Excess returns and spot range changes

	Excess returns						Spot rate changes				
	holding period h						holding period h				
f	**1**	**3**	**6**	**9**	**12**	**f**	**1**	**3**	**6**	**9**	**12**
1	4.62***	-0.54	2.04	-0.06	2.19*	**1**	5.03**	0.8	4.29**	1.08	3.15
3	2	1.24	0.65	0.01	0.34	**3**	4.39*	0.88	0.21	1.62	2.48
6	3.93*	0.33	0.3	-0.65	-0.34	**6**	4.13	-0.92	-1.99	-2.06	3.81
9	4.16***	0.08	-2.98**	-1.94	-2.27*	**9**	7.54***	-1.12	-0.54	-2.68	-0.19
12	3.33**	0.81	0.88	-0.36	-0.33	**12**	5.81**	2-97	0.68	2.81	-2.32

Panel B: Sharpe ratios

	Excess returns						Spot rate changes				
	holding period h						holding period h				
f	**1**	**3**	**6**	**9**	**12**	**f**	**1**	**3**	**6**	**9**	**12**
1	0.87	-0.14	0.44	-0.04	0.48	**1**	0.56	0.06	0.57	0.09	0.43
3	0.36	0.23	0.12	0.02	0.05	**3**	0.44	0.07	-0.01	0.15	0.28
6	0.77	0.05	0.03	-0.17	-0.09	**6**	0.45	-0.15	-0.26	-0.32	0.38
9	0.81	-0.01	-0.63	-0.47	-0.55	**9**	0.87	-0.18	-0.11	-0.37	-0.06
12	0.64	0.15	0.15	-0.1	-0.09	**12**	0.66	0.35	0.04	0.3	-0.31

One could accordingly conclude, that MA timing is not a neccesary approach in the FX market. I claim that this is not the case. Menkhoff *et al.* (2012) show that transaction costs are a big issue for currency momentum strategies, as the mostly traded currencies are skewed to the high transaction cost ones. Lesmond *et al.* (2004) also finds that momentum strategies are significantly less profitable when we calculate with such costs. All in all, it is crucial to minimize the proportion of the trading days! Due to the nature of the moving average rule, it substantially decreases this proportion.

4. Carry anomaly

4.1. **What is the Carry anomaly?** The Carry trade is a popular trading strategy that borrows in currencies with low interest rates and invest in currencies with high interest rates. The return of the strategy is the interest rate differential. As I mentioned in the introduction, according to the uncovered interest rate parity, if investors are risk neutral and form expectation rationally, exchange rates will eliminate any gain arising from the interest rate differentials.

However, a number of empirical studies show that high interest rate currencies tend to appreciate, and low interest rate currencies tend to depreciate. As a consequence, carry trades form a profitable investment. The violation of the UIP often referred as the "forward premium puzzle"(see e.q Fama (1984)) - is precisely what makes Carry traders succesful.

There is an extensive literature in macroeconomics and finance on the forward premium puzzle, which focuses implicitly on the mean return of the carry trade. Meese & Rogoff (1983) find that exchange rates follow a "near random walk" allowing investors to take advantage of the interest differential without suffering an exchange rate depreciation[5]. Moreover, Burnside *et al.* (2007) show empirically, that the return of the carry trade portfolio is uncorrelated to standard risk factors, attributing instead the forward premium to market frictions (bid-ask spreads, price pressure etc.).

4.2. **Charachterizing Carry returns** In Table 3, you can find the annualized results of different carry strategies. In the left side of Panel A, the excess returns provide evidence that any carry strategy yields significantly very high and substantial returns. The similarity in the numbers has a crucial feature. We do not need to specify the holding period in our trading, since the expected yearly return would be at least 5%! This is an evidence of the out-of-sample efficiency of the carry trades, which we do not have for the momentum ones. In its paper, Lustig *et al.* (2011) show that carry trades are mostly driven by interest rate differentials. I also have similar results, as is on the right side of Panel A.

Looking at Panel B, one could find the Sharpe-ratios of the different strategies. These are absolutely high, and confirm, that the strategies work quite well, even when considering risks.

[5]It is only a near random walk, as high-interest-bearing currencies even tend to appreciate.

Table 3. Carry returns and Sharpe ratios

This table contains excess returns and pure spot rate changes for C_h strategies / high-minus-low portfolios (Panel A). Therefore the return decomposition is observable. The holding period varies between 1 and 12 months. Columns h denote holding periods for the dollar neutral portfolio. The returns of the strategies are highly autocorrelated, therefore I applied the Newey West test for caputre the significance of the returns. The nullhypothes is that the average return is zero, and the counter hypothesis claims that it is different from zero. *** means 1% signficance level ,** means 5% and * means 10%, respectively. Panel B shows annualized Sharpe ratios. The sample period is January 2005 - January 2018 for G10 currencies.

Panel A: Excess returns and spot range changes

Excess returns					Spot rate changes				
holding period h					holding period h				
1	**3**	**6**	**9**	**12**	**1**	**3**	**6**	**9**	**12**
4.99***	5.72***	5.28***	5.03***	4.15**	2.31	2.71	2.54	2.86	2.15

Panel B: Sharpe ratios: Excess returns and spot rate changes

Excess returns					Spot rate changes				
holding period h					holding period h				
1	**3**	**6**	**9**	**12**	**1**	**3**	**6**	**9**	**12**
0.83	0.95	0.86	0.82	0.64	0.31	0.37	0.34	0.39	0.27

It is pretty straightforward, that the MA market timing captures the spot rate changes, but the results in Table 4 are surprising. The three portfolio for each holding periods are formed by sorting according to the interest rate. Taking the high-minus-low portfolio, and time the trades yields substantially bigger spot rate changes than the whole excess returns. However, as the excess returns are lower than the previous ones, we cannot use this additional information for performing better. The Sharpe-ratios in Panel B are high enough, to argue again next to the MA version of carry trading. Reducing the transaction cost as much as possible is definitely an important feature of currency trading.

Table 4. Carry returns and Sharpe ratios based on MA timing

This table contains excess returns and pure spot rate changes for C_h strategies / high-minus-low portfolios (Panel A) extended with MA timing. The lag for the MA trading rule is 10 days. The holding period varies between 1 and 12 months. Columns h denote holding periods for the dollar neutral portfolio. The returns of the strategies are highly autocorrelated, therefore I applied the Newey West test for caputre the significance of the returns. The nullhypothes is that the average return is zero, and the counter hypothesis claims that it is different from zero. *** means 1% signficance level ,** means 5% and * means 10%, respectively. Panel B shows annualized Sharpe ratios. The sample period is January 2005 - January 2018 for G10 currencies.

Panel A: Excess returns and spot range changes

Excess returns					Spot rate changes				
holding period h					holding period h				
1	**3**	**6**	**9**	**12**	**1**	**3**	**6**	**9**	**12**
3.22***	3.37***	3.5***	2.78*	2.63***	6.9***	7.18***	6.79***	7.01***	4.94***

Panel B: Sharpe ratios: Excess returns and spot rate changes

Excess returns					Spot rate changes				
holding period h					holding period h				
1	**3**	**6**	**9**	**12**	**1**	**3**	**6**	**9**	**12**
0.87	0.91	0.93	0.73	0.65	1.48	1.57	1.44	1.49	0.99

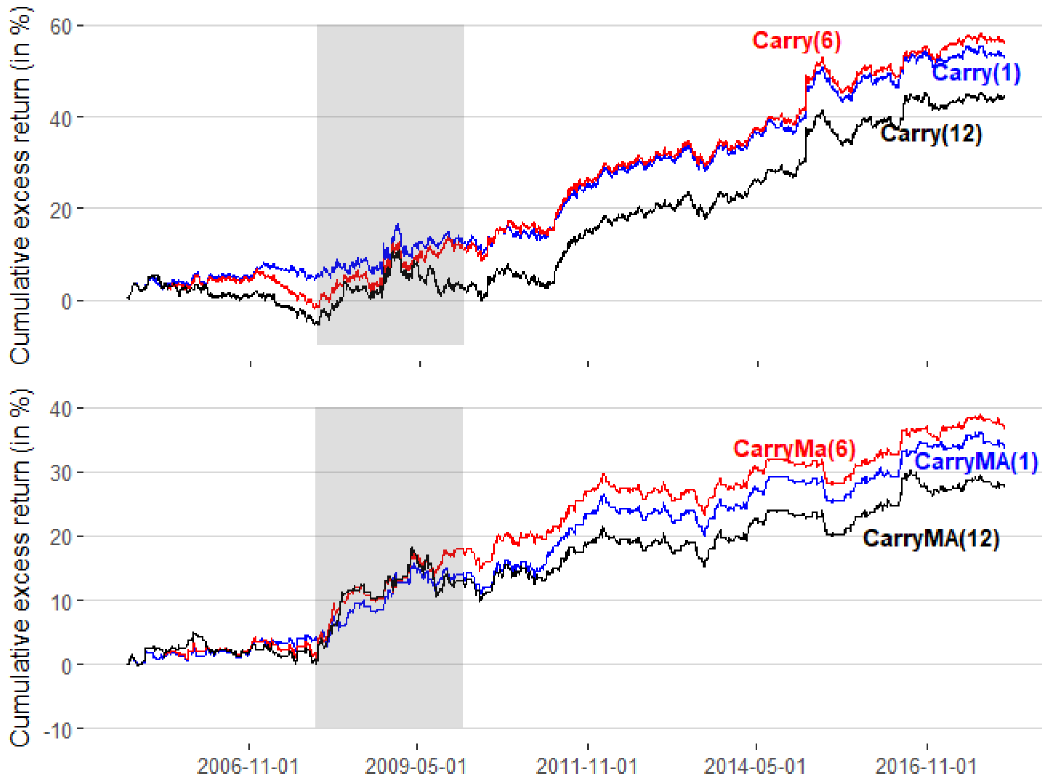
If we investigate figure 4.1, we can observe that the timed carry strategies (bottom figure) do not go under zero at all. By looking at the picture, we can say that the MA ones are less volatile than the simple carry trades, therefore they have advantages considering risks. The volatilities of course have to be lower than the simple pairs, in order to maintain the level of the Sharpe-ratio.

5. Volatility sorting

Han *et al.* (2013) shows that trading on the volatility decile portfolios in the stock market is unequivocally profitable. They argue that the timed returns on the volatility portfolios are positive and inreasing with the volatility deciles, ranging from 8.42% p.a to 18.70% p.a. They also examine whether momentum can explain the abnormal returns of theirs, as both of them are trend-following strategies. They get, however, that momentum has no significant explanatory power to the abnormal returns of the volatility sorted returns.

Figure 4.1. P&L of carry strategies

Cumulative excess returns of carry strategies. The figure shows cumulative excess returns, which are not adjusted for transaction costs, accruing to three different carry returns. The blue line corresponds for the C_1 strategy, the red for the C_2, and the black for the C_3, respectively. The shaded area corresponds to the great recession. 10-day moving average timing was applied to momentum strategies in the bottom figure, where the argument stands for the holding period. G10 currencies were used in the sample period of January 2005 - January 2018.



As of this result, I had the idea to investigate what happens in the FX market when the sort is based on volatility / information uncertainty.

5.1. **Charachterizing Volatility returns** Table 5 and Table 6 contains all the relevant information of the different volatility strategies - without timing and with it. Interestingly, as it turns out, the volatility currency high-minus-low portfolios do not generate any significant excess return annualy. It is worth noticing that the pure spot rate changes are greater, and there are ones with 10% significance, but these do not seem in the excess returns.

By looking at the results, one can convince himself/herself, that the volatility effect does not exist in the foreign exchange markets. There might be several reasons for this. For example, a puzzling feature of currencies is that dramatic exchange rate movements occasionaly happen without fundamental news announcements, like the large depreciation of the U.S dollar againts the Japanese yen on October 7 and 8, 1998. This reflects, that the volatility is not a unique feature of a currency, i.e. there is no reason for a currency to be more volatile, if it has performed well. We can conclude, that volatility does not have explanatory power in terms of the currency excess returns.

Table 5. Volatilty returns and Sharpe ratios

This table shows annualized average returns for different volatility high-minus-low portfolios. The rows show formation periods (f), and the columns indicate holding periods (h) in months. The left side of Panel A contains excess returns (logreturns adjusted for interest rate differentials) based spot price volatility sorting, whereas the right side tracks only the pure spot rate change based on the same sorting. The returns of the strategies are highly autocorrelated, therefore I applied the Newey West test for caputre the significance of the returns. The nullhypothes is that the average return is zero, and the counter hypothesis claims that it is different from zero. *** means 1% signficance level ,** means 5% and * means 10%, respectively. Panel B shows annualized Sharpe ratios. The sample period is January 2005 - January 2018 for G10 currencies.

Panel A: Excess returns and spot range changes

	Excess returns						Spot rate changes				
	holding period h						holding period h				
f	**1**	**3**	**6**	**9**	**12**	**f**	**1**	**3**	**6**	**9**	**12**
1	0.64	-0.45	0.57	0.52	0.25	**1**	1.02	0.52	1.84	2.07	1.12
3	0.5	1.15	1.02	1.26	-0.08	**3**	0.96	1.57	2.16	2.21	1.02
6	0.95	0.79	0.43	1.45	0.43	**6**	1.65	2.43	2.51	2.93*	1.71
9	1.06	1.6	2.05	2.02	1.9	**9**	2.89	3.39*	3.13*	2.56	2.52
12	1.29	1.25	1.28	0.18	1.39	**12**	2.76	2.46	2.41	0.9	2.09

Panel B: Sharpe ratios

	Excess returns						Spot rate changes				
	holding period h						holding period h				
f	**1**	**3**	**6**	**9**	**12**	**f**	**1**	**3**	**6**	**9**	**12**
1	0.08	-0.11	0.07	0.06	0.02	**1**	0.11	0.04	0.25	0.27	0.14
3	0.05	0.17	0.15	0.2	-0.04	**3**	0.1	0.19	0.29	0.31	0.11
6	0.13	0.11	0.05	0.25	0.05	**6**	0.21	0.34	0.35	0.47	0.25
9	0.14	0.25	0.33	0.35	0.34	**9**	0.39	0.49	0.44	0.38	0.39
12	0.19	0.18	0.2	0.01	0.22	**12**	0.39	0.33	0.34	0.12	0.29

Table 6. Volatilty returns and Sharpe ratios based on MA timing

This table shows annualized average returns for different volatility high-minus-low portfolios extended with MA timing. The lag for the moving average trading rule is 10 days. The rows show formation periods (f), and the columns indicate holding periods (h) in months. The left side of Panel A contains excess returns (logreturns adjusted for interest rate differentials) based spot price volatility sorting, whereas the right side tracks only the pure spot rate change based on the same sorting. The returns of the strategies are highly autocorrelated, therefore I applied the Newey West test for caputre the significance of the returns. The nullhypothes is that the average return is zero, and the counter hypothesis claims that it is different from zero. *** means 1% signficance level ,** means 5% and * means 10%, respectively. Panel B shows annualized Sharpe ratios. The sample period is January 2005 - January 2018 for G10 currencies.

Panel A: Excess returns and spot range changes

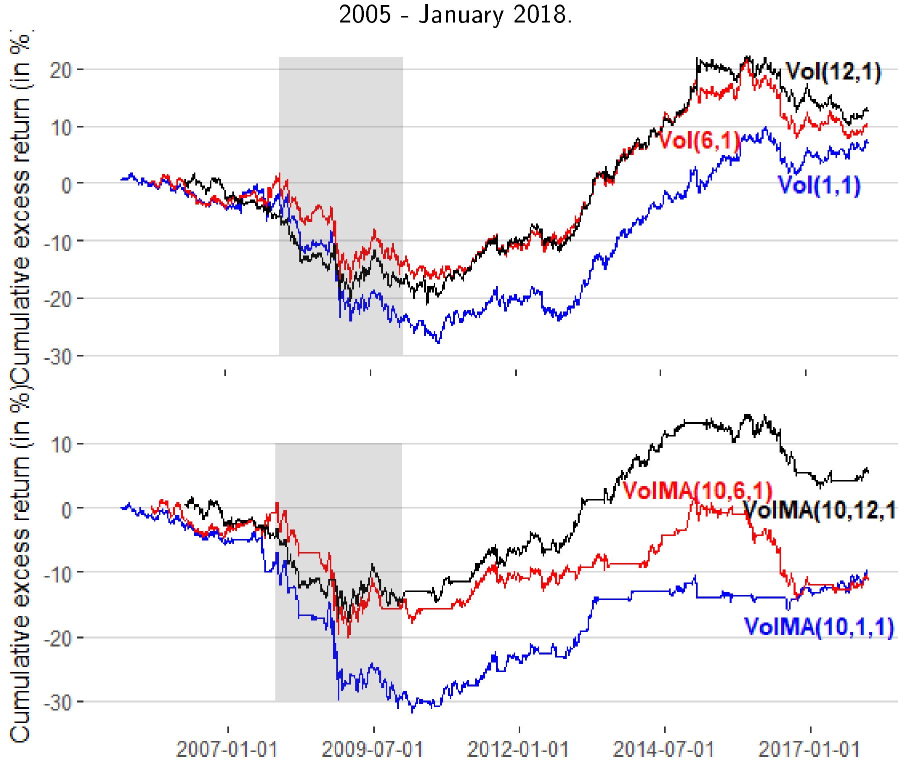
	Excess returns						Spot rate changes				
	holding period h						holding period h				
f	**1**	**3**	**6**	**9**	**12**	**f**	**1**	**3**	**6**	**9**	**12**
1	-0.98	-1.82	-1.56	-2.13	-1.54	**1**	0.96	0.47	1.78	2.02	1.06
3	-0.35	0.03	-1.3	-2.06	-0.41	**3**	1.03	1.64	2.23	2.29	1.09
6	-1.09	-0.58	-0.31	-0.49	-1.64	**6**	1.61	2.4	2.49	2.9*	1.68
9	-0.06	1.68	0.22	0.27	0.4	**9**	2.96	3.46*	3.2	2.63	2.59
12	0.56	0.25	0.95	0.04	1	**12**	2.82	2.51	2.47	0.95	2.14

Panel B: Sharpe ratios

	Excess returns						Spot rate changes				
	holding period h						holding period h				
f	**1**	**3**	**6**	**9**	**12**	**f**	**1**	**3**	**6**	**9**	**12**
1	-0.22	-0.39	-0.34	-0.45	-0.34	**1**	0.1	0.04	0.24	0.26	0.13
3	-0.1	-0.02	-0.31	-0.51	-0.12	**3**	0.11	0.2	0.3	0.32	0.12
6	-0.23	-0.14	-0.08	-0.13	-0.37	**6**	0.2	0.33	0.35	0.46	0.24
9	-0.04	0.35	0.03	0.05	0.07	**9**	0.39	0.5	0.45	0.39	0.4
12	0.09	0.02	0.15	-0.02	0.16	**12**	0.4	0.34	0.35	0.13	0.3

Figure 5.1. P&L of Volatility strategies

Cumulative excess returns of volatility based strategies. The figure shows cumulative excess returns, which are not adjusted for transaction costs, accruing to three different volatility returns. The blue line corresponds for the $VOL_{1,1}$ strategy, the red for the VOL, and the black for the $VOL_{12,1}$, respectively. The shaded area corresponds to the great recession. 10-day moving average timing was applied to momentum strategies in the bottom figure, where the argument stands for the holding period. G10 currencies were used in the sample period of January 2005 - January 2018.



6. Correlation structure

In Table 7, one can see the correlation structure of all pure strategies / high-minus-low portfolios listed above. We can see, that there is basically no correlation between the different type strategies, considering all type of formation period-holding period pairs. In each type, the correlation matrix contains quite high coefficients, which seems reasonable. Hence, it seems fair to conlcude, that returns of each type (momentum, carry, volatility) strategies are likely to share a strong common component, which are different from the others.

That excess returns to carry trades and momentum strategis are basically uncorrelated in FX market appears in line with the real-world strategies of many currency investors who combine momentum and carry trade positions ins their portfolio to take advantage of diversification benefit form the following two strategis simultaneously.

Table 7. Correlations between the strategies

This table shows the correlation matrix of the different strategies momentum, carry, volatility strategies. The indices in the corner means formation period and holding period. For Carry strategies, only the holding period counts, therefore I mark them as a feature of the respective strategy. The sample consists of the G10 currencies, and covers the period January 2005 - January 2018.

	$MOM_{1,1}$	$MOM_{1,6}$	$MOM_{1,12}$	C_1	C_6	C_{12}	$VOL_{1,1}$	$VOL_{1,6}$	$VOL_{1,12}$
$MOM_{1,1}$	1								
$MOM_{1,6}$	0.203	1							
$MOM_{1,12}$	0.088	0.6	1						
C_1	0.011	0.009	0.011	1					
C_6	0.001	0.004	0.001	0.903	1				
C_{12}	0.008	0.006	-0.008	0.855	0.909	1			
$VOL_{1,1}$	-0.0003	0.018	0.038	-0.028	-0.038	-0.322	1		
$VOL_{1,6}$	-0.024	0.056	-0.003	-0.019	-0.017	-0.0128	0.848	1	
$VOL_{1,12}$	-0.037	-0.046	-0.036	-0.01	-0.011	-0.0056	0.824	0.907	1

7. A new approach - Double Sorting

Next, According to Menkhoff *et al.* (2012) I provide results based on double sorts. To this end, I double sort currencies into three portfolios depending on their interest rate (carry feature), and then into another three portfolios depending on their lagged excess return (momentum feature). Table 8 shows results for these double sorts for formation periods $f = 1,\ 6,\ 12$ months. There is no material difference between carry returns amongh high versus low momentum currencies, especially in the low and middle momentum portfolios. Take for example the very first partial table, and see that 7.81% is the high-minus-low carry trade for the bucket M_L, and it is 6.78% for M_M, respectively.

As above, we do not find a strong relation between momentum and carry trade strategies and the double sort suggests that they are independent. In fact, going long in currencies with high lagged excess returns and high interest rates whilst sorting currencies with low lagged excess returns and low interest rates can generate an excess return of **11.27%** per annum, which is the final result of this paper.

Table 8. Double sorting

This table shows annualized excess returns for double sorted portfolios. All currencies in the sample are first sorted into three groups by their interest rate (C_i). The portfolios are hence denoted by C_l, C_M, C_H. Next, currencies within each of the 3 subgroups are getting sorted by their f months momentum based on lagged excess returns. Columns M_L, M_M, $M_H$denote the sorted ordered currencies respectively. Columns Δ_M show the return difference between high and low momentum portfolios in each group, whereas columns Δ_C has the value of the difference between high and low interest rate groups. The lower-right cell in each subpanel shows the return difference between the top signal portfolio and the worst signal portfolio. All of the values are percentages, and the stars mean significance level based on the Newey West HAC t-statistics. The sample contains the G10 currencies form January 2005 to January 2018.

Carry trade and momentum

	$f=1,\ h=1$					$f=6,\ h=1$					$f=12,\ h=1$			
	M_L	M_M	M_H	Δ_M		M_L	M_M	M_H	Δ_M		M_L	M_M	M_H	Δ_M
C_L	-2.85	-1.85	-1.4	1.45	C_L	-2.81	-1	-3	-0.19	C_L	-3.69	-5.7*	-0.9	2.79
C_M	1.55	1.43	1.34	-0.21	C_M	3.1	-0.4	1.28	-1.82	C_M	-0.9	0.5	-0.7	0.2
C_H	4.96	4.93	1.65	-3.31	C_H	4.26	5.12	2.46	-1.8	C_H	1.9	1.43	7.58*	5.68
Δ_C	7.81	6.78	4.05	4.5	Δ_C	7.07	6.12	5.46	5.27	Δ_C	5.59	7.13	8.48	**11.27***

8. Conclusion

I have empirically investigated momentum, carry and volatility based strategies in the FX market. Momentum relies on return continuation among winner and loser currencies, whereas Carry goes long in high interest rate currencies, and goes short in low interest rate currencies. The volatility of an asset captures information uncertainty, and we could hope that after many studies in the stock market, it is an existing phenomena in the FX market as well. I find that momentum and carry yield surprisingly high average annual excess returns of up to 7 %. I conclude, that volatility sorting is not an efficient trading strategy in the foreign exchange market.

I applied a more sophisticated way to trade the strategies, namely the moving average market timing. This rule is based on the 10 day lagged spot price average of an asset and its current value. I have argued next to this more complex strategy, as the respective Sharpe-ratios did not decrease, but the proportion of trading days did. Therefore one could substantially reduce the costs of the trading with market timing.

Moreover, as it turned out, currency momentum strategies are very different from the carry trade. Hence, it comes as no surprise that momentum is not well captured by the global factors that have been shown to be related to carry trade returns in the earlier literature. Rather, momentum and carry trade are different phenomena, that require different explanation.

Based on the independence of the strategies, I configured the so-called double sorting method in the FX market. After sorting by interest rates, and then by lagged excess returns, I could find a strategy that yields 11.27% annualy in 10% significance level.

Please be aware of using the strategies, as the paper only shows results in-sample. Note that the empirical investigation was applied to the G10 currencies from January 2005 to January 2018. However, I provided evidence that the carry strategies could work out-sample as well.

References

Asness, Clifford S, Moskowitz, Tobias J, & Pedersen, Lasse Heje. 2013. Value and momentum everywhere. *The Journal of Finance*, **68**(3), 929–985.

Avramov, Doron, Chordia, Tarun, Jostova, Gergana, & Philipov, Alexander. 2007. Momentum and credit rating. *The Journal of Finance*, **62**(5), 2503–2520.

Blume, Lawrence, Easley, David, & O'hara, Maureen. 1994. Market statistics and technical analysis: The role of volume. *The Journal of Finance*, **49**(1), 153–181.

Brock, William, Lakonishok, Josef, & LeBaron, Blake. 1992. Simple technical trading rules and the stochastic properties of stock returns. *The Journal of finance*, **47**(5), 1731–1764.

Brown, David P, & Jennings, Robert H. 1989. On technical analysis. *The Review of Financial Studies*, **2**(4), 527–551.

Burnside, Craig, Eichenbaum, Martin, & Rebelo, Sergio. 2007. The returns to currency speculation in emerging markets. *American Economic Review*, **97**(2), 333–338.

Chan, Louis KC, Jegadeesh, Narasimhan, & Lakonishok, Josef. 1996. Momentum strategies. *The Journal of Finance*, **51**(5), 1681–1713.

Eisdorfer, Assaf. 2008. Delisted firms and momentum profits. *Journal of Financial Markets*, **11**(2), 160–179.

Fama, Eugene F. 1984. Forward and spot exchange rates. *Journal of monetary economics*, **14**(3), 319–338.

Fama, Eugene F, & French, Kenneth R. 1996. Multifactor explanations of asset pricing anomalies. *The journal of finance*, **51**(1), 55–84.

Han, Yufeng, Yang, Ke, & Zhou, Guofu. 2013. A new anomaly: The cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis*, **48**(5), 1433–1461.

HONG, HARRISON, LIM, TERENCE, & STEIN, JEREMY C. 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, **55**(1), 265–295.

JEGADEESH, NARASIMHAN, & TITMAN, SHERIDAN. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, **48**(1), 65–91.

LEBARON, BLAKE. 1999. Technical trading rule profitability and foreign exchange intervention. *Journal of international economics*, **49**(1), 125–143.

LESMOND, DAVID A, SCHILL, MICHAEL J, & ZHOU, CHUNSHENG. 2004. The illusory nature of momentum profits. *Journal of financial economics*, **71**(2), 349–380.

LUSTIG, HANNO, ROUSSANOV, NIKOLAI, & VERDELHAN, ADRIEN. 2011. Common risk factors in currency markets. *The Review of Financial Studies*, **24**(11), 3731–3777.

MARSHALL, BEN R, NGUYEN, NHUT H, & VISALTANACHOTI, NUTTAWAT. 2017. Time series momentum and moving average trading rules. *Quantitative Finance*, **17**(3), 405–421.

MEESE, RICHARD A, & ROGOFF, KENNETH. 1983. Do they fit out of sample? *Journal of international economics*, **14**, 3–24.

MENKHOFF, LUKAS, SARNO, LUCIO, SCHMELING, MAIK, & SCHRIMPF, ANDREAS. 2012. Currency momentum strategies. *Journal of Financial Economics*, **106**(3), 660–684.

NEELY, CHRISTOPHER J. 2002. The temporal pattern of trading rule returns and exchange rate intervention: intervention does not generate technical trading profits. *Journal of International Economics*, **58**(1), 211–232.

NEELY, CHRISTOPHER J, RAPACH, DAVID E, TU, JUN, & ZHOU, GUOFU. 2014. Forecasting the equity risk premium: the role of technical indicators. *Management Science*, **60**(7), 1772–1791.

OKUNEV, JOHN, & WHITE, DEREK. 2003. Do momentum-based strategies still work in foreign currency markets? *Journal of Financial and Quantitative Analysis*, **38**(2), 425–447.

PATTON, ANDREW J, & RAMADORAI, TARUN. 2013. On the high-frequency dynamics of hedge fund risk exposures. *The Journal of Finance*, **68**(2), 597–635.

POJARLIEV, MOMTCHIL, & LEVICH, RICHARD M. 2010. Trades of the living dead: style differences, style persistence and performance of currency fund managers. *Journal of International Money and Finance*, **29**(8), 1752–1775.

SAGI, JACOB S, & SEASHOLES, MARK S. 2007. Firm-specific attributes and the cross-section of momentum. *Journal of Financial Economics*, **84**(2), 389–434.

SCHWERT, G WILLIAM. 2003. Anomalies and market efficiency. *Handbook of the Economics of Finance*, **1**, 939–974.

ZHU, YINGZI, & ZHOU, GUOFU. 2009. Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics*, **92**(3), 519–544.