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MOMENTUM AND CARRY TRADE IN FX MARKET

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ABSTRACT

This thesis analyzes the relationship between different forms of popular investment strategies, carry trade and momentum, and currency excess returns. Momentum can be applied by going long in currencies that performed well in the previous periods and shorting those that performed poorly. Carry trade is similar to momentum, but instead of performance, it uses interest rate premiums as the signal for sorting the currencies into portfolios. The most profitable form of momentum is a strategy sorted on a signal calculated using excess returns, not returns. Moreover, both carry trade and momentum perform best when formed immediately after the signal is recorded instead of delaying the formation for a month. All those strategies produce significant positive excess returns. In the sample, carry trade strategies outperform momentum. The best performing strategies are those for shorter formation and holding periods, which can achieve up to 20 percent of annualized excess return. The performance of these strategies can be further improved by mixing them, as they exhibit low correlations. All mixed strategies produce significant positive returns and mean-variance optimized portfolios slightly improve the risk-adjusted returns. Furthermore, in the last 10 years, the profitability of momentum strategies radically decreased compared to earlier reports, while the profitability of carry trade remained stable. This calls for more extensive research into the changes in profitability of these strategies over the years.

Keywords: Currencies, Momentum, Carry, FX, Investment Strategies

JEL codes: G11, G15

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CHAPTER 1 Introduction

The foreign exchange market is considered to be an attractive environment for investors, thanks to its high liquidity and low transaction costs. It is regarded as an ideal environment for implementing more complex investment strategies due to the lack of barriers to short selling (Menkhoff, Sarno, Schmeling, & Schrimpf, 2012b). This feature enables investors to trade in both bull and bear market, which allows for profit maximization. In theory, Forex seems to be a perfect environment for investing. In practice, we could also observe an increasing interest in this market over the years. According to Drehmann and Sushko (2022) the trading volumes of Forex grew by around one billion from 2019 to 2022. Moreover, currently the market is almost six times larger than it was only 20 years ago. This rapid growth highlights the continuous need for further research in this dynamic market.

The most popular strategies applied in Forex include momentum and carry trade. Momentum is known for achieving high abnormal returns and has been studied across different asset classes and markets. Momentum can be applied by taking a long position in assets that have had high past returns and a short position in assets that had low returns in the past (Jegadeesh & Titman, 1993). Many papers delve deeper into that topic and try to search for a justification for this surprisingly profitable strategy. Researchers identify multiple factors that might explain the momentum, such as transaction costs or investor under- and over-reaction, however, a consensus still has not been reached (Wiest, 2022; Hong & Stein, 1999). Another strategy widely described in the literature is carry trade. It has been documented that by going long in currencies that have high interest rates and shorting those that have low interest rates one can achieve positive returns (Brunnermeier, Nagel, & Pedersen, 2008). Both momentum and carry trade seem to be similar and hence they are expected to be highly correlated. However, Menkhoff et al. (2012b) discover a low correlation between the two and so, by applying a mix of the strategies, diversification benefits can be achieved. Hence, one would expect that by combining carry trade with momentum, the risk-adjusted returns should be improved.

Although carry trade is widely used and researched, different forms of this investment strategy have not been investigated as thoroughly. Burnside (2012), when comparing various forms of carry trade, highlights that the equally weighted form achieves the highest returns in the sample. Nevertheless, when comparing carry trade with momentum, usually only one form of this strategy is considered, and it is not well justified why this specific form was chosen for the comparison. Therefore, it seems significant to investigate different forms of momentum and carry trade to assess which strategy will lead to the highest returns and which form should be used in a mixed strategy to maximize profits. While Menkhoff et al. (2012b) proves that carry trade is superior to momentum, Orlov (2016) claims that the returns of momentum are higher, both for the excess and risk-adjusted returns. Further, Burnside, Eichenbaum and Rebelo (2011) investigate the mixed strategy and prove that the risk-adjusted returns improve significantly when adding carry trade. Overall, after a careful study of existing literature, the following research question was formed: "**How do different momentum and carry trade strategies affect excess and risk-adjusted returns on the FX market for the period 1997-2023?**".

The sample period (1997-2023) was chosen not only to implement the most recent data in this research but also to be able to divide the sample into two subsamples, 1997-2010 and 2011-2023. This allows for a comparison between this paper and older literature that usually uses data till 2010 (Burnside et al., 2011; Menkhoff et al., 2012b). In consequence, I will be able to test whether, indeed, there have been any changes in the profitability of these strategies, implying the need for more extensive and updated research in this market. The sample contains spot and forward rates recorded at the end of each month and includes the currencies of the following 30 territories: Australia, Brazil, Canada, Czech Republic, Denmark, Egypt, Euro area, Hong Kong, Hungary, Iceland, India, Indonesia, Japan, Kuwait, Malaysia, Mexico, New Zealand, Norway, Philippines, Poland, Russia, Saudi Arabia, Singapore, South Africa, South Korea, Sweden, Switzerland, Taiwan, Thailand, United Kingdom. This choice was strictly driven by the data availability and past literature. Both spot and forward rates quoted against dollar were retrieved from Refinitiv via Datastream. In the analysis, firstly the formation of portfolios is explained in detail. For the momentum strategies, I use 1-, 3-, 6-, 9-, and 12-month formation (denoted as f) and holding (h) periods. Then, different f-h mixes are used to find the most profitable strategy. Similar strategy is followed for the carry trade, but there will be only one formation period of 1 month and 1-, 3-, 6-, 9-, and 12-month holding periods. Moreover, inspired by Burnside (2012), I implement an equally weighted portfolio for both momentum and carry trade. Next, the returns and excess returns to all those strategies are computed. To compare profitability, the average excess returns and the Sharpe ratios are presented and analyzed. To obtain excess returns and Sharpe ratios, I use one month currency forward contract following Atanasov and Nitschka (2014). Moreover, I investigate the correlations between these strategies to assess which strategy mix can be the most profitable.

Through my research question, I expect to advance the existing literature by a thorough comparison of different forms of carry trade and momentum using the most recent data. According to existing literature, these two strategies should have a low correlation. Thus, by implementing the mix of the strategies, one could improve the risk-adjusted returns (Menkhoff et al., 2012b). I hypothesize that carry trade will be superior to the momentum strategy in both excess returns and risk-adjusted returns. Furthermore, I expect to answer the question of whether the mixed strategy improves the risk-adjusted returns. Lastly, when comparing the two subsamples, I anticipate subtle differences over the years due to market expansion. Such findings would alert for more research into the FX market, using the most recent data and hence leaving room for new discoveries regarding the changes in profitability of investment strategies in Forex across the years.

The remainder of this paper is structured as follows. Section 2 discusses the previous research and relevant literature. Section 3 focuses on the data selection and sample description, as well as descriptive statistics. In section 4, I explain the methods used in this analysis. In section 5, the results of the analysis are presented and discussed in the context of existing literature. Finally, in section 6, I formulate conclusions.

CHAPTER 2 Theoretical Framework

In this section, I will present insights from literature related to momentum and carry trade, as well as the mixed strategies presented in the existing research. This section should serve as the theoretical framework and aid in understanding the relevance of different investment strategies in the foreign exchange market.

2.1 Momentum

Some of the very popular investment strategies exploit historical trends to predict future outcomes. One of them is momentum, which ranks assets based on their past performance and buys those that performed well while selling those that performed poorly in the previous periods (Liu, Strong, & Xu, 1999). The ranking process utilizes a signal, which is usually formed based on the changes in the prices in the past. Hence, a momentum signal for a formation period of n can be calculated using this formula:

$$M_t = \frac{P_{t-1}}{P_{t-1-n}} - 1. \tag{2.1}$$

The first ones to thoroughly study momentum were Jegadeesh and Titman (1993). In their study, based on US stock returns, they find that the stocks that performed well in the past (winners) continue to perform well in the future. The same tendency applies to the stocks that performed poorly (losers). Hence, by longing winners and shorting losers one can achieve high positive returns. However, those abnormal returns also have their limits. Jegadeesh and Titman (1993) tested different formation and holding periods and conclude that after 12 months of holding period, the portfolio experiences negative abnormal returns.

After the seminal paper by Jegadeesh and Titman (1993), many follow-up studies were published. Wiest (2022), in his literature review, compares the work of different researchers regarding the momentum phenomenon. Throughout the years, many tried to find a justification to the abnormal profits this strategy generates. In result, two lines of research explaining momentum developed in the literature: behavioral and risk-based explanations. Behavioral explanations include investors over- and under- reaction and other irrational behaviors and biases. This explanation carries a particular challenge as it must specify what drives the simultaneous over-reaction to certain events faced by the investors and under-reaction to others (Hong & Stein, 1999). Hong and Stein (1999) take up this challenge and introduce a model with two types of traders: “news-watchers” and “momentum-traders”. They find that the former is responsible for the under-reaction, while the latter for the over-reaction. On the other hand, the risk-based explanations stem from two theories. First, that the higher returns are compensation for higher risk exposure, which persists in the future. Second, that the riskiness of stocks might increase with positive returns and decrease with negative returns (Wiest, 2022). Many of those theories are mutually exclusive and a consensus on the explanation of momentum still has not been reached (Menkhoff, Sarno, Schmeling, & Schrimpf, 2012b).

Moreover, Wiest (2022) discusses the extensions of momentum research into new markets and asset groups. Momentum has been documented to exist in commodity futures, corporate bonds, and cryptocurrencies. Asness, Moskowitz and Pedersen (2013) go further and state that momentum can be found everywhere. They find momentum across eight markets and asset classes, such as equities, equity indices, government bonds, commodity futures and currencies. Although Asness et al. (2013) mention that momentum exists everywhere, their main focus is on world equities. Menkhoff et al. (2012b) also take a closer look at the momentum research done in different markets but decided to focus on the currency momentum. The authors claim that, in comparison to other markets, literature regarding currency momentum followed a slightly different path. They notice that there is a knowledge gap in the momentum in the cross-section of the currencies. Most papers focus on the time series momentum of single exchange rates. They compare this approach to technical trading, where based on past signals one can predict future prices (Menkhoff & Taylor, 2007). Only limited research focuses on a larger sample of currencies. Menkhoff et al. (2012b) studied the largest sample of currencies so far, analyzing 48 countries, both developed and emerging. They find that time series momentum is different from regular technical trading. Moreover, they highlight that cross-sectional momentum outperforms an equally weighted portfolio of time series momentum. The researchers go further and compare momentum to another strategy widely used in Forex, carry trade.

2.2 Carry trade

Brunnermeier, Nagel and Pedersen (2008) define carry trade as an investment strategy that involves selling low interest rate currencies and investing in high interest rate currencies. It seems quite like the earlier discussed momentum, however, carry trade utilizes a signal based on the interest rate premium, while momentum forms such a signal based on returns. Nevertheless, to truly understand the mechanism behind carry trade, the concept of uncovered interest parity (UIP) must be introduced first.

$$E(S_1) = S_0 \frac{1 + i_d}{1 + i_f} \tag{2.2}$$

$E(S_1)$ = The expected value of the spot rate

S_0 = Spot rate

i_d = Domestic interest rate

i_f = Foreign interest rate

When UIP holds, by definition, the difference between the interest rates of two countries should be equal to the expected change in the exchange rates between their currencies (Lothian, 2016). Yet, Fama (1984) proves through empirical analysis that this does not hold in reality. The forward exchange rate is often inaccurate in the prediction of the future spot exchange rate. This is referred to as the forward premium puzzle (FAMA puzzle).

The carry trade strategy exploits this forward premium puzzle. By shorting the currencies with low interest rates and longing those with high interests, investors should achieve positive profits. If UIP holds, the profit from carry trade is offset by the depreciation of the investment currency. Nonetheless, Fama (1984) finds that the currency depreciates only a little allowing for positive profits. This discovery altered scientists to delve deeper into the topic of the profitability of carry trade.

Carry trade strategy can be carried out in a traditional way by shorting low interest rate currencies and longing high ones. However, there has been an alternative approach developed, which simplifies this procedure by utilizing forward contracts (Lustig, Roussanov & Verdelhan, 2011). The exchange rate is covered by the forward contracts and hence by buying forward currencies which are at a forward discount and selling those which are at a forward premium, carry trade strategy can be implemented (Burnside, Eichenbaum, & Rebelo, 2011). This also translates the UIP to the covered interest parity (CIP) (Bilson, Brailsford, & Rajaguru, 2022).

$$F_0 = S_0 \frac{1 + i_d}{1 + i_f} \tag{2.3}$$

F_0 = Forward rate

S_0 = Spot rate

i_d = Domestic interest rate

i_f = Foreign interest rate

Burnside (2012) utilized this method while examining possible reasons for the abnormally high carry trade profits. One possible explanation is simply that the strategy is very risky and so, the profits need to reflect a high risk premium. The author reviews different factor models and tests their effectiveness in explaining the carry trade profits. Starting with traditional models such as CAPM or Fama-French three-factor model, Burnside (2012) concludes that they fail to explain carry trade. Going forward with less traditional models, better tailored to price currency returns, three-factor models were found to be quite successful in pricing currencies but not stocks. Hence, the difference between stocks and currency markets is highlighted. Further, the author compares different forms of carry trade and stock returns, where three following strategies are utilized: average of individual currency carry trade, equally weighted carry trade and high-minus-low carry trade. When comparing the Sharpe ratios of these strategies, investing in the average of individual carry trades or stocks appears to be significantly less profitable than the carry trade strategies. This is mostly due to the much higher volatility of the returns on individual carry trade and stocks. Equally weighted carry trade appears to be the most profitable. Hence, the form of carry trade matters greatly for the performance of a portfolio.

In opposition to momentum, carry trade research focused mostly on the FX market. Even though, this strategy can be applied to other markets, cryptocurrencies captured the most attention from the alternative environments (Christin, Routledge, Soska, Zetlin-Jones, 2022). Although the limited availability of cryptocurrencies futures slightly hindered this research, many scientists showed increasing interest in this topic in the past two years. One of them, Christin et al. (2022) managed to prove that the carry trade is unusually profitable and can achieve Sharpe ratios ranging from 7 to 10.

2.3 Mixed strategy and contributions

Carry trade has always been compared to momentum, but the results of these comparisons tend to be different. Orlov (2016) claims that momentum performs better both in terms of returns and Sharpe ratios. On the other hand, Menkhoff et al. (2012b) conclude that carry trade achieves higher returns than momentum. Even though both researchers used the same sample and applied similar strategies, there seems to be a certain inconsistency in the profitability of those strategies, which could be caused by the difference in the period in which the studies were conducted.

The comparison between these strategies extends beyond their returns. Menkhoff et al. (2012b) document low correlation between momentum and carry trade and through double sorts analysis conclude that the strategies are independent of each other. This signifies that by combining these two strategies one can achieve diversification benefits and hence the risk-adjusted returns can be increased. Nevertheless, the authors leave the question of the profitability of the mixed strategy to further research.

Burnside et al. (2011) are one of the very few researchers that decided to test the mixed strategy. Firstly, researchers compare carry trade to momentum. They utilize two different forms for each strategy, the carry trade/momentum of a single currency and an equally weighted portfolio of all individual carry trades/momentums. When applying the strategies to a single currency, on average, momentum is superior to carry trade. However, when comparing the equally weighted portfolio, carry trade does slightly better in terms of returns and significantly better in terms of risk-adjusted returns. Later, they produce a mixed strategy by investing 50 percent in equally weighted carry trade and 50 percent in an equally weighted momentum portfolio. This strategy appears to outperform any other strategy tested by the researchers in terms of risk-adjusted returns. This is in line with the low correlation between the two strategies.

Olszewski and Zhou (2013) go a step further and create three mixed portfolios, equally weighted, minimum variance, and mean-variance utility maximization. Again, although excess returns produced by these strategies do not outperform pure momentum or pure carry trade strategies, the risk-adjusted returns, measured by Sharpe ratios, do improve. The best results are recorded for an equally weighted portfolio, followed by the minimum variance. The mean-variance utility portfolio performs worse than the pure momentum strategy.

Although momentum and carry trade have been documented widely in the existing literature, a comparison of these strategies signifies a room for further research. Burnside et al. (2011), as well as Olszewski and Zhou (2013), perform an analysis of the mixed strategy. However, only one form of both carry trade and momentum is used. A question arises whether the form they utilized is the most profitable. Hence, I plan to advance the existing literature by a thorough comparison of different forms of carry trade and momentum in order to pick the strategy that achieves the highest returns and/or risk-adjusted returns. This process will include comparisons of different momentum signals and the effect of the delayed formation of the portfolio. Once the best form of the strategies is selected, I expect carry trade to have slightly higher returns than momentum and to outperform momentum in terms of risk-adjusted returns. Later by examining the profitability as well as correlations between different strategies, I will attempt to create mixed strategies which maximize risk-adjusted profits. Lastly, I intend to compare two subsamples to investigate whether the strategies became more profitable in recent years due to rapid market expansion.

CHAPTER 3 Data

In this section, I introduce the dataset used for this research. I describe the data collection technique and any data transformation applied. Moreover, the descriptive statistics are discussed at the end of this section.

To examine the influence of different currency investment strategies on returns and risk-adjusted returns, I use 26 years of data, starting from January 1997 up until January 2023. This sample should be large enough to prevent any biases and give a correct representation of reality. Further, this period is divided into two equal subsamples. Since I lose some data points for the portfolio formation, subsample A will start from January 1998 to June 2010, and subsample B from July 2010 to January 2023. This allows for a comparison with older literature, as most past studies utilized a sample up until 2010 (Burnside, Eichenbaum, & Rebelo, 2011; Menkhoff, Sarno, Schmeling, & Schrimpf, 2012b). Due to rapid market expansion, more sophisticated investment strategies became more accessible and hence there might be a difference in the profitability of these strategies over the years.

To retrieve data needed for my analysis, I use Datastream, owned by Refinitiv. This database contains a wide range of financial and economic data covering information on major asset classes, such as global equities, commodities, or currencies. In addition to providing 70 years of data across 175 countries, Datastream also contains necessary tools needed for financial analysis of market trends, economic cycles, and profitability of investment strategies. This database is widely used among scientists executing their research in the field of finance and economics (Burnside et al., 2011; Menkhoff et al., 2012b) and hence it is regarded as a reliable source of information.

To calculate returns for the strategies, spot rates are obtained from Datastream. Moreover, to calculate excess returns and estimate the interest rate premiums for carry trade strategies, the one-month forward rate is needed. Both spot and forward rates are recorded at the end of each month and quoted against the dollar. I download daily data and leave only the last observation from each month, as the monthly data in this database is presented as the average for the whole month. The sample will cover the currencies of the following 30 territories: Australia, Brazil, Canada, Czech Republic, Denmark, Egypt, Euro area, Hong Kong, Hungary, Iceland, India, Indonesia, Japan, Kuwait, Malaysia, Mexico, New Zealand, Norway, Philippines, Poland, Russia, Saudi Arabia, Singapore, South Africa, South Korea, Sweden, Switzerland, Taiwan, Thailand, United Kingdom. This choice was strictly driven by the data availability and the sample used in the past literature (Menkhoff, Sarno, Schmeling, & Schrimpf, 2012a; Menkhoff et al., 2011). Since my sample starts just before the introduction of Euro in January 1999, for simplicity, I decided not to include any countries from the Euro area. This way my sample slightly differs from that used by previous researchers. Nevertheless, Lustig, Roussanov and Verdelhan (2011) also excluded those countries from the sample after the introduction of euro as the inclusion of a currency with rapidly decreasing supply might significantly affect the currency's value. Further, following the example of Lustig et al. (2011), who excluded observations indicating large failures of CIP, I decided to delete observations for Indonesia from the end of December 2000 to the end of May 2007. Moreover, some forward rates were only available in later years. Hence, the number of currencies available varies across the sample period (Figure.1).

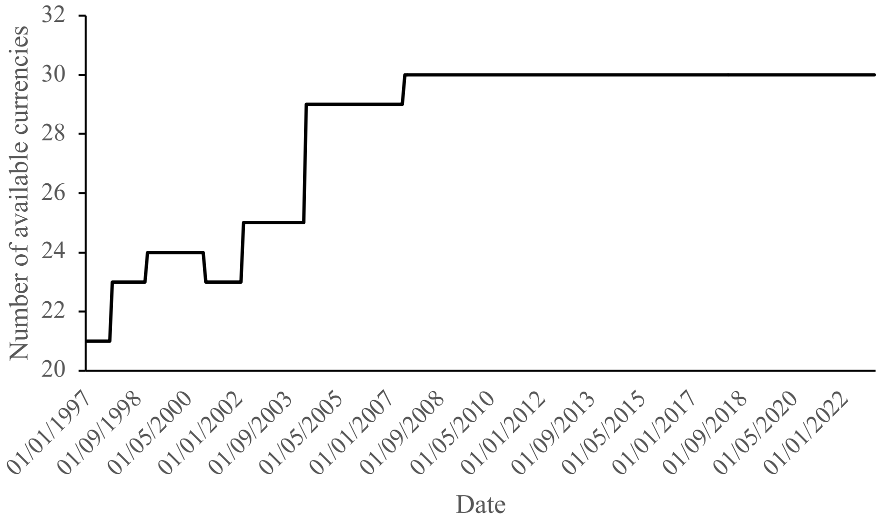

Figure 1. Number of available currencies in the dataset over time.

At the beginning of the sample period, there are 21 available currencies. This number increases over the years and reaches 30 in November 2007. For comparison, Lustig et al. (2011) had only 9 currencies at the beginning of the sample period. To maximize the size of available observations, I decided to use data from both Refinitiv, as well as WM/Refinitiv. In the end, instead of having a sample size of 315 months x 30 countries = 9450 observations, the sample size is equal to 8826 observations. The information on the specific dates for which the currencies are available, as well as the descriptive statistics of the returns on spot rates and excess returns are available in Table A1 and Table A2 in Appendix A. The monthly returns on spot rates range from almost -0.29 to 1.012. The largest volatility is recorded for Indonesia. Although the currencies experience high volatility, that is not reflected in the mean returns. The highest average monthly return is for Egypt, 0.009. A similar tendency applies to the excess returns. Hence, investing long-term in those currencies is not as profitable as short-term trades, which utilize the rapid changes in prices.

CHAPTER 4 Methods

For all strategies, returns as well as excess returns are calculated. This can be done following the approach presented in Section 4.1. Additionally, for all momentum, carry trade and mixed strategies, I run an OLS regression with Newey-West standard errors to test whether the excess returns are different from zero. I use 6 lags as it seems an optimal amount given that my data is monthly and considering the analysis of autocorrelations and partial autocorrelations. Further, I often present the Sharpe ratios, which are commonly used to measure risk-adjusted returns. They can be calculated by dividing the average excess returns by the standard deviation of returns. Sharpe ratio is an annual statistic; hence both the average excess returns and the standard deviation are annualized by multiplying by 12 and a square root of 12, respectively. The rest of this section should familiarize the reader with the methods used in the analysis of momentum (Section 4.1.1), carry trade (Section 4.1.2), and mixed strategies (Section 4.2).

4.1 Portfolio formation

Firstly, the returns for each currency are calculated using the following formula:

$$r_t = \frac{s_{t+1}}{s_t} - 1. \tag{4.1}$$

S_t represents the spot rate at time t and s_{t+1} is the spot rate at time t+1. Hence, the return is express as the changes in spot rates.

Secondly, I follow the example of Atanasov and Nitschka (2014) and define excess returns as deviations from the UIP condition:

$$rx_{t+1} = i_t^f - i_t - \Delta\ln(s_{t+1}^f), \tag{4.2}$$

where the Δs_{t+1}^f is the change in the log spot rate of a foreign country relative to home country at time t+1 and i_t^f and i_t are the interest rates of a foreign and home country at time t, respectively.

Accounting for the CIP condition, the difference between the interest rates should be roughly equal to the forward discount, which can be presented as the difference between log forward rate and log spot rate of a foreign country at time t (Atanasov & Nitschka, 2014):

$$i_t^f - i_t = \ln(f_t^f) - \ln(s_t^f). \tag{4.3}$$

Plugging into the first formula:

$$rx_{t+1} = \ln(f_t^f) - \ln(s_t^f) - \ln(\Delta s_{t+1}^f). \tag{4.4}$$

Hence, in Forex, the excess returns (rx_{t+1}) on buying a currency in a forward market and selling it in the spot market after a month can be calculated following this formula:

$$rx_{t+1} = \ln(f_t^f) - \ln(s_{t+1}^f), \tag{4.5}$$

where excess returns can be presented as the difference between the natural logarithm of the forward rate at time t and the natural logarithm of spot rate at time t+1.

4.1.1 Carry trade

The carry trade portfolios are sorted based on one month lagged forward discount, which can be presented as the difference between log forward and log spot price at time t. Then, the currencies are divided into five baskets based on the forward discount. The first basket includes six currencies with the highest forward discount and the last one consists of currencies with the lowest. As the number of currencies varies over time, I decided to always include six currencies in the first basket and six in the last basket. The rest of the currencies should be equally distributed between the remaining three baskets.

The first strategy involves investing one dollar equally into five baskets and is called the equally weighted (EW) carry trade (Burnside, 2012). The second strategy involves investing one dollar in the first basket (highest forward discount) and shorting one dollar invested in the fifth basket. This strategy should resemble momentum, but instead of using momentum signals, I am using forward discounts. I decided to further extend this strategy by using five different holding periods, h = 1-, 3-, 6-, 9-, 12-months. It is important to highlight that the bid amount differs between the equally weighted carry trade and the rest of the strategies. All portfolios are rebalanced every month. The resulting portfolios are often referred to as C(f,h), which denotes a high-minus-low carry trade strategy for f-month formation and h-month holding period. Moreover, to match the returns with momentum, returns for all strategies will be starting from January 1998.

After examining the excess and risk-adjusted returns for carry trade, I test the effect of lagged formation on the profitability of these strategies. This is explained further in the example of momentum in Section 4.1.2. This comparison for carry trade strategies follows the exact same approach as for the momentum.

Moreover, I present the results for two subsamples to assess the change in the profitability of these strategies over the years. Subsample A contains data up till June 2010, and subsample B, from July 2010 till January 2023. Those subsamples contain almost an equal amount of data points. This comparison includes the excess returns as well as the Sharpe ratios. Further, I test whether the difference between the two subsamples is significant using a t-test. The null hypothesis is that the difference is zero, while the alternative hypothesis says that the mean of subsample A is higher. I reject null if the p-value is lower than 0.1. This test disregards the time dimension of the data and hence the results should be interpreted carefully.

To see whether there is a structural difference in the time series of returns, I perform an Augmented Dickey Fuller (ADF) test to assess whether the series is stationary. The null hypothesis for the ADF test is that the series is non-stationary and the alternative hypothesis states that it is stationary. If the p-value is smaller than 0.1, I reject the null hypothesis.

Lastly, to further compare the two subsamples, I perform a Chow test. The null hypothesis of this test is that there is no structural change between the two time series. To perform this test, I use the 'chowtest' command in Stata. This command tests the difference between the parameters of indicated model for two subsamples. However, first, such model needs to be specified. For this test, I follow the standard procedure of applying a linear regression, where the returns are regressed on their lagged values. The choice of lag is determined by the model fit and significance of the coefficient in the regression. To find the most appropriate lag length, I regress the returns on different lags, starting from the lag of 1 month up till 12 months. Each model includes only one lag. The specifications of lag length used in the models are included in Table E1. The p-values for the Chow tests are reported in a table. If the p-value is smaller than 0.1, I reject the null.

4.1.2 Momentum

Throughout the analysis, I am mostly comparing 25 momentum strategies. I implement five formation and holding periods of 1-, 3-, 6-, 9-, and 12- months. Once the momentum signals are determined, the six currencies with the highest signal are used as the winners and the six currencies with the lowest signal are the losers. The signals of both losers and winners are matched with corresponding returns in that month. Then the average returns of winners and losers is calculated by dividing the total sum of the returns by six. These are the returns to the momentum winners-only strategy and losers-only strategy. To calculate the returns of the high-minus-low strategy the losers-only returns are subtracted from the winner-only returns. The same procedure is followed for the excess returns. I name the resulting portfolios MOM(f,h), which denotes a high-minus-low momentum strategy for the f-month formation and h-month holding period. Additionally, I present the equally weighted (EW) momentum, which follows the same procedure as an equally weighted carry trade. These portfolios are rebalanced every month. Moreover, since I lose some datapoint to determine the momentum signals, returns for all strategies are starting from January 1998.

However, to construct momentum strategies, firstly the momentum signals for each formation period must be determined. A description of this step is usually omitted in the existing literature and hence, I decided to see how using different momentum signals affects the excess returns for momentum strategies. Depending on the length of the period the formula used changes slightly. The general formula for momentum signal, widely used in different markets, with n formation period is determined as:

$$M_t = \frac{P_{t-1}}{P_{t-1-n}} - 1. \tag{4.6}$$

This signal will be referred to as a return signal.

On the other hand, following the example of Menkhoff et al. (2012b), I also utilize momentum signal based on the excess returns. As in my research, I only use a 1-month forward rate, I can calculate the returns for only one month following the formula 4.5. Hence, I accumulate the returns to form signals for longer formation periods than one month. Following this approach, the momentum signal for the formation period of 3 months is determined by the cumulative excess returns for the last three months. For simplicity, this signal will often be called an excess return signal. The strategies based on the two signals will be compared using the excess returns as well as the risk-adjusted returns. Moreover, I perform a paired sample t-test to assess whether the average excess returns for strategy based on the excess return signal are significantly higher than those for the return signal. The null hypothesis states that the difference between the mean excess returns between these strategies is zero, whereas the alternative hypothesis posits that the mean excess returns for portfolios based on excess return signal are higher. The differences between the mean monthly returns and the p-values are reported in the tables. The null hypothesis is rejected when the p-value is lower than 0.1. It is worth keeping in mind that t-test is not tailored to be performed on time series data due to its lack of robustness to autocorrelation. However, in this comparison the time-dimension is not the main objective, hence it will be ignored. Nevertheless, the results should be interpreted carefully, as the independence condition could be violated.

Furthermore, as for carry trade, I want to investigate the influence of lagged formation on the performance of these portfolios. Hence, I compare the portfolios formed immediately after the signal is recorded with the portfolios formed with one month delay. This follows from the research of Jegadeesh and Titman (1993), who prove that using lagged returns with a one-week delay achieves better results than investing in this strategy right after the momentum signal. For simplicity, as the spot rates and forward rates are recorded monthly, I extend this delay period to one month, which is a common practice among other researchers studying momentum. In this analysis, I use the excess returns for momentum formed based on both return and excess return signal. Moreover, to assess whether the difference between momentum returns for lagged and non-lagged formation is significant, I will use a paired sample t-test. The null hypothesis is that the difference between the mean excess returns between these strategies is zero, whereas the alternative hypothesis varies slightly per test and posits that one strategy performs better than the other. All tests are one-sided, and the specifications are provided in the description of the tables. In tables, the differences between the mean monthly returns and the p-values are reported. For p-values lower than 0.1, the null is rejected. The focus of the t-tests, I perform, is on the comparison of the means of two time series. As the time dimension is not the subject of this test, I am going to ignore it, as explained earlier.

I compare the excess returns and risk-adjusted returns of two subsamples to see whether the profitability of these strategies changes throughout the years. Subsample A contains data up till June 2010 and subsample B from July 2010 till January 2023. Those subsamples contain approximately an equal amount of data points. Further, I test whether the difference between the two subsamples is significant using a paired sample t-test. The procedure for this test is the same as described for carry trade. Moreover, to examine whether there is a structural difference in the time series of returns, I perform an

Augmented Dickey Fuller (ADF) test to assess whether the series are stationary. The null hypothesis for the ADF test is that the series is non-stationary and the alternative hypothesis states that it is stationary. If the p-value is smaller than 0.1, I reject the null hypothesis.

Complimentary to ADF test, I perform a Chow test. I apply the exact same methods as described at the end of Section 4.1.1 for carry trade.

4.2 Developing a mixed strategy

To construct mixed strategies, I first need to perform a careful examination of the profitability of different forms of momentum and carry trade. For this purpose, I analyze the excess returns and Sharpe ratios of each strategy for the most profitable forms of momentum and carry trade. Furthermore, I analyze correlations between momentum and carry trade. I choose three carry trade and three momentum strategies that have low correlations and high profitability in order to maximize the risk-adjusted returns of the mixed strategy. I form different mixed strategies in an attempt to find the most profitable mix. Partially inspired by Olszewski and Zhou (2013), I use three different approaches to portfolio formation: equally weighted portfolio, minimum risk portfolio, and mean-variance maximization. The equally weighted portfolio involves investing an equal amount in selected momentum and carry trade strategy. The minimum risk portfolio uses the solver function (in Excel) with the objective to minimize the variance of the portfolio. The solver adjusts the weights of carry trade and momentum to minimize the variance of the resulting portfolio. Lastly, the mean-variance maximization, follows a similar procedure as for the minimum risk portfolio but uses the Sharpe ratio as the objective of the optimization. This way the weights are adjusted so that the risk-adjusted returns are maximized. Naturally, the last portfolio should achieve the best results, having the maximization of risk-adjusted returns as the objective of the mixed strategy. However, the other approaches will be presented for comparison.

CHAPTER 5 Results & Discussion

This section is divided into three main subsections discussing the analysis related to momentum (Section 5.1), carry trade (Section 5.2), and mixed strategy (Section 5.3). For each of these sections, various methods are utilized, and the results are thoroughly described and discussed.

5.1 Momentum

5.1.1 Excess returns based on different signals

Firstly, the excess returns will be analyzed to assess which form of momentum strategy is the most profitable. I go a step further in this investigation and compare strategies based on two different signals. As the FX market is quite specific when it comes to excess returns calculations, it is not straightforward how the momentum signal should be calculated. In most markets, this signal comes from changes in prices, hence the formula for the signal for the f-formation period is very similar to the formula for returns for this period. However, in the foreign exchange market it is popular to determine this signal based on excess returns. Hence in this section, I am going to compare the momentum excess returns for portfolios sorted based on the momentum signal determined by returns and excess returns.

Table 1. Momentum excess returns based on different signals.

Table 1 presents annualized excess returns for 26 momentum strategies, including portfolios with f= 1-, 3-, 6-, 9-, and 12-months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. Additionally, the equally weighted momentum strategy is included. Panel A presents those strategies formed based on signals formed based on returns, whereas Panel B strategies based on excess return signal. In the parentheses, the t-statistics of a Newey-West regression is presented. *, **, and *** denotes statistical significance at the 10%, 5% and 1%, respectively.

	Holding period *h*					
f	1	3	6	9	12	EW
Panel A. Momentum based on return signal						
1	-4.966	-1.813	-0.993	-0.832	-1.228	1.835
	[-3.20***]	[-1.75*]	[-1.40]	[-1.32]	[-2.12**]	[1.44]
3	-2.852	-0.143	-0.894	-1.187	-1.182	
	[-1.70*]	[-0.11]	[-0.88]	[-1.28]	[-1.36]	
6	-2.069	-1.570	-2.152	-2.339	-1.207	
	[-1.25]	[-1.02]	[-1.52]	[-1.79*]	[-0.92]	
9	-3.639	-2.800	-2.562	-1.894	-0.480	
	[-1.96*]	[-1.65*]	[-1.60]	[-1.22]	[-0.31]	
12	-3.339	-2.127	-1.188	-0.678	0.187	
	[-1.67*]	[-1.23]	[-0.70]	[-0.42]	[0.13]	
Panel B. Momentum based on excess return signal						
1	11.078	7.628	6.170	5.319	4.860	0.992
	[5.67***]	[5.17***]	[5.24***]	[4.71***]	[4.33***]	[1.27]
3	9.575	6.273	5.905	5.792	4.953	
	[4.77***]	[3.66***]	[3.92***]	[3.82***]	[3.27***]	
6	8.929	7.386	6.998	6.256	7.126	
	[4.37***]	[3.77***]	[3.45***]	[3.17***]	[2.39**]	
9	9.159	8.100	6.706	5.463	4.579	
	[3.79***]	[3.60***]	[2.99***]	[2.53**]	[2.18**]	
12	7.154	5.979	4.526	3.927	3.169	
	[2.94***]	[2.67***]	[2.00**]	[1.80*]	[1.53]	

Visibly, strategies formed based on the excess return signals are more profitable and significant. For strategies formed based on returns, most of the results are insignificant. This means that those strategies are very unlikely to produce any returns different than zero. Moreover, the sign and magnitude of the performance change often and do not exhibit any pattern, meaning that they might be more sensitive to the changes to the holding and formation periods and hence less predictable and reliable. This highlights the uniqueness of this strategy in the FX market, as in opposition to other markets the strategies formed based on return signal do not produce any abnormal returns. This can be compared with Jegadeesh and Titman (1993), who find that momentum based on return signal produces abnormal returns in US equities. Literature regarding Forex does not explicitly mention which signal was used in the formation of portfolios. However, this finding proves that most researchers likely use the momentum signal based on excess returns. Hence, moving forward, I will be mostly referring to this strategy in my analysis.

Further, results in Panel B, exhibit a similar pattern, as to what was found by Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). The most profitable strategies are usually, those with one month holding period. The profitability decreases gradually when this period is getting longer. Further, results for the MOM(12,12) are insignificant, which is also in line with the literature, as researchers find that returns for longer maturities tend to be either small or negative and insignificant. Lastly, when comparing the equally weighted strategy to Burnside (2012), I discover some inconsistencies. In my analysis, the equally weighted portfolio is insignificant, while in Burnside (2012) this strategy achieves much higher significant returns. This could be the outcome of using a slightly different sample, as well as different period for the study.

Additionally, in Table D1, I test for the significance of the difference between the two strategies using a paired sample t-test. According to the test the mean momentum excess returns formed based on the return signal are significantly lower than the mean excess returns for the excess return signal. This applies to all strategies besides the EW portfolio.

Table 2. Sharpe ratios for momentum strategies based on different signals.

Table 2 presents Sharpe ratios for 26 momentum strategies, including portfolios with f= 1-, 3-, 6-, 9-, and 12- months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. Additionally, the equally weighted momentum strategy is included. Panel A presents those strategies formed based on signals formed based on returns, whereas Panel B strategies based on excess return signal.

	Holding period *h*					
f	1	3	6	9	12	EW
	Panel A. Momentum based on return signal					
1	-0.503	-0.312	-0.213	-0.221	-0.359	0.309
3	-0.280	-0.018	-0.138	-0.210	-0.219	
6	-0.221	-0.183	-0.269	-0.324	-0.122	
9	-0.363	-0.297	-0.278	-0.220	-0.062	
12	-0.331	-0.225	-0.130	-0.079	0.024	
	Panel B. Momentum based on excess return signal					
1	1.085	1.083	1.038	1.232	1.310	0.168
3	0.951	0.700	0.809	1.005	0.938	
6	0.868	0.748	0.775	0.784	0.851	
9	0.845	0.786	0.700	0.615	0.550	
12	0.675	0.599	0.481	0.450	0.382	

The Sharpe ratios for these strategies follow a slightly different pattern than the excess returns. For the formation period of one month, the risk-adjusted returns mostly increase with the holding period. The most profitable strategy is MOM(1,12). This pattern does not hold for other formation periods; it is rather irregular. This is very different from what Menkhoff et al. (2012b) found, as according to their findings the Sharpe ratios exhibit the same pattern as excess returns. Even though the returns decrease for longer holding periods, the Sharpe ratios are increasing. This indicates that the strategies that are held longer experience less volatility on average.

5.1.2. Lagged formation of the portfolio

Based on Jagadeesh and Titman (1993), I take two different approaches to creating portfolios. In their paper, they document that the portfolios formed one week after recording the momentum signal, tend to yield higher returns than portfolios formed immediately after the formation period. Hence, in this section, I am going to compare the results for portfolios, both for return signal and excess return signal, for the lagged formation (one month delay) and immediate formation.

In Table B1, I compare the excess returns for strategies based on returns with lagged formation to those without lagged formation. I find that the lagged formation portfolio is slightly more profitable than the excess returns without lagged formation. However, these results are still insignificant. This further assures about the poor implication of signal based on price changes (returns) in the FX market. Moreover, when inspecting Table D2, I can confirm that the excess returns for momentum portfolios based on the return signal with lagged formation are significantly higher than without lagged formation for almost all portfolios. However, the difference is not that high and for some strategies it is insignificant. Hence, the effect of lagged formation for momentum based on the return signal is quite sensitive to and dependent on the formation and holding period.

Table 3. Momentum excess returns based on excess return signal and lagged formation.

Table 3 presents annualized excess returns for 26 momentum strategies, including portfolios with f= 1-, 3-, 6-, 9-, and 12- months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. Both panels include results for the momentum strategy formed based on the excess return signal. Panel A presents excess returns for strategy without lagged formation, whereas Panel B indicates the results with lagged formation. In the parentheses, the t-statistics of a Newey-West regression is presented. *, **, and *** denotes statistical significance at the 10%, 5% and 1%, respectively.

	Holding period *h*				
f	1	3	6	9	12
	Panel A. Momentum without lagged formation				
1	11.078	7.628	6.170	5.319	4.860
	[5.67***]	[5.17***]	[5.24***]	[4.71***]	[4.33***]
3	9.575	6.273	5.905	5.792	4.953
	[4.77***]	[3.66***]	[3.92***]	[3.82***]	[3.27***]
6	8.929	7.386	6.998	6.256	7.126
	[4.37***]	[3.77***]	[3.45***]	[3.17***]	[2.39**]
9	9.159	8.100	6.706	5.463	4.579
	[3.79***]	[3.60***]	[2.99***]	[2.53**]	[2.18**]
12	7.154	5.979	4.526	3.927	3.169
	[2.94***]	[2.67***]	[2.00**]	[1.80*]	[1.53]
	Panel B. Momentum with lagged formation				
1	4.657	4.668	4.407	4.474	3.785
	[2.49**]	[3.32***]	[3.49***]	[4.00***]	[3.40***]
3	5.209	4.410	4.670	5.135	3.798
	[2.61***]	[2.53**]	[2.71***]	[3.18***]	[2.38**]
6	6.676	5.768	6.004	5.215	6.061
	[3.30***]	[2.71***]	[2.77***]	[2.62***]	[1.85*]
9	7.394	6.295	5.238	4.140	3.075
	[3.19***]	[2.74***]	[2.27**]	[1.90*]	[1.45]
12	5.009	4.338	3.262	2.978	2.348
	[2.20**]	[1.90*]	[1.40]	[1.36]	[1.11]

The results in Table 3 indicate that the lagged formation has a negative effect on the profitability of excess returns for portfolios formed based on the excess return signal. The pattern that the portfolios with lagged formation exhibit changes slightly. The excess returns are decreasing with the holding period but increasing with the formation period up to 6 months and then again gradually decreasing. Moreover, in Table C1, the Sharpe ratios for lagged formation behave rather randomly. This is similar to what was seen in the Sharpe ratios for non-lagged formation. Nevertheless, portfolios with lagged formation consistently achieve lower risk-adjusted returns. Further, in Table D3, based on the paired sample t-test, I can further confirm that the lagged formation has a negative significant effect on the mean excess momentum returns formed on the excess return signal.

In opposition to Jegadeesh and Titman (1993), the lagged formation negatively impacts the excess returns for momentum based on the excess return signal, in my sample. This does not apply to the portfolios formed based on return signal. Hence, I conclude that the portfolios based on excess return signal behave differently than when formed based on return signal. This highlights that the optimal portfolio for my sample should be based on the excess return signal and formed immediately after the formation signal.

5.1.3. Subsample comparison

Being interested in the comparisons of profitability of these portfolios over time, I decided to divide my sample into two subsamples to be able to assess whether there has been a difference in the excess returns over the years.

Table 4. Subsample comparison for momentum excess returns.

Table 4 presents annualized excess returns for 26 momentum strategies, including portfolios with f= 1-, 3-, 6-, 9-, and 12-months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. Additionally, the equally weighted momentum strategy is included. Both panels include results for the momentum strategy formed based on the excess return signal. Panel A presents results for subsample A, which runs up till June 2010. Panel B indicates the results for subsample B, July 2010 – March 2023. The two subsamples contain equal number of datapoints. In the parentheses, the t-statistics of a Newey-West regression is presented. *, **, and *** denotes statistical significance at the 10%, 5% and 1%, respectively.

	Holding period *h*					
f	1	3	6	9	12	EW
			Panel A. Subsample A			
1	14.54	10.64	8.44	7.69	6.72	3.76
	[6.37***]	[5.07***]	[4.35***]	[4.34***]	[3.12***]	[1.94*]
3	13.13	10.16	8.24	8.14	6.87	
	[6.72***]	[4.73***]	[3.63***]	[3.78***]	[2.54**]	
6	12.23	10.61	9.70	8.81	6.53	
	[5.64***]	[3.54***]	[3.08***]	[2.70***]	[1.85*]	
9	13.80	12.32	9.56	8.43	6.89	
	[4.88***]	[3.46***]	[2.81***]	[2.42**]	[1.83*]	
12	10.97	8.97	6.97	6.57	6.15	
	[4.11***]	[2.93***]	[2.03**]	[1.95*]	[1.85*]	
			Panel B. Subsample B			
1	7.64	4.63	3.92	2.96	3.01	-0.54
	[2.50**]	[2.05**]	[1.87*]	[1.33]	[1.07]	[-0.36]
3	6.04	2.41	3.59	3.46	3.04	
	[1.98**]	[0.95]	[1.62]	[1.37]	[1.17]	
6	5.65	4.18	4.32	3.72	2.61	
	[2.23**]	[1.86*]	[1.76*]	[1.49]	[0.86]	
9	4.55	3.90	3.87	2.51	2.29	
	[2.02**]	[1.91*]	[1.65]	[1.04]	[0.54]	
12	3.36	3.00	2.10	1.31	0.21	
	[2.11**]	[1.66*]	[1.29]	[1.03]	[0.09]	

The excess returns are much higher for the subsample A for all the strategies. Moreover, the equally weighted strategy, which previously was insignificant, is significant for the subsample A at 10% level, which is consistent with Burnside (2012). Further, it is visible that most results in panel B for longer holding periods become insignificant. Hence, they cannot be assumed to be different from zero.

Taking a closer look at Table C2, I see that the Sharpe ratios are smaller for the second subsample. Moreover, the first subsample, in some cases, outperforms the full sample. The highest Sharpe ratio is recorded for the MOM(1,12) and is equal to 2.066. Moreover, the Sharpe ratio of the equally weighted momentum is positive and very similar to what is seen in the paper written by Burnside, Eichenbauma and Rebelo (2011).

In Table D4, I compare the subsamples with the use of paired sample t-test and find that the monthly excess returns in subsample A are significantly higher than in subsample B for all strategies. Keeping in mind that the t-test is not the most suitable test for comparison of time series, I decided to further assess this difference using an Augmented Dickey Fuller test. This way I should be able to see whether there has been a change in the stationarity of the two time series, which would indicate a significant structural difference.

Table 5. Augmented Dickey Fuller test.

Table 5 presents annualized excess returns for 26 momentum strategies, including portfolios with f= 1-, 3-, 6-, 9-, and 12-months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. Additionally, the equally weighted momentum strategy is included. Both panels include results for the momentum strategy formed based on the excess return signal. Panel A presents results for subsample A, which runs up till June 2010. Panel B indicates the results for subsample B, July 2010 – March 2023. The two subsamples contain equal number of datapoints. In the parentheses, the t-statistics of a Newey-West regression is presented. *, **, and *** denotes statistical significance at the 10%, 5% and 1%, respectively.

			Holding period *h*			
f	1	3	6	9	12	EW
			Panel A. Subsample A			
1	0.010	0.023	0.005	0.067	0.017	0.001
3	0.024	0.007	0.005	0.019	0.024	
6	0.005	0.014	0.038	0.043	0.038	
9	0.047	0.048	0.068	0.060	0.069	
12	0.112	0.078	0.061	0.039	0.012	
			Panel B. Subsample B			
1	0.509	0.504	0.449	0.311	0.091	0.003
3	0.305	0.209	0.312	0.204	0.041	
6	0.377	0.235	0.139	0.099	0.014	
9	0.265	0.178	0.091	0.031	0.011	
12	0.149	0.126	0.017	0.007	0.001	

For subsample A, the strategies are mostly significant. This does not hold for subsample B, where most of the results are insignificant, meaning that the time series for subsample B become non-stationary. This showcases the difference between the two subsamples. The first time series can be described with the use of simple autoregressive model and the second time series requires an ARIMA model, as it needs to be differenced. Nonetheless, I also perform a Chow test (Table 6), which partially contradicts the results of the ADF test. A significant structural difference is only visible for the shorter formation periods. Most of the results are insignificant, meaning that the parameters of the model do not differ between the two subsamples. Nevertheless, based on this analysis, it can be said that the return for momentum strategies for formation period of 1 month (expect for the 12-month holding period) are significantly different between the subsamples.

Table 6. Chow test for the subsamples of momentum returns.

Table 6 presents the p-values of a Chow test for monthly excess returns for 26 momentum strategies formed based on excess return signal for non-lagged formation for two subsamples. The strategies include portfolios with f= 1-, 3-, 6-, 9-, and 12- months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. Additionally, the equally weighted momentum strategy is included. The null hypothesis for this test says that there is no significant structural difference between the two time series. Subsample A is up till June 2010, and subsample B runs from July 2010 till January 2023.

	Holding period *h*					
f	1	3	6	9	12	EW
1	0.039	0.001	0.010	0.022	0.230	0.005
3	0.135	0.020	0.310	0.314	0.490	
6	0.286	0.397	0.528	0.319	0.425	
9	0.153	0.246	0.581	0.581	0.638	
12	0.378	0.503	0.587	0.621	0.438	

In conclusion, this discovery highlights the importance of careful comparisons with the past literature. Moreover, it signifies a need for further research into the changes in profitability of these strategies in the FX market over the years.

5.2 Carry Trade

5.2.1 Excess returns and the effect of lagged formation

In this section, I perform the analysis of excess returns obtained from six carry trade strategies applied in this research. Moreover, as in Section 5.1.3, I will be analyzing the impact of lagged formation on the profitability of these portfolios.

Table 7. Carry trade excess returns and lagged formation.

Table 7 presents annualized excess returns for 6 carry trade strategies, including portfolios with h= 1-, 3-, 6-, 9-, and 12- months holding periods and 1-month formation period. Additionally, the equally weighted carry trade strategy is included. Panel A presents excess returns for strategies without lagged formation, whereas Panel B indicates the results with lagged formation. In the parentheses, the t-statistics of a Newey-West regression is presented. *, **, and *** denotes statistical significance at the 10%, 5% and 1%, respectively.

	Holding period *h*					
f	1	3	6	9	12	EW
	Panel A. Carry trade					
1	21.42	13.39	11.31	9.78	8.71	1.54
	[10.90***]	[7.90***]	[6.68***]	[6.09***]	[5.51***]	[1.22]
	Panel B. Carry trade with lagged formation					
1	10.58	9.56	9.43	8.73	7.82	
	[5.65***]	[5.27***]	[5.51***]	[5.45***]	[5.13***]	

The carry trade strategy produces significant positive returns for all strategies, besides the equally weighted carry trade. When the holding period increases the profitability of this strategy decreases. This pattern is similar to what I noticed in momentum excess returns. Also, for all holding periods, this strategy outperforms momentum. Moreover, the portfolios which were formed with one month delay after the formation period tend to be less profitable than those formed immediately. This can be further confirmed by looking at Table D5, where I use a paired sample t-test to test for the significance of the difference between the average monthly carry trade returns in excess with and without lagged formation.

The average monthly returns for the lagged formation are significantly lower for all carry trade portfolios.

Table 8. Sharpe ratios for carry trade strategies and lagged formation.

Table 8 presents Sharpe ratios for 6 carry trade strategies, including portfolios with h= 1-, 3-, 6-, 9-, and 12- months holding periods and 1-month formation period. Additionally, the equally weighted carry trade strategy is included. Panel A presents excess returns for strategies without lagged formation, whereas Panel B indicates the results with lagged formation.

	Holding period *h*				
f	1	3	6	9	12
	Panel A. Momentum signal based on excess returns				
1	2.514	1.844	1.546	1.382	1.181
	Panel B. Momentum signal based on excess returns lagged formation				
1	1.274	1.278	1.350	1.318	1.160

On the other hand, the Sharpe ratios present a different pattern than those for momentum portfolios of a 1-month formation period. While for momentum the Sharpe ratios were increasing with the holding period, for carry trade they tend to be decreasing. A slightly different pattern is seen for the portfolios with lagged formation. The Sharpe ratios are increasing with a holding period up to the 6-month and then gradually decrease.

Considering both excess and risk-adjusted returns, I see that the non-lagged portfolios perform better than the portfolios with delayed formation. Hence, for the rest of this paper, I mostly focus on the non-lagged portfolios for carry trade.

5.2.2 Subsamples

Similarly, as in Section 5.1.3, I compare two subsamples, A and B, to assess whether there has been a change in the profitability of those strategies.

Table 9. Subsample comparison for carry trade excess returns.

Table 9 presents annualized excess returns for 6 carry trade strategies, including portfolios with h= 1-, 3-, 6-, 9-, and 12- months holding periods and 1-month formation period. Additionally, the equally weighted carry trade strategy is included. Panel A presents results for subsample A, January 1998 - June 2010. Panel B indicates the results for subsample B, July 2010 – March 2023. The two subsamples contain an equal number of datapoints. In the parentheses, the t-statistics of a Newey-West regression is presented. *, **, and *** denotes statistical significance at the 10%, 5% and 1%, respectively.

	Holding period *h*					
f	1	3	6	9	12	EW
			Panel A. Subsample A			
1	23.39	14.75	12.53	11.06	10.44	3.64
	[11.19***]	[6.11***]	[4.91***]	[4.32***]	[4.03***]	[1.87*]
			Panel B. Subsample B			
1	19.47	12.04	10.11	8.50	7.00	-0.54
	[5.90***]	[5.08***]	[4.50***]	[4.42***]	[4.00***]	[-0.36]

Based on Table 9, a clear decrease in excess returns is visible for subsample B. This is consistent with what was found for the momentum strategies. All returns are significant and positive, with an exception for the equally weighted carry trade in subsample B. The EW strategy in subsample A is only slightly smaller than what was found by Burnside, Eichenbaum, and Rebelo (2011).

Moreover, looking at the Sharpe ratios (Table C3), the risk-adjusted returns for the first subsample are higher, with the highest score of 2.763 for C(1,1). The Sharpe ratios in both subsamples are decreasing with the holding period. Again, the equally weighted portfolio performs worse than the one documented in Burnside et al. (2011).

To further examine the differences between the two subsamples, I perform a paired sample t-test. The results (Table D6) indicate that the difference between the two subsamples is only significant for C(1,1) and EW portfolio. The rest of the differences are insignificant, meaning that they are not statistically different from zero. These results differ from what I have found for momentum.

Table 10. Augmented Dickey Fuller test for carry trade. Testing stationarity of two subsamples.

Table 10 presents annualized excess returns for 6 carry trade strategies, including portfolios with h= 1-, 3-, 6-, 9-, and 12-months holding periods and 1-month formation period. Additionally, the equally weighted carry trade strategy is included. Panel A presents results for subsample A, January 1998 - June 2010. Panel B indicates the results for subsample B, July 2010 – March 2023. The two subsamples contain equal number of datapoints. In the parentheses, the t-statistics of a Newey-West regression is presented. *, **, and *** denotes statistical significance at the 10%, 5% and 1%, respectively.

			Holding period *h*			
f	1	3	6	9	12	EW
			Panel A. Subsample A			
1	0.001	0.013	0.014	0.022	0.015	0.001
			Panel B. Subsample B			
1	0.877	0.873	0.873	0.711	0.199	0.003

Additionally, using the ADF test to assess whether the two time series are stationary, I detect a possible structural difference between the subsamples. For the subsample A, the p-value is lower than 0.1 and hence the null of non-stationarity is rejected. On the other hand, for subsample B, for all strategies besides the EW portfolio, the null cannot be rejected and hence I can suspect that the time series are non-stationary. This highlights the structural difference between the two subsamples, which I formally test using a Chow test (Table 11).

Although the ADF test indicated that there has been a change in stationarity of these time-series, Chow-test proves that there is no significant structural difference between the two subsamples. The parameters of the tested model seem to be equal for both subsamples.

Table 11. Chow test for the subsamples of carry trade returns.

Table 11 presents the p-value of a Chow test for monthly excess returns for 6 carry trade strategies for two subsamples, including portfolios with 1- months formation (f) period and h= 1-, 3-, 6-, 9-, and 12- months holding periods, as well as equally weighted portfolio. The null hypothesis for this test says that there is no significant structural difference between the two time series. Subsample A is up till June 2010, and subsample B runs from July 2010 till January 2023.

	Holding period *h*					
f	1	3	6	9	12	EW
1	0.361	0.585	0.608	0.312	0.250	0.240

Despite the fact that I detect a difference in the stationarity of these time series, the mean returns between the two subsamples are not significantly different. Moreover, Chow break test confirms that there is no significant difference between subsamples. This finding raises a question: why are the momentum returns (only for strategies based on 1-month formation period) different for the two periods, while the returns of carry trade are not? These results urge further research regarding the seasonality and changes in profitability of these strategies.

5.3 Mixed strategy

The goal of the mixed strategy is to increase the Sharpe ratios by taking advantage of the low correlation between the strategies and hence diversification. To determine which strategies should be used in the mixed portfolios, the correlations and profitability are compared.

Based on the previous analysis, I decided to compare only the non-lagged strategy for carry trade and non-lagged momentum based on the excess return signal. Moreover, I decided to include only the 1-month formation period for momentum, as these are the most profitable strategies (Table 1). Moreover, the equally weighted portfolios will not be taken into consideration due to their poor performance and insignificant results. In the sample, the carry trade portfolios outperform all momentum portfolios (Table 7). The results are significant for both strategies. Moreover, in terms of risk-adjusted returns, the carry trade is again the dominant strategy.

Table 12. Correlations between momentum and carry trade.

Table 12 presents correlations for momentum and carry trade strategies, including portfolios with h= 1-, 3-, 6-, 9-, and 12-months holding periods and 1-month formation period.

	M(1,1)	*M(1,3)*	*M(1,6)*	*M(1,9)*	*M(1,12)*	*C(1,1)*	*C(1,3)*	*C(1,6)*	*C(1,9)*	*C(1,12)*
M(1,1)	1.00									
M(1,3)	0.73	1.00								
M(1,6)	0.53	0.77	1.00							
M(1,9)	0.45	0.67	0.89	1.00						
M(1,12)	0.41	0.57	0.74	0.86	1.00					
C(1,1)	0.27	0.44	0.42	0.37	0.36	1.00				
C(1,3)	0.06	0.36	0.34	0.37	0.43	0.78	1.00			
C(1,6)	-0.07	0.18	0.29	0.36	0.44	0.67	0.91	1.00		
C(1,9)	-0.11	0.13	0.23	0.36	0.45	0.60	0.86	0.97	1.00	
C(1,12)	-0.14	0.08	0.15	0.28	0.44	0.50	0.78	0.90	0.96	1.00

The correlations between different forms of momentum and between different forms of carry are much higher than those between momentum and carry trade portfolios. This signifies a possibility of improvement of risk-adjusted returns by mixing the two strategies. Similar low correlation was found in the existing literature, for example by Menkhoff et al. (2012b).

When looking at Table 2, the highest risk-adjusted returns are detected for MOM(1,12) followed by MOM(1,9) and MOM(1,1). For carry trade, the highest Sharpe ratio is visible for the C(1,1) followed by C(1,3) and C(1,6) (Table 8). When analyzing the correlations, while keeping in mind the results for risk-adjusted returns, I decided to select MOM(1,1), MOM(1,9), MOM(1,12), C(1,1), C(1,3), and C(1,6) to utilize in my mixed strategies.

I decided to implement three different approaches: equally weighted portfolio, minimum variance portfolio and mean-variance maximization. The Sharpe ratios as well as the excess returns are reported in Table 13. In the interpretation, I will mainly focus on the Sharpe ratios, as they are the objective of the mixed strategy. However, it is worth mentioning that all those strategies produce positive and significant returns. Minimum variance portfolios achieve the lowest excess returns but also are the least risky. Although they might not perform too well compared to the rest, they might still be attractive for risk-averse investors. 50/50 portfolio performs relatively well and has the big advantage of being easy to implement. Nevertheless, none of the 50/50 strategies or minimum variance portfolios outperform the pure C(1,1) portfolio. This portfolio yields a Sharpe ratio of 2.514, which is noticeably higher than what is seen for the mixed strategies.

As suspected, the best-performing portfolios, both in terms of excess returns and risk-adjusted returns, are the mean-variance optimized portfolios. Moreover, when comparing them with the C(1,1) strategy, there is a slight increase in the risk-adjusted returns for all mixed strategies created with C(1,1). The highest Sharpe ratio is equal to 2.557 and is recorded for the mixed mean-variance portfolio of M(1,12) and C(1,1). Although the equally weighted or minimum variance strategy did not upgrade the risk-adjusted returns, as in Olszewski and Zhou (2013), the mean-variance portfolios can be classified as successful. This is in line with finance theory, as the mean-variance portfolio is usually referred to as the optimal portfolio. Hence, I conclude that creating a mixed portfolio with carefully selected momentum and carry trade strategies can improve the profitability in the FX market.

Table 13. Subsample comparison for carry trade excess returns.

Table 13 presents excess returns and Sharpe ratios for 27 mixed strategies, including C(1,1), C(1,3), C(1,6), M(1,1), M(1,9), and M(1,12). The approaches used for different mixed include an equally weighted strategy, minimum variance, and mean-variance portfolios. Panel A presents excess returns, whereas Panel B indicates the Sharpe ratios. In the parentheses, the t-statistics of a Newey-West regression is presented. *, **, and *** denotes statistical significance at the 10%, 5% and 1%, respectively.

	Equally weighted strategy			Minimum variance			Mean-variance		
	M(1,1)	M(1,9)	M(1,12)	M(1,1)	M(1,9)	M(1,12)	M(1,1)	M(1,9)	M(1,12)
Panel A. Excess returns									
C(1,1)	16.25	13.37	13.14	17.70	5.84	11.40	20.82	20.13	18.47
	[9.44***]	[6.59***]	[9.88***]	[10.16***]	[5.19***]	[9.22***]	[10.88***]	[10.86***]	[10.79***]
C(1,3)	12.23	9.35	9.12	12.64	6.41	8.95	12.75	10.27	12.13
	[8.31***]	[9.85***]	[7.33***]	[8.62***]	[5.74***]	[7.26***]	[8.46***]	[10.31***]	[7.87***]
C(1,6)	11.20	8.32	8.09	11.23	6.20	7.91	11.23	8.26	10.23
	[7.90***]	[7.51***]	[6.37***]	[7.96***]	[5.50***]	[6.31***]	[7.65***]	[6.57***]	[6.68***]
Panel B. Sharpe ratios									
C(1,1)	2.097	2.398	2.273	2.327	1.357	2.009	2.524	2.520	2.557
C(1,3)	1.889	1.913	1.637	2.068	1.524	1.607	2.076	1.929	1.870
C(1,6)	1.802	1.710	1.413	1.909	1.481	1.383	1.909	1.710	1.573

CHAPTER 6 Conclusion

In this paper, I investigate the influence of different carry trade and momentum strategies on excess returns and risk-adjusted returns. There are several factors identified that affect excess returns for these strategies. For momentum, a commonly used signal based on returns does not achieve positive or significant profits in the FX market. In the attempt to create a profitable strategy an alternative method, utilizing the excess returns for the sorting process, was applied, and found to achieve significant positive returns for almost all momentum strategies presented in this paper. Another factor that plays a significant role in the profitability of Forex investment strategies is the lagged formation of the strategy. According to Jegadeesh and Titman (1983), delaying the formation of a portfolio by one week after the signal is recorded should increase returns. This is indeed present in the momentum strategy formed based on the return signal. Nevertheless, returns of momentum based on excess return signal and carry trade are higher for the non-lagged portfolios. These findings highlight the uniqueness of the currency market and urge great attention while choosing the appropriate strategies to be applied. Furthermore, as suspected, carry trade was found to outperform the momentum strategy in the sample. The most profitable strategy, C(1,1), achieved around 20% of annualized excess returns and a Sharpe ratio of 2.514.

I also examine the differences between the profitability of these strategies over the years by a comparison of two subsamples. It appears that for the period of 1998-2010, the strategies produce much higher returns than for the period 2011-2023. However, these results are insignificant for carry trade strategies. Moreover, when comparing the stationarity of the time series for two subsamples, the first subsample appears to be mostly stationary (for both momentum and carry trade), while the second is non-stationary. Nonetheless, the Chow test presents contradicting results to ADF. Only momentum strategies for shorter formation periods can be seen as significantly different for the two subsamples. These findings leave room for further research regarding the changes in profitability of these strategies over the years. Moreover, the reason why only the momentum returns , and not the carry trade, experienced significant changes should be addressed.

Lastly, I successfully attempt to create a mixed strategy including momentum and carry trade to improve the risk-adjusted returns. Based on the low correlations and high risk-adjusted returns, I select six strategies to be used in the mixed portfolios, namely C(1,1), C(1,3), C(1,6), M(1,1), M(1,9), and M(1,12). I apply three different portfolio formation methods inspired by Olszewski and Zhou (2013) and form 27 strategies that produce positive significant returns. Momentum strategies mixed with C(1,1) achieve Sharpe ratios which outperform pure C(1,1) strategy. The highest risk-adjusted returns are recorded for the mean-variance optimized portfolio of M(1,12) and C(1,1). These findings are in line with past literature, which suggests that mixing these two strategies provides diversification benefits.

Nevertheless, this analysis has its drawbacks. The effect of the lagged formation, the difference of momentum signals and the subsample comparison were tested for significance using a t-test. As the returns are time series data, the independence condition of this test might be violated. Although, in this analysis, the time dimension was not crucial, in the future, a test that will account for the correlation between observations should be utilized. Moreover, the transaction costs were disregarded in this analysis. Hence, an additional analysis could investigate the effect of transaction costs on the profitability of these strategies as done by Menkhoff, Sarno, Schmeling, and Schrimpf (2012b). Lastly, future research could further investigate the differences in the momentum strategy sorted based on different signals and delve deeper into possible explanations of the differences.

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APPENDIX A Descriptive statistics

Table A1. Descriptive statistics of the returns on spot rates.

Table A1 shows descriptive statistics of the returns on spot rates. Spot rates are recorded at the end of each month. The returns are calculated by dividing spot rate for current month by the spot rate from previous month and subtracting 1. The descriptive statistics include mean. standard deviation. and minimum and maximum observation for each country from the sample. Moreover. the number of observations together with the specific dates in which the observations were recorded are provided. All observations provided until January 2023.

Country	*Date*	*Number of observations*	*Mean*	*Standard deviation*	*Min*	*Max*
Australia	01.1997	313	0.001	0.036	-0.084	0.196
Brazil	04.2004	226	0.004	0.047	-0.110	0.182
Canada	01.1997	313	0.000	0.025	-0.086	0.139
Czech Republic	01.1997	313	0.000	0.035	-0.096	0.135
Denmark	01.1997	313	0.001	0.028	-0.093	0.106
Egypt	04.2004	226	0.009	0.074	-0.154	1.012
Euro area	01.1999	289	0.001	0.028	-0.087	0.108
Hong Kong	01.1997	313	0.000	0.001	-0.007	0.005
Hungary	11.1997	303	0.003	0.039	-0.104	0.226
Iceland	04.2004	226	0.004	0.041	-0.149	0.272
India	11.1997	303	0.003	0.020	-0.066	0.080
Indonesia	01.1997-11.2000 07.2007-01.2023	235	0.007	0.107	-0.290	0.811
Japan	01.1997	313	0.001	0.030	-0.151	0.092
Kuwait	01.1997	313	0.000	0.006	-0.024	0.049
Malaysia	01.1997	313	0.002	0.023	-0.118	0.111
Mexico	01.1997	313	0.003	0.033	-0.083	0.209
New Zealand	01.1997	313	0.001	0.037	-0.122	0.153
Norway	01.1997	313	0.002	0.033	-0.076	0.146
Philippines	01.1997	313	0.003	0.024	-0.078	0.159
Poland	03.2002	251	0.001	0.039	-0.095	0.176
Russia	04.2004	226	0.006	0.056	-0.229	0.371
Saudi Arabia	01.1997	313	0.000	0.001	-0.009	0.011
Singapore	01.1997	313	0.000	0.017	-0.054	0.086
South Africa	01.1997	313	0.005	0.047	-0.116	0.181
South Korea	03.2002	251	0.000	0.031	-0.140	0.145
Sweden	01.1997	313	0.002	0.032	-0.087	0.125
Switzerland	01.1997	313	-0.001	0.028	-0.124	0.126
Taiwan	01.1997	313	0.000	0.016	-0.059	0.078
Thailand	01.1997	313	0.001	0.033	-0.187	0.306
United Kingdom	01.1997	313	0.001	0.025	-0.081	0.103

Table A2. Descriptive statistics of the excess returns.

This table shows descriptive statistics of the excess returns. Spot rates and 1-month forward rates are recorded at the end of each month. The returns are calculated by subtracting the natural logarithm of the spot rate for current month from the natural logarithm of the forward rate from previous month. The descriptive statistics include mean. standard deviation. and minimum and maximum observation for each country from the sample. Moreover. the number of observations is provided.

Country	*Number of observations*	*Mean*	*Standard deviation*	*Min*	*Max*
Australia	313	-0.002	0.018	-0.078	0.040
Brazil	226	0.002	0.020	-0.071	0.054
Canada	313	0.000	0.011	-0.058	0.037
Czech Republic	313	0.001	0.015	-0.052	0.043
Denmark	313	-0.001	0.012	-0.044	0.043
Egypt	226	0.003	0.020	-0.215	0.081
Euro area	289	0.000	0.012	-0.046	0.040
Hong Kong	313	0.000	0.001	-0.002	0.005
Hungary	303	0.002	0.016	-0.046	0.091
Iceland	226	0.000	0.017	-0.101	0.075
India	303	0.001	0.009	-0.030	0.033
Indonesia	234	-0.001	0.032	-0.259	0.168
Japan	313	-0.001	0.013	-0.039	0.069
Kuwait	313	0.000	0.003	-0.017	0.017
Malaysia	313	0.005	0.013	-0.046	0.054
Mexico	313	0.001	0.014	-0.076	0.039
NewZealand	313	0.001	0.018	-0.067	0.056
Norway	313	0.000	0.014	-0.055	0.033
Philippines	313	0.000	0.010	-0.060	0.039
Poland	251	0.001	0.017	-0.069	0.042
Russia	226	0.001	0.024	-0.134	0.130
Saudi Arabia	313	0.000	0.000	-0.005	0.003
Singapore	313	0.000	0.007	-0.036	0.026
South Africa	313	0.000	0.021	-0.086	0.054
South Korea	251	0.000	0.014	-0.058	0.062
Sweden	313	-0.001	0.014	-0.048	0.039
Switzerland	313	-0.001	0.012	-0.057	0.051
Taiwan	313	0.000	0.007	-0.033	0.026
Thailand	313	0.002	0.015	-0.091	0.092
United Kingdom	313	0.000	0.011	-0.044	0.037

APPENDIX B Momentum excess returns based on return signal and lagged formation.

Table B1. Momentum excess returns based on return signal and lagged formation.

Table B1 presents annualized excess returns for 26 momentum strategies, including portfolios with f= 1-, 3-, 6-, 9-, and 12-months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. Both panels include results for the momentum strategy formed based on the return signal. Panel A presents excess returns for strategy without lagged formation, whereas Panel B indicates the results with lagged formation. In the parentheses, the t-statistics of a Newey-West regression is presented. *, **, and *** denotes statistical significance at the 10%, 5% and 1%, respectively.

	Holding period *h*				
f	1	3	6	9	12
	Panel A. Momentum based on return signal				
1	-4.966	-1.813	-0.993	-0.832	-1.228
	[-3.20***]	[-1.75*]	[-1.40]	[-1.32]	[-2.12**]
3	-2.852	-0.143	-0.894	-1.187	-1.182
	[-1.70*]	[-0.11]	[-0.88]	[-1.28]	[-1.36]
6	-2.069	-1.570	-2.152	-2.339	-1.207
	[-1.25]	[-1.02]	[-1.52]	[-1.79*]	[-0.92]
9	-3.639	-2.800	-2.562	-1.894	-0.480
	[-1.96*]	[-1.65*]	[-1.60]	[-1.22]	[-0.31]
12	-3.339	-2.127	-1.188	-0.678	0.187
	[-1.67*]	[-1.23]	[-0.70]	[-0.42]	[0.13]
	Panel B. Momentum based on return signal with lagged formation				
1	0.73	0.69	0.37	-0.14	-0.45
	[0.44]	[0.64]	[0.49]	[-0.24]	[-0.80]
3	0.95	1.27	0.04	-0.91	-0.48
	[0.58]	[0.97]	[0.04]	[-0.96]	[-0.51]
6	-0.25	-0.90	-1.88	-1.80	-0.45
	[-0.14]	[-0.57]	[-1.27]	[-1.36]	[-0.34]
9	-1.31	-1.59	-1.72	-0.81	0.91
	[-0.76]	[-0.95]	[-1.05]	[-0.51]	[0.60]
12	-0.83	-0.75	-0.07	0.35	1.04
	[-0.49]	[-0.43]	[-0.04]	[0.22]	[0.69]

APPENDIX C Sharpe ratios

Table C1. Sharpe ratios for momentum strategies and lagged formation.

Table C1 presents Sharpe ratios for 25 momentum strategies, including portfolios with f= 1-, 3-, 6-, 9-, and 12- months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. Panel A presents strategies based on signals formed based on returns, whereas Panel B strategies based on excess return signal.

	Holding period *h*				
f	1	3	6	9	12
Panel A. Momentum based on excess return signal					
1	1.085	1.083	1.038	1.232	1.310
3	0.951	0.700	0.809	1.005	0.938
6	0.868	0.748	0.775	0.784	0.851
9	0.845	0.786	0.700	0.615	0.550
12	0.675	0.599	0.481	0.450	0.382
Panel B. Momentum based on excess return signal with lagged formation					
1	0.516	0.698	0.882	1.127	1.022
3	0.533	0.517	0.718	0.932	0.729
6	0.659	0.619	0.705	0.686	0.703
9	0.718	0.659	0.591	0.515	0.416
12	0.516	0.460	0.379	0.378	0.310

Table C2. Sharpe ratios for two subsamples of momentum.

Table C2 presents Sharpe ratios for 26 momentum strategies, including portfolios with f= 1-, 3-, 6-, 9-, and 12- months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. Additionally, the equally weighted momentum strategy is included. Both panels include results for the momentum strategy formed based on the excess return signal. Panel A presents results for subsample A, which runs up till June 2010. Panel B indicates the results for subsample B, July 2010 – March 2023. The two subsamples contain equal number of datapoints.

	Holding period *h*					
f	1	3	6	9	12	EW
Panel A. Subsample A						
1	1.378	1.529	1.345	1.824	2.066	0.646
3	1.277	1.085	1.011	1.282	1.195	
6	1.113	1.000	1.016	1.090	0.860	
9	1.237	1.138	0.934	0.880	0.732	
12	0.972	0.829	0.684	0.686	0.666	
Panel B. Subsample B						
1	0.781	0.659	0.706	0.678	0.731	-0.093
3	0.617	0.285	0.568	0.679	0.636	
6	0.594	0.462	0.508	0.472	0.370	
9	0.437	0.403	0.435	0.309	0.322	
12	0.343	0.331	0.245	0.167	0.028	

Table C3. Sharpe ratios for two subsamples of carry trade.

Table C3 presents Sharpe ratios for 26 momentum strategies, including portfolios with 1 month formation period and h= 1-, 3- , 6-, 9-, and 12- months holding periods. Additionally, the equally weighted momentum strategy is included. Both panels include results for the momentum strategy formed based on the excess return signal. Panel A presents results for subsample A, which runs up till June 2010. Panel B indicates the results for subsample B, July 2010 – March 2023. The two subsamples contain equal number of datapoints.

			Holding period *h*			
f	1	3	6	9	12	EW
			Panel A. Subsample A			
1	2.763	2.117	1.737	1.537	1.339	0.622
			Panel B. Subsample B			
1	2.273	1.598	1.362	1.221	1.007	-0.093

APPENDIX D Statistical testing using t-test

Table D1. Statistical difference between momentum excess returns based on return signal and excess return signal.

Table D1 presents the average difference between monthly excess returns for 26 momentum strategies formed based on return signal or excess return signal, including portfolios with f= 1-, 3-, 6-, 9-, and 12- months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. Additionally, the equally weighted momentum strategy is included. In the parentheses, the p-value of a paired sample t-test is presented. The difference represents the average excess returns for the return signal subtracted from the average excess returns for the excess return signal.

	Holding period *h*					
f	1	3	6	9	12	EW
1	1.337	0.787	0.597	0.513	0.507	-0.019
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[1.000]
3	1.036	0.535	0.567	0.582	0.511	
	[0.000]	[0.017]	[0.003]	[0.006]	[0.005]	
6	0.917	0.746	0.763	0.716	0.481	
	[0.001]	[0.004]	[0.001]	[0.001]	[0.012]	
9	1.066	0.908	0.772	0.613	0.422	
	[0.000]	[0.001]	[0.003]	[0.009]	[0.045]	
12	0.874	0.676	0.476	0.384	0.249	
	[0.003]	[0.010]	[0.042]	[0.069]	[0.152]	

Table D2. Statistical difference between momentum returns based on return signal with and without lagged formation.

Table D2 presents the average difference between the monthly excess returns for 25 momentum strategies formed based on return signal for the lagged and non-lagged formation. The strategies include portfolios with f= 1-, 3-, 6-, 9-, and 12- months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. In the parentheses, the p-value of a paired sample t-test is presented. The difference represents the average excess returns for the non-lagged formation subtracted from the lagged formation.

	Holding period *h*				
f	1	3	6	9	12
1	0.433	0.182	0.080	0.033	0.046
	[0.009]	[0.003]	[0.005]	[0.001]	[0.021]
3	0.275	0.076	0.036	-0.008	0.033
	[0.019]	[0.147]	[0.143]	[0.633]	[0.058]
6	0.107	0.011	-0.016	0.013	0.031
	[0.145]	[0.414]	[0.689]	[0.264]	[0.058]
9	0.156	0.057	0.027	0.046	0.072
	[0.027]	[0.084]	[0.162]	[0.017]	[0.000]
12	0.169	0.075	0.053	0.045	0.030
	[0.020]	[0.035]	[0.015]	[0.010]	[0.037]

Table D3. Statistical difference between momentum excess returns based on excess return signal with and without lagged formation.

Table D3 presents the average difference between the monthly excess returns for 25 momentum strategies formed based on excess return signal for the lagged and non-lagged formation. The strategies include portfolios with f= 1-, 3-, 6-, 9-, and 12- months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. In the parentheses, the p-value of a paired sample t-test is presented. The difference represents the average excess returns for the non-lagged formation subtracted from the lagged formation.

	Holding period *h*				
f	1	3	6	9	12
1	-0.495	-0.222	-0.116	-0.055	-0.083
	[0.002]	[0.001]	[0.000]	[0.004]	[0.000]
3	-0.324	-0.116	-0.068	-0.034	-0.081
	[0.003]	[0.054]	[0.025]	[0.074]	[0.000]
6	-0.148	-0.094	-0.047	-0.063	-0.051
	[0.042]	[0.028]	[0.061]	[0.002]	[0.008]
9	-0.110	-0.110	-0.081	-0.069	-0.083
	[0.095]	[0.005]	[0.002]	[0.001]	[0.000]
12	-0.139	-0.097	-0.065	-0.039	-0.028
	[0.035]	[0.010]	[0.008]	[0.039]	[0.085]

Table D4. Subsample comparison using paired t-test for momentum strategies.

Table D4 presents the average difference between monthly excess returns for 26 momentum strategies formed based on excess return signal with non-lagged formation for two subsamples. The strategies include portfolios with f= 1-, 3-, 6-, 9-, and 12- months formation periods and h= 1-, 3-, 6-, 9-, and 12- months holding periods. Additionally, the equally weighted momentum strategy is included. In the parentheses, the p-value of a paired sample t-test is presented. Subsample A is up till June 2010, and subsample B runs from July 2010 till January 2023. The difference represents the average excess returns for the subsample B subtracted from the subsample A.

	Holding period *h*					
f	1	3	6	9	12	EW
1	0.607	0.518	0.364	0.374	0.289	0.361
	[0.022]	[0.006]	[0.016]	[0.005]	[0.012]	[0.030]
3	0.559	0.629	0.345	0.363	0.304	
	[0.032]	[0.008]	[0.062]	[0.033]	[0.053]	
6	0.515	0.502	0.438	0.428	0.324	
	[0.062]	[0.057]	[0.071]	[0.055]	[0.099]	
9	0.766	0.707	0.476	0.491	0.359	
	[0.015]	[0.017]	[0.068]	[0.048]	[0.100]	
12	0.674	0.532	0.403	0.418	0.427	
	[0.029]	[0.060]	[0.101]	[0.078]	[0.061]	

Table D5. Statistical difference between carry trade excess returns with and without lagged formation.

Table D5 presents the average difference between monthly excess returns for 5 carry trade strategies with or without lagged formation, including portfolios with 1- months formation (f) period and h= 1-, 3-, 6-, 9-, and 12- months holding periods. In the parentheses, the p-value of the paired sample t-test is presented. The difference represents the average excess returns for the non-lagged formation subtracted from the lagged formation.

	Holding period *h*				
f	1	3	6	9	12
1	-0.885	-0.338	-0.187	-0.120	-0.114
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Table D6. Subsample comparison using paired sample t-test for carry trade strategies.

Table D6 presents the average difference between monthly excess returns for 6 carry trade strategies for two subsamples, including portfolios with 1- months formation (f) period and h= 1-, 3-, 6-, 9-, and 12- months holding periods, as well as equally weighted portfolio. In the parentheses, the p-value of a paired sample t-test is presented. Subsample A is up till June 2010, and subsample B runs from July 2010 till January 2023. The difference represents the average excess returns for the subsample B subtracted from the subsample A.

	Holding period *h*					
f	1	3	6	9	12	EW
1	0.391	0.215	0.164	0.173	0.235	0.350
	[0.077]	[0.192]	[0.253]	[0.226]	[0.150]	[0.034]

APPENDIX E Chow test

Table E1. Lag specification for the model used for Chow tests.

Table E1 presents the length of lags for a Chow test for comparison of subsamples. Each lag indicates the model specification used in the Chow test. For each model only one lag was included, which is presented in the table. The Panel A presents results for momentum strategies, while Panel B for carry trade.

	Holding period *h*					
f	1	3	6	9	12	EW
Panel A. Momentum						
1	2	2	2	2	1	6
3	3	9	1	1	1	
6	1	1	1	1	1	
9	1	1	1	1	1	
12	1	1	1	1	1	
Panel B. Carry trade						
1	2	2	2	1	1	2