Retail investors' trading behavior in foreign exchange markets

Working Paper

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Abstract Based on positioning data from oanda.com, one of the largest foreign exchange (FX) trading platforms in the world, we study the trading behavior of retail investors on a daily basis for 14 currency pairs. We examine whether retail investors can gain useful insights from the aggregated investor's positioning and to which extent established behavioral biases can be observed for the average investor. Using a quantile regression framework, we find that the trading operations of a representative investor exhibit a combination of short term contrarian and long term trend following characteristics. Implementing a trading strategy which mimicks the positioning of the average investor, we observe strong signs of the disposition effect. Overall, retail investors' approach to market timing, paired with an asymmetry in realizing gains and losses, tends to result in systematic underperformance compared to a simple buy&hold strategy for an equally weighted portfolio of the currency pairs in our data set.

Keywords: foreign exchange; retail investor; behavioral finance; trading; quantile regression

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1 Introduction

When studying behavioral phenomena in financial markets, retail investors hardly appear in a favorable light. Various studies have analyzed their behavior and performance based on individual and aggregated accounts of trading data. An excellent summary of recent research focused on individual investors' behaviors and biases can be found in Barber & Odean (2013). For an extensive overview on judgmental heuristics in general see Kahneman *et al.* (1982).

Retail investors' participation in the FX markets has increased substantially during the last decade, above all due to easier access to online brokerage margin accounts and lower fees: The comprehensive study of Rime & Schrimpf (2013) shows that in 2013 retail trading in their sample covering 53 countries accounted for 3.5% and 3.8% of total and spot turnover, respectively. According to their study, the largest volumes of retail trading occur in the USA and Japan, followed by Great Britain and Switzerland. Consequently, the number of academic papers researching the topic has flourished over the years, as have trading tools, apps and websites for the individual investor. Looking at FX brokers, most platforms today offer analytical resources, as well as general market education and guidance on behavioral biases[1] in addition to the actual trading service. Given the increased availability of research on their own (disadvantageous) behavior and equipped with modern tools to analyze data, one would assume a continuous improvement of the average individual investor's trading performance. We pursue this and other questions regarding the trading behavior of retail investors in the FX market based on a long term data set of daily average retail investor positioning from oanda.com, one of the largest FX trading platforms in the world. Oanda.com makes the last 120 days of average positioning data in FX markets available to its customers[2] and updates it on a daily basis. As '[...] the trading approaches of individual investors are surprisingly systematic' (Barber, Odean & Zhu, 2009, p.549) which is why we consider it appropriate to

[1] e.g. forex.com, icmbrokers.com, oanda.com forex labs
[2] access to the data was public until end of 2018

use the Oanda's positioning data to represent an 'average retail investor'. We follow the approach of Odean (1998) to examine behavioral phenomena at an aggregate level. Using the average positioning data we examine how, on the one hand, this investor reacts to real world financial events and, on the other hand, whether the investor displays signs of behavioral biases. Our positioning data consists of the percentage of average daily open long positions for 14 currency pairs. We refer to the average investor being "net long" in a certain currency pair, e.g. EUR/USD if we observe more than 50% of open long positions. This implies that a majority of investors are "net short" the USD/EUR pair. By construction, Oanda.com reports aggregated positioning for one direction of a pair of currencies, which is defined by the ISO 4217 convention and we will stick with this notation. Overall, we discover that the average investor exhibits signs of several well documented behavioral biases. When considering the average investor's positioning in a simple strategy, we find significant signs of the disposition effect (Shefrin & Statman, 1985) as the investor appears to be more reluctant to realize losses than gains. Moreover, we analyze the financial impact of these biases on the average investor's profit/loss: The average investor would have suffered an annualized loss of -6.78% with a volatility of 2.61%, while a simple buy-and-hold strategy in the underlying currencies would have produced a significantly smaller annualized loss of -0.43% with a similar volatility of 2.50%. Our results confirm the general observation in the literature that individual investors perform poorly on average, see e.g. Barber & Odean (2000). In contrast to Choe & Eom (2009), who show that the disposition effect is more pronounced for long positions, it is nearly equally prevalent for both trading directions in our case. The decomposition into long and short trades shows that both trade directions contribute about equally to the overall performance of the portfolio, which means that investors' timing on neither direction is favorable. Overall, investors are about three times more likely to realize a gain compared to a loss based on the data we analyzed. This is two times the size of the value observed by Barber & Odean (2000) in their study on the trading behavior of $10,000$ housholds with accounts at discount brokerage firms analyzed over the 1987 to 1993 period.

Regarding the economic value and potential learning effects of having the positioning data at the investor's disposal, we do not observe an improvement of the average retail investor's trading performance over time.

Furthermore, we examine whether the average FX investor can be classified as being a contrarian or momentum investor. Very recently Baltzer *et al.* (2019) have examined a dataset with the complete ownership structure of the German stock market and can clearly pinpoint private investors as contrarians. Examining the positioning of our average investor, we expect to gain a more nuanced view on the relationship between past returns and the trading style of the retail investor by employing a quantile regression framework. We discover that the average investor's preference for a contrarian- or momentum-like-trading-style depends both on the horizon and the quantiles of the preceding return distribution. We estimate how size and sign of daily, weekly and monthly returns influence subsequent positioning in each currency. We observe a significant negative relationship between short term (daily) and mid term (weekly) returns and subsequent positioning which indicates contrarian behavior (negative feedback trading). The effect is stronger for upper quantiles of the return distribution. In contrast to Koga *et al.* (2016) whose findings designate Japanese FX retail investors as momentum traders for short term time horizons, the average retail FX investor in our case emerges as being contrarian in the short term but trend following in the long term (monthly). The majority of currency pairs show a strong correlation between positive returns and subsequent positioning.[3] Correspondingly, negative returns and positioning are negatively correlated, however the relationship is not statistically significant. Both effects are stronger for the upper and lower quantiles of the preceding return distribution, respectively. The remainder of this paper is structured as follows: Section 2 provides an overview of research on retail investors' trading style, especially in FX markets. Section 3 describes our dataset and exemplarily scrutinizes how the average investor reacts to prominent financial

[3]This observation supports the findings of Barber, Odean & Zhu (2009) on the buying behavior of private investors in asset markets, whose preferences are strongly driven towards assets with strong recent performance.

events. Section 4 examines the economic value of the positioning data and offers insights into the trading style of the average investor based on a quantile regression. Section 5 concludes and makes some recommendations for further research based on our findings.

2 Contrarian retail investors in foreign exchange markets?

Currency data from oanda.com has already been used by several papers. While the data source of those papers remains the same as for our own paper, those differ from our own research in central aspects. As those papers make interesting discoveries regarding investor behavior using Oanda data, their essential points shall be summarized here: Focusing on the EUR/USD currency pair and order-flow data Nolte & Nolte (2016) discover that the aggregate order flow of investors contains exploitable information improving intraday out-of-sample forecasts over the next 20 and 30 minutes. Therefore, regarding the intraday horizon, the findings of Nolte & Nolte (2016) do not designate the flow data of FX investors as noise.[4] Nolte & Nolte (2012) examine intraday data of Oanda concerning various currency pairs and discover that investors show some 'monitoring effect' as they behave differently when they hold an open position and that past price movements influence the investors' order flow. Closest to the empirical analysis of our own paper is the research by Nolte & Voev (2011). While they analyze a dataset of Oanda intraday data of 30 currency pairs spanning one month, they confirm the disposition effect especially for small investors. Furthermore, they discover that large investors become more risk-averse by positive returns of their portfolio and are more likely to close their positions, while for small investors, the profit/loss of their portfolio does not alter their likeliness to close/open a position. Nolte (2012) studies the shape of the disposition effect over the entire profit and loss region and uses Oanda data on

[4] Nolte & Nolte (2016, p.16) state that is it not clear whether this exploitable information is incorporated into the price process due to some prognostic skills of the FX investors and resulting upward price pressure due to the consistent errors of the FX investors being exploited by interbank dealers.

the most actively traded currency pair, at this time, EUR/USD for the period 1.10.2003 to 14.05.2004. He employs a panel survival approach and finds that unsuccessful investors have a stronger disposition effect and that investors employing complex trading strategies show a weakened disposition effect.

To summarize, while hitherto papers employing Oanda currency data concentrate on analyzing high frequency datasets with a rather limited time span, we take an alternative research route by employing a dataset that spans a very extensive time period. Furthermore, while Firth (2015) discovers that the size of the disposition effect has a positive relationship with inferior risk-adjusted investment performance , we investigate whether this relationship could affect our average retail investor.

Besides the disposition effect, another characteristic of individual investors' behavior discovered in many studies is their tendency of acting in a contrarian way, see Kaniel *et al.* (2008). Also the very recent study of Baltzer *et al.* (2019), who examine a vast dataset of the complete German stock market points towards private investors being contrarians while professional investors (funds and foreign investors) being momentum traders. As Kubińska *et al.* (2012) discover in an internet investment simulation study, contrarian traders are more prone to the disposition effect. Hence, we expect retail investors' actions in FX markets to be strongly driven by the disposition effect if they are indeed contrarian traders.

Concerning FX markets and the specific trading style of retail investors the research area is rather sparse. Koga *et al.* (2016) are one of the few studies to scrutinise the actions of retail investors in the FX market. They use an extensive dataset (July 2006-September 2011) covering the aggregate positioning of retail investors regarding 9 different currencies versus the JPY. Using a momentum-measure by Grinblatt *et al.* (1995) and distinguishing between buy momentum and sell momentum, they discover that Japanese retail investors are momentum traders for short horizons especially for sell trades against the JPY. The most extensive paper covering the trading style of retail investors, Menkhoff *et al.* (2016) pinpoints private investors as being contrarians as well. Menkhoff *et al.* (2016) use a 10-

year-dataset of order flow for up to 15 currencies and cover different types of investors. They find that the order flow contains significant information for future exchange rates and can be used for largely profitable investment strategies. As the order flow of professional investors is found to be linked to permanent shifts in future exchange rates, Menkhoff *et al.* (2016) interpret this as a sign for the superior ability of this group to process fundamental information. Meanwhile, the flows of individual investors seem to designate this group as uninformed. 'Bought minus sold' (BMS) portfolios (buy currencies with the highest, sell currencies with the lowest order flow) of the professional investors have a largely positive Sharpe Ratio of 1.79, while the portfolio of individual investors portfolio has a Sharpe ratio of -1.55 (Menkhoff *et al.*, 2016, p. 612). Menkhoff *et al.* (2016) also remark different trading styles of the subgroups of investors: While the professional investors tend to follow the trend regarding past currency returns, individual investors show strong signs of being 'contrarians' (Menkhoff *et al.*, 2016, p. 604).

Our analysis follows the preceding works, but investigates the reasons determining the trading style of retail investors more closely using quantile regression and focuses on different horizons. We show that position changes of retail investors largely depend on the preceding return distribution and on the investment horizon. Analyzing short and mid term horizons, the quantile regression shows that an average retail investor can be designated as contrarian investor. We therefore support the findings of Kaniel *et al.* (2008) for these horizons. However, investors in our sample also show trend following behavior in response to positive monthly past returns. These findings are similar to the analysis of Barber *et al.* (2009) on individual investors stock market performance. They find that individual investors are net sellers of stocks with strong performance over recent periods but net buyers of stocks with strong performance over longer periods (Barber, Odean & Zhu, 2009, p.545). The authors attribute this effect to the forward looking nature of buys and backward looking nature of sells. In the following, we describe our dataset and descriptively gain first impressions on the contrarian nature of the average retail investor following financial events with major impact on the currency markets.

3 Empirical analysis

3.1 Data description

The dataset stems from oanda.com, one of the largest retail currency trading platforms in the world with an average daily trading volume of 5.5 billion US$[5]. The positioning data contains the percentage of average daily open long positions of traders for 14 currency pairs at 4pm UTC, ranging from 24.04.2013 to 06.01.2018. E.g. a positioning of 75% in the EUR/USD currency pair at a given point of time t means that 75% of open positions in this currency pair were long EUR against USD, whereas 25% of open positions were short EUR against USD (or in other words long USD against EUR).

We obtain daily spot FX prices for the corresponding currency pairs and time point from the same source.

Descriptive statistics of the daily average percentage of long positions and the spot returns can be found in tables 3 and 4, respectively. For more than half of the currency pairs investors are on average net long with standard deviations of net long positioning ranging between 7% to 17%. The five currency pairs with the largest value of average net longs are negatively skewed, which means investors are in general more likely to be long these pairs. On the other hand, most of the currency pairs in which investors are on average short are Euro denominated (EUR/AUD, EUR/USD, EUR/GBP, EUR/GBP), which might be explained by diversification or hedging positions of European investors. Returns are all centered around 0 with similar standard deviations of 1% and varying signs of overkurtosis and mostly negative skew. All time-series show stationarity at a significance level of 5% based on the Augmented-Dickey Fuller test.

[5]fairreporters.net, average volume as of August 2016, measured between 1st of July and 15th of August.

3.2 Positioning around single events and correlation analysis

For simpler referencing and graphical illustration we group the positioning data in four subgroups.

[Figure 1 is about here.]

Figure 1 shows the grouped positions of each currency pair smoothed by a 20-day moving average for reasons of visibility of major trends and gives us insights into investors behavior during several major events from 2013 to 2018. Starting in June 2013, we observe a decrease in GBP/USD long positions, paired with an increase in EUR/GBP longs, most likely due to the selling pressure on the GBP fuelled by recession fears and David Camerons pledge to hold a referendum on Britain's membership in the EU.

[Figure 2 is about here.]

Figure 2 compares the 20-day average log price change and change in positioning of a subset of the GBP/USD and EUR/GBP on a rescaled basis. On average, investors seem to take a contrarian view to current market developments, increasing their positions in falling markets and decreasing them when markets rise. This behavior is most visible between May 2013 and August 2014 , while for other timeframes (e.g. for GBP/USD between October 2014 and June 2015) cyclical behavior does prevail.

[Figure 3 is about here.]

After the Brexit vote in June 2016, contrarian behavior of various degrees can be observed for all GBP related currency pairs in our dataset (see Figure 3).

Investor behavior around various single events is also visible in the CHF currency pairs, see Figure 4. GBP/CHF shows major increase in net long positions in August 2014, presumably driven by speculations of a hawkish UK inflation report on 13 August. After expectations were not met, positions were corrected and even changed into net short GBP/CHF. For the CHF revaluation in January 2015, results are mixed. The EUR/CHF, positions decrease in line with the revaluation and increase shortly after the reversal. For on the other hand USD/CHF contrarian behavior is strongly visible from mid 2013 to the end of 2014.

[Figure 4 is about here.]

A cross correlation analysis of relative changes in positioning x_t and log returns y_t gives us a more detailed picture of the relationship between both variables. While returns influencing positioning is rational from an investment perspective, changes in positioning might also be a valuable predictor for returns if investors are able to identify underlying price trends or reversals. To assess this presumption we calculate the cross correlation between returns and changes in positioning. As an example, figure 5 shows the results for six of the main currency pairs.

[Figure 5 is about here.]

The line in the middle of each picture shows the contemporaneous correlation of the returns and positioning changes for a lag$=0$, which is unsurprisingly the highest value (e.g. higher than -0.4 for the EUR/USD). The lines on the left hand side of each picture show the correlation between y_t and lagged changes in positioning x_{t-k}, $k = 1, \ldots, 25$. The opposite holds for the right hand side. A closer look at figure 5 shows that x_t is negatively correlated with y_t for most of the currencies, thus indicating contrarian behavior. Contemporaneous correlations are positive for the EUR/JPY and GBP/JPY, implying a short term trend following behavior. However, for both currency pairs the correlations between $x_{t+1,t+2}$ and y_t are again significantly negative. For the USD/CHF, USD/JPY and EUR/JPY, x_{t-1} does have small but significant correlation with y_t. In some cases, e.g. EUR/JPY, EUR/GBP and GBP/JPY, longer dated lags of changes in positioning still have significant correlation with future returns.

4 Trader positioning as source of information

Based on the observed patterns of behavior implied by the cross-correlograms, one of the questions that arise is if investors speculation on short term price trends or reversals is systematically paying off. On the other hand, we are interested if an individual investor could actually use the information on positioning published on oanda.com to improve his own trading behavior.

If the average investor is indeed timing the market correctly and increase long positions in falling markets while selling once markets have recovered, a replication strategy of his behavior should yield a positive payoff.

We study the daily performance of the average investor who holds an equally weighted portfolio of all 14 currency pairs based on the daily average positioning in our dataset. We group the currencies in four (foreign) currency denominated accounts: EUR, USD, JPY and GBP.

As an investment strategy, a long position for a currency pair at time t is established if at the same time more than 50% investors are long in this currency. If less than 50% of investors are long, we establish a short position in the currency. In this strategy, we are 'entirely long' or 'fully short' when the average positioning is above/below 50%. As a variation of this strategy (called $naive_{net}$), we take into account the magnitude of the respective long or short position: If e.g. 80% investors are long (and subsequently 20% are short), the resulting net difference of $80 - 20 = 60\%$ constitutes our 'net long position'. Assuming the base currency to be EUR, we convert all returns from a foreign currency position back to EUR once an opposite trade is established.

[Figure 6 is about here.]

Figure 6 shows the cumulative (EUR) return of the strategy described above (naive strategy) and a simple equally weighted buy&hold portfolio of all currency pairs (in EUR).

[6] Descriptive statistics of both strategies can be found in table 1.

[Table 1 is about here.]

The buy&hold portfolio yields an average yearly return of -0.43% with a maximum drawdown of 7.13%, while the naive strategy mimicking daily positioning leads to an average annual loss of -6.78%. The average investor would have suffered a maximum drawdown of 35.15%. Yearly volatilities are in similar ranges at 2.50% for the buy&hold portfolio, 2.61% for the naive strategy, respectively. Even though positions are adjusted daily, the average long position of the naive strategy has a duration of approximately 23 days, while the average short position lasts 13 days, see table 2.

[Table 2 is about here.]

To further study the reasons for underperformance, we investigate if investors suffer from the disposition effect, meaning selling winners too early and holding loser for too long.

Following Odean (1998) we calculate the proportions of winners realized (PWR) and proportions of losers realized (PLR) for every asset (currency) in our naive strategy as follows:

$$PWR = \frac{\text{\#of sales at gain}}{\text{\#of selling opportunities at gain}} \tag{1}$$

$$PLR = \frac{\text{\#of sales at loss}}{\text{\#of selling opportunities at loss}}. \tag{2}$$

First, we split the performance of each asset in the naive strategy into (net) long and (net) short positions. Second, every time the investor enters a position, we count a gain or loss as realized once the investor switches his position. For example, if the average positioning in EUR/USD at time t is long, the investor establishes a long position. Assume the average positioning in EUR/USD changes 10 days later at $t+10$ to short and the trade is closed. The realized return is calculated as the log-return between t and $t+10$. We count the number

[6] The $naive_{net}$ strategy yields qualitatively similar results which are ommited for the sake of brevity.

of selling opportunities during this time as the number of days the closing of the position would have resulted in a gain respectively loss in relation to the date the position was first established.

The average disposition effect d is defined as $d = PWR - PLR \in [-1; 1]$. An investor with measure of $d = 1$ will always seize his selling opportunities if those are in the profit area, while he will never sell a losing position.

Similar to Odean (1998) we test whether the difference of PWR and PLR is significant. We thereby aim to examine, whether there is a relationship between the investment performance of the naive strategy in the single currencies and a significant disposition effect, as Firth (2015) have documented a positive link between the size of the disposition effect and sub-par investment performance. Therefore, we calculate standard errors for each currency and for long and short positions separately:

$$se = \sqrt{\frac{PWR(1-PWR)}{n_{sg}+n_{sog}} + \frac{PLR(1-PLR)}{n_{sl}+n_{sol}}} \tag{3}$$

where n_{sg}, n_{sog}, n_{sl} and n_{sol} are the number of sales at gain, sale opportunities at gain, sales at loss and sale opportunities at loss. Following Firth (2015), we investigate the interrelationship between investment performance and the size of the disposition effect. We conduct this investigation separately for long and short positions to examine, whether long positions and short positions could be inherently different and display different behavioral characteristics. Table 5 shows this for long positions of the naive investment strategy in each currency, while table 7 displays the same analysis for short positions (table 6 and table 8 in the Appendix show the same analysis for the $naive_{net}$ strategy and the results are qualitatively similar).

[Table 5 is about here.] [Table 7 is about here.]

Regarding the Sharpe ratios of the average retail investors' long strategies, Table 5 shows that the risk-adjusted investment performance is negative in most of the markets (with the exception of the EUR/JPY currency pair). When ranking the strategies in ascending order, starting by those with the 'most negative' Sharpe ratios, we observe that out of the 5 worst strategies (the currency pairs EUR/USD, NZD/USD, AUD/USD, EUR/GBP, GBP/USD), 3 (NZD/USD, AUD/USD and GBP/USD) show a significant disposition effect. While this relationship does not seem overwhelming, the results of table 7, which analyzes the 'short leg' of the naive strategy, paints a more clear-cut picture: the investment performance of the average retail investor is quite bad in all markets (except AUD/JPY). More interestingly, linking investment performance and disposition effect, out of the 10 'most negative' Sharpe ratios, 8 have a significant disposition effect. To summarize: Especially when using short positions, our average investor shows a significant disposition effect which could be the decisive driver behind the disastrous risk-adjusted performance.

Furthermore, the naive trading strategy based on the positioning data of the average investor shows also a hefty asymmetry in realizing gains and losses. Comparing the average disposition effect d in table 5 and 7, we find that on average 18% of the available gains are realized, as opposed to 6.6% percent of available losses. For short positions, on average 28.8% of available gains are realized, while investors are realizing only 9.4% of losses. Hence investors are roughly 3 more likely to realize a gain as opposed to a loss in both trading directions. Analyzing more closely the different currency pairs in table 5 and table 7, the ratio PWR/PLR also shows this strong disposition effect of the average retail investor for allmost all currencies.

4.1 Quantile regression analysis

Given the systematic way positioning leads to negative performance and investors' asymmetric behavior in realizing gains and losses, we want to proceed by analyzing in more detail how returns influence positioning. Therefore, we study the relationship between previous positioning and returns using a quantile regression framework. Since our aim is not forecasting future returns or positioning but the simultaneous influence of positioning on returns, we deliberately include contemporaneous positioning and returns. Quantile regression allows us to drop the assumption that variables operate the same at the upper tails of the distribution as at the mean. Hence, this methodology allows us to identify how different subgroups of returns influence subsequent positioning and if investors react differently for price changes of different size and sign.

4.1.1 Methodology

In the quantile regression framework we are interested in estimating the effect of a set of n covariates, $x_{1,\dots,n}$ on the τ-th conditional quantiles $Q^{(\tau)}(y_t|x_t)$ of the distribution of positioning, see e.g. Koenker (2005). In contrast to our analysis in Section 3.2 we use a set of returns x_t to predict the distribution of future positioning. To keep the estimation parsimonious while including a large number of regressors we use daily returns x_t as well as weekly and monthly moving averages.

Give the relative change in positioning $y_t = \frac{Pos_t - Pos_{t-1}}{Pos_{t-1}}$, where Pos_t is the average investors positioning at time point t for a certain currency pair, the quantile regression equation for the p-th conditional quantiles $Q^{(\tau)}$ of the relative change in positioning can be written similar to a linear regression model as:

$$Q^{(\tau)}(y_t|x_{d;t}, x_{w;t}, x_{m;t}) = \beta_0^{(\tau)} + \beta_d^{(\tau)} \cdot x_{d;t} + \beta_w^{(\tau)} \cdot x_{w;t} + \beta_m^{(\tau)} \cdot x_{m;t} + \varepsilon_t^{(\tau)}, \qquad \varepsilon_t^{(\tau)} \overset{iid}{\sim} (0, \sigma^2), \quad (4)$$

where $x_{d;t}^{(\cdot)} = x_t$ is the short term, $x_{w;t}^{(\cdot)}$ and $x_{m;t}^{(\cdot)}$ are the average mid- and long term log returns. They are defined as $x_{w;t}^{(\cdot)} = 5^{-1}\sum_{i=1}^{5} x_{t-i+1}$ and $x_{m;t}^{(\cdot)} = 20^{-1}\sum_{i=1}^{20} x_{t-i+1}$. The model can be estimated using least squares by assuming that the conditional quantile functions $Q^{(\tau)}$ are only location (and more generally also scale) shifts of one another with a common slope parameter $\beta_0^{(\tau)} = \beta_0$, see e.g. Koenker & Bassett (1978).

4.1.2 Model fit and interpretation

We analyze the fit of the quantile regression analysis compared to a linear regression on our dataset to highlight the differences between both approaches and study the additional information about the return-positioning relationship.

Figure 8 exemplatory shows the quantile regression estimates (black) and standard deviations (grey) for the daily ($\beta_d^{(\tau)}$), weekly ($\beta_w^{(\tau)}$) and monthly ($\beta_m^{(\tau)}$) regressors for the USD/JPY and quantiles $\tau = 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95$ on the x-axis. Red solid and dotted line are the estimates and standard deviations for a corresponding linear regression. The daily and weekly parameter estimates for the simple regression are negative. This is consistent with the short term contrarian behavior as already indicated by our correlation analysis in section 3.2. However, the monthly regression parameter is positive but insignificant allowing for no clear interpretation. For a more detailed view we turn to Figure 7, which shows a summary of the estimated parameter values of the quantile regression for each of the 14 currencies and quantiles. Black dots mark parameter estimates that are significant at a 5% level. Overall, a significant relationship between contemporaneous returns and positioning can be observed for nearly all of the currencies. Short term parameters are negative except for the GBP/JPY and EUR/JPY, thus implicating contrarian behavior. The relationship is slightly stronger for upper quantiles, For the mid term (weekly) regressor a set of currencies shows significant negative relationship but mostly for quantiles $\tau = 0.5, 0.75$. In case of both currency pairs GBP/JPY and EUR/JPY, which showed short term trend following, weekly regressors indicate contrarian behavior. For EUR/JPY the effect is stronger for lower quantiles. The short term trend following behavior in both currencies could be explained by the safe-haven characteristics of the JPY and the assumption of a predominantly European client base in our sample. If home currencies such as the GPB and EUR devaluate quickly due to external effects, investors tend to react by quickly shifting into safe-haven currencies and hence selling their respective home currency against it. A reversal of the contrarian behavior can be observed for the long term (monthly) component, where the majority of currencies show a significant positive relationship with increasing magnitude for $\tau = 0.75, 0.9, 0.95$. Hence, positive long term return trends lead to similar trends in positioning, while the same does not hold (significantly) for the lower quantile and thus negative long term trends. Comparing our results to the results of Baltzer *et al.* (2019), we cannot pinpoint private investors as being simply contrarian investors. The quantile regression paints a more nuanced picture: While being contrarians in the short run, retail investors in the FX market try to "jump on the moving train" when they observe longer-lasting periods of positive returns. Our study of the investment performance of an average retail investors reveals, that they are (on average) not very successful in their endeavours, as the average retail investor is strongly affected by the disposition effect in both his long- and short strategies. Using the positioning data of oanda.com as input for an own trading strategy in FX markets therefore should always bear in mind this behavioral bias of the average retail investor.

5 Conclusion

This paper studies the trading behavior and performance of retail investors in the FX market based on aggregated positioning data provided by one of the largest FX platforms in the world. We analyze the interaction between positioning and price data of 14 currency pairs based on a quantile regression framework. We find signs of market timing behavior on different time-horizons as well as strong signs of the disposition effect. As a consequence, investors underperform a simple buy&hold strategy. While hedging and short squeezes might explain investors behavior on individual currencies, on average retail investors in the FX market confirm similar findings on behavioral biases from studies on equity and futures markets.

Appendix

	Naive Strategy	Naive long	Naive short	buy&hold
μ %	-6.78	-3.67	-3.24	-0.43
σ %	2.61	2.35	1.03	2.50
Sharpe Ratio	-2.60	-1.56	-3.13	-0.17
Max. Drawdown %	35.15	19.80	16.23	7.13
Calmar ratio	-0.19	-0.19	-0.20	-0.06

Table 1: Performance statistics naive strategy and buy&hold

	avg. holding long	avg. holding short
AUD/JPY	68.76	3.56
AUD/USD	18.58	6.08
EUR/AUD	4.57	46.92
EUR/CHF	43.55	11.29
EUR/GBP	8.79	21.15
EUR/JPY	4.32	13.93
EUR/USD	8.44	26.51
GBP/CHF	32.15	4.23
GBP/JPY	9.26	6.65
GBP/USD	12.88	11.62
NZD/USD	10.83	7.60
USD/CAD	11.17	12.65
USD/CHF	40.37	5.40
USD/JPY	42.48	6.88
Avg. holding period	22.58	13.17

Table 2: Average holding period in days for long and short positions of the naive strategy.

	AUD/JPY	AUD/USD	EUR/AUD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/CHF	GBP/JPY	GBP/USD	NZD/USD	USD/CAD	USD/CHF	USD/JPY
μ	64.27	56.43	37.31	63.82	44.30	44.03	42.70	60.87	51.72	48.59	52.34	49.60	61.87	59.03
σ	7.88	8.67	8.95	16.85	10.67	7.97	9.97	9.44	7.73	11.46	10.11	9.89	9.51	7.83
skew	-0.39	0.02	0.49	-0.23	0.30	0.18	0.30	-0.22	-0.09	-0.49	-0.05	0.12	-0.42	-0.36
kurt	-0.33	-0.60	0.78	-0.72	-0.22	-0.48	-0.45	0.40	-0.45	-0.64	-0.19	-0.23	-0.12	-0.32
pval ADF	0.01	0.01	0.02	0.03	0.01	0.01	0.01	0.01	0.01	0.05	0.01	0.01	0.01	0.01

Table 3: Descriptive statistics daily net long positions (%)

	AUD/JPY	AUD/USD	EUR/AUD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/CHF	GBP/JPY	GBP/USD	NZD/USD	USD/CAD	USD/CHF	USD/JPY
μ	-0.00	-0.00	0.00	-0.00	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00
σ	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01
skew	-0.65	-0.19	0.33	-13.61	1.13	-0.62	0.07	-4.98	-2.88	-2.21	-0.15	-0.21	-5.12	-0.13
kurt	4.60	1.81	2.49	322.52	12.03	7.99	1.93	73.31	43.26	33.04	2.09	2.11	82.77	3.59
pval ADF	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 4: Descriptive statistics daily spot returns

	AUD/JPY	AUD/USD	EUR/AUD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/CHF	GBP/JPY	GBP/USD	NZD/USD	USD/CAD	USD/CHF	USD/JPY
μ %	-0.02	-10.08	-0.75	-3.18	-4.32	0.01	-7.22	-3.72	-0.00	-4.24	-10.82	-3.22	-0.43	-0.01
σ %	0.10	8.40	1.56	8.28	5.79	0.04	4.60	10.26	0.10	7.44	7.63	4.01	9.53	0.07
Sharpe Ratio	-0.15	-1.20	-0.48	-0.38	-0.74	0.15	-1.57	-0.36	-0.03	-0.57	-1.42	-0.80	-0.04	-0.10
Max. Drawdown %	0.28	64.12	5.93	24.75	30.16	0.08	43.00	28.37	0.31	34.47	63.48	18.79	18.87	0.18
Calmar ratio	-0.05	-0.16	-0.13	-0.13	-0.14	0.08	-0.17	-0.13	-0.01	-0.12	-0.17	-0.17	-0.02	-0.04
PWR	0.11	0.16	0.45	0.04	0.11	0.36	0.22	0.04	0.19	0.25	0.28	0.19	0.03	0.09
PLR	0.00	0.04	0.16	0.02	0.12	0.16	0.11	0.03	0.07	0.04	0.07	0.07	0.02	0.01
$d = PWR - PLR$	0.10	0.12	0.29	0.03	-0.01	0.20	0.11	0.02	0.12	0.21	0.20	0.12	0.01	0.08
t-stat	3.67	3.58	2.91	1.67	-0.19	4.10	1.22	1.38	4.67	5.61	4.17	3.07	1.00	4.20
n_{sg}	12.00	17.00	9.00	8.00	7.00	36.00	4.00	15.00	45.00	28.00	19.00	18.00	10.00	18.00
n_{sog}	113.00	105.00	20.00	181.00	65.00	100.00	18.00	355.00	240.00	110.00	69.00	96.00	304.00	194.00
n_{sl}	5.00	33.00	12.00	14.00	32.00	30.00	30.00	19.00	32.00	22.00	47.00	34.00	17.00	7.00
n_{sol}	1056.00	824.00	76.00	775.00	277.00	185.00	268.00	738.00	473.00	534.00	646.00	485.00	786.00	868.00
PWR/PLR	22.43	4.04	2.85	2.45	0.93	2.22	1.99	1.64	2.77	6.18	3.78	2.67	1.52	11.51

Table 5: Test for difference of PWR and PLR for long positions and performance for the naive investment strategy

	AUD/JPY	AUD/USD	EUR/AUD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/CHF	GBP/JPY	GBP/USD	NZD/USD	USD/CAD	USD/CHF	USD/JPY
μ %	-0.02	-3.53	-0.00	-2.33	-1.01	0.00	-1.20	-2.13	0.01	-1.48	-2.55	-0.57	-0.74	-0.01
σ %	0.04	2.34	0.22	3.75	0.91	0.00	0.72	4.78	0.02	1.36	1.70	0.68	4.47	0.02
Sharpe Ratio	-0.46	-1.51	-0.01	-0.62	-1.11	0.32	-1.66	-0.45	0.63	-1.09	-1.50	-0.84	-0.17	-0.64
Max. Drawdown %	0.15	21.03	0.64	13.27	6.32	0.01	6.79	14.04	0.03	8.88	13.94	3.48	12.53	0.10
Calmar ratio	-0.12	-0.17	-0.00	-0.18	-0.16	0.21	-0.18	-0.15	0.36	-0.17	-0.18	-0.16	-0.06	-0.14
PWR	0.06	0.15	0.31	0.11	0.13	0.33	0.20	0.04	0.12	0.21	0.32	0.16	0.04	0.11
PLR	0.01	0.04	0.19	0.02	0.11	0.16	0.11	0.03	0.09	0.05	0.06	0.07	0.02	0.01
$d = PWL - PLR$	0.05	0.11	0.12	0.09	0.03	0.17	0.09	0.01	0.03	0.16	0.26	0.09	0.03	0.10
t-stat	2.76	3.65	1.36	2.48	0.60	3.68	0.90	1.10	1.35	4.50	5.69	2.67	2.08	3.91
n_{sg}	9.00	19.00	8.00	7.00	9.00	39.00	3.00	13.00	43.00	24.00	27.00	20.00	13.00	15.00
n_{sog}	146.00	128.00	26.00	64.00	67.00	118.00	15.00	320.00	349.00	114.00	85.00	128.00	298.00	131.00
n_{sl}	8.00	31.00	13.00	15.00	30.00	27.00	31.00	21.00	34.00	26.00	39.00	32.00	14.00	10.00
n_{sol}	1023.00	801.00	70.00	894.00	276.00	167.00	272.00	773.00	364.00	530.00	630.00	453.00	792.00	931.00
PWR/PLR	7.88	3.84	1.66	6.52	1.24	2.04	1.75	1.50	1.32	4.29	5.13	2.21	2.47	10.66

Table 6: Test for difference of PWR and PLR for long positions and performance for the naive investment strategy based on net positioning

	AUD/JPY	AUD/USD	EUR/AUD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/CHF	GBP/JPY	GBP/USD	NZD/USD	USD/CAD	USD/CHF	USD/JPY
μ %	0.00	-6.22	-3.17	-2.53	-4.96	-0.00	-5.98	-2.70	-0.00	-2.65	-8.62	-5.71	-1.21	-0.03
σ %	0.01	3.91	5.40	1.83	8.37	0.06	5.13	2.00	0.05	3.79	5.52	3.46	1.90	0.03
Sharpe Ratio	0.34	-1.59	-0.59	-1.38	-0.59	-0.03	-1.17	-1.35	-0.10	-0.70	-1.56	-1.65	-0.63	-0.89
Max. Drawdown %	0.03	34.19	17.81	12.75	34.38	0.16	30.90	13.53	0.24	17.77	46.81	31.30	7.48	0.21
Calmar ratio	0.18	-0.18	-0.18	-0.20	-0.14	-0.01	-0.19	-0.20	-0.02	-0.15	-0.18	-0.18	-0.16	-0.13
PWR	0.50	0.15	0.19	0.50	0.10	0.21	0.10	0.47	0.23	0.29	0.31	0.30	0.30	0.39
PLR	0.20	0.17	0.01	0.07	0.04	0.03	0.03	0.20	0.11	0.05	0.10	0.05	0.16	0.09
$d = PWR - PLR$	0.30	-0.02	0.18	0.43	0.06	0.18	0.06	0.27	0.12	0.24	0.21	0.25	0.14	0.30
t-stat	2.61	-0.55	3.77	3.64	2.72	6.55	1.91	2.55	3.69	5.40	4.41	5.39	1.60	3.82
n_{sg}	8.00	13.00	11.00	6.00	16.00	42.00	7.00	8.00	40.00	25.00	24.00	23.00	7.00	12.00
n_{sog}	16.00	88.00	57.00	12.00	161.00	198.00	72.00	17.00	173.00	87.00	77.00	76.00	23.00	31.00
n_{sl}	8.00	36.00	13.00	15.00	25.00	25.00	28.00	23.00	37.00	25.00	43.00	28.00	18.00	12.00
n_{sol}	41.00	210.00	1068.00	225.00	706.00	735.00	856.00	114.00	339.00	494.00	432.00	569.00	112.00	134.00
PWR/PLR	2.56	0.86	15.85	7.50	2.81	6.24	2.97	2.33	2.12	5.68	3.13	6.15	1.89	4.32

Table 7: Test for difference of PWR and PLR for short positions and performance for the naive investment strategy

	AUD/JPY	AUD/USD	EUR/AUD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/CHF	GBP/JPY	GBP/USD	NZD/USD	USD/CAD	USD/CHF	USD/JPY
μ %	0.00	-0.69	-1.57	-0.69	-1.96	-0.00	-2.50	-0.40	-0.00	-0.96	-1.54	-1.44	-0.18	-0.00
σ %	0.00	0.46	1.62	0.53	2.03	0.01	1.10	0.30	0.01	0.87	0.87	0.66	0.28	0.00
Sharpe Ratio	0.03	-1.51	-0.97	-1.31	-0.97	-0.30	-2.27	-1.31	-0.08	-1.10	-1.78	-2.19	-0.65	-1.14
Max. Drawdown %	0.00	3.53	8.46	3.48	12.03	0.06	12.42	1.98	0.04	5.37	8.02	7.60	1.14	0.03
Calmar ratio	0.01	-0.20	-0.19	-0.20	-0.16	-0.06	-0.20	-0.20	-0.02	-0.18	-0.19	-0.19	-0.16	-0.15
PWR	0.39	0.12	0.06	0.22	0.08	0.12	0.17	0.39	0.21	0.15	0.30	0.27	0.24	0.33
PLR	0.23	0.21	0.01	0.04	0.04	0.04	0.02	0.21	0.12	0.07	0.10	0.05	0.16	0.08
$d = PWL - PLR$	0.16	-0.09	0.05	0.18	0.05	0.08	0.15	0.18	0.10	0.09	0.20	0.22	0.08	0.24
t-stat	1.38	-2.29	3.14	3.47	2.01	4.82	3.94	1.70	3.02	2.83	4.46	4.66	1.11	3.66
n_{sg}	7.00	20.00	14.00	13.00	13.00	47.00	15.00	7.00	38.00	21.00	26.00	20.00	9.00	14.00
n_{sog}	18.00	163.00	235.00	58.00	153.00	388.00	87.00	18.00	177.00	138.00	87.00	73.00	37.00	43.00
n_{sl}	9.00	29.00	10.00	8.00	28.00	20.00	20.00	24.00	39.00	29.00	41.00	31.00	16.00	10.00
n_{sol}	39.00	135.00	891.00	179.00	714.00	545.00	841.00	113.00	335.00	443.00	422.00	572.00	98.00	122.00
PWR/PLR	1.69	0.57	5.31	5.02	2.17	3.30	7.25	1.83	1.84	2.32	3.08	5.06	1.49	3.97

Table 8: Test for difference of PWR and PLR for short positions and performance for the naive investment strategy based on net positioning

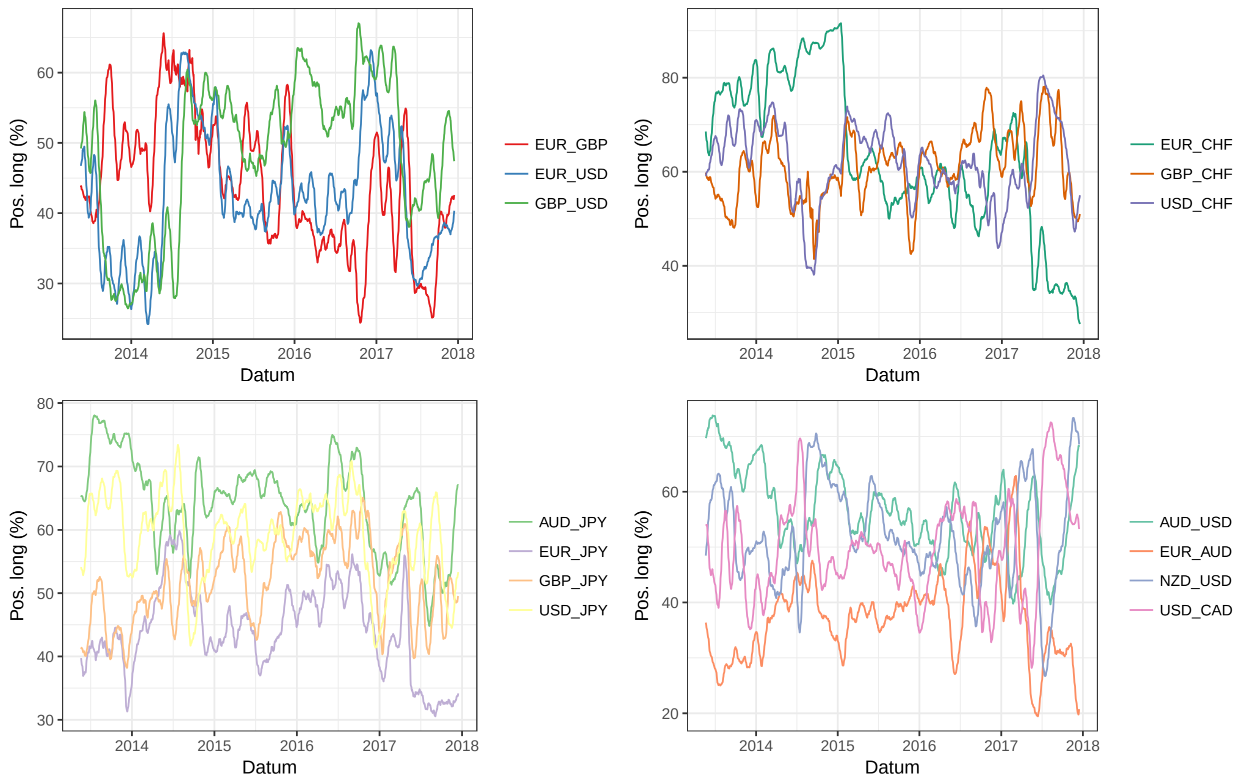

Figure 1: Smoothed daily net long positions (%)

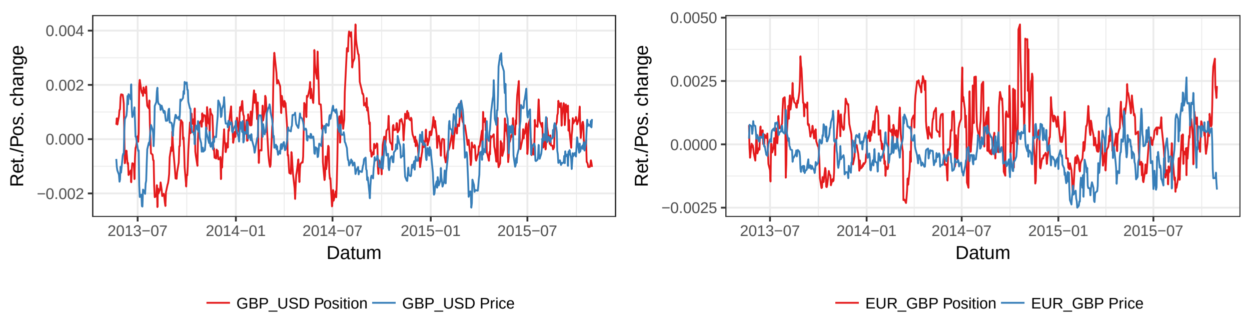

Figure 2: 20-day average log price change and change in positioning (rescaled)

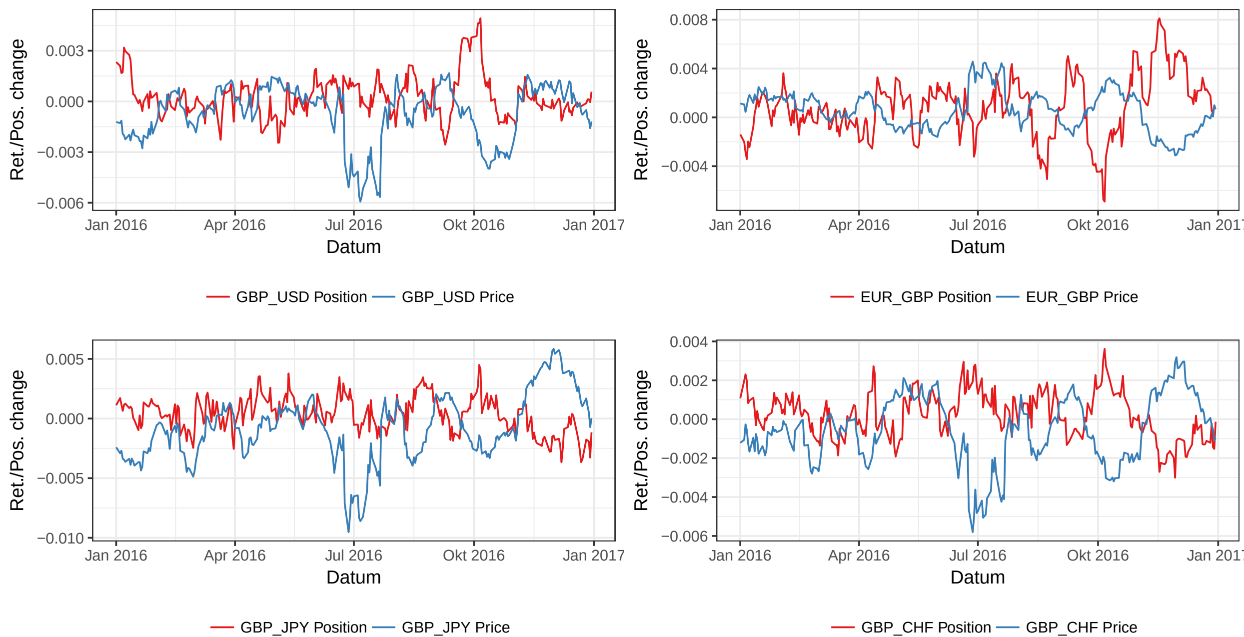

Figure 3: 20-day average log price change and change in positioning (rescaled) for GBP currency pairs

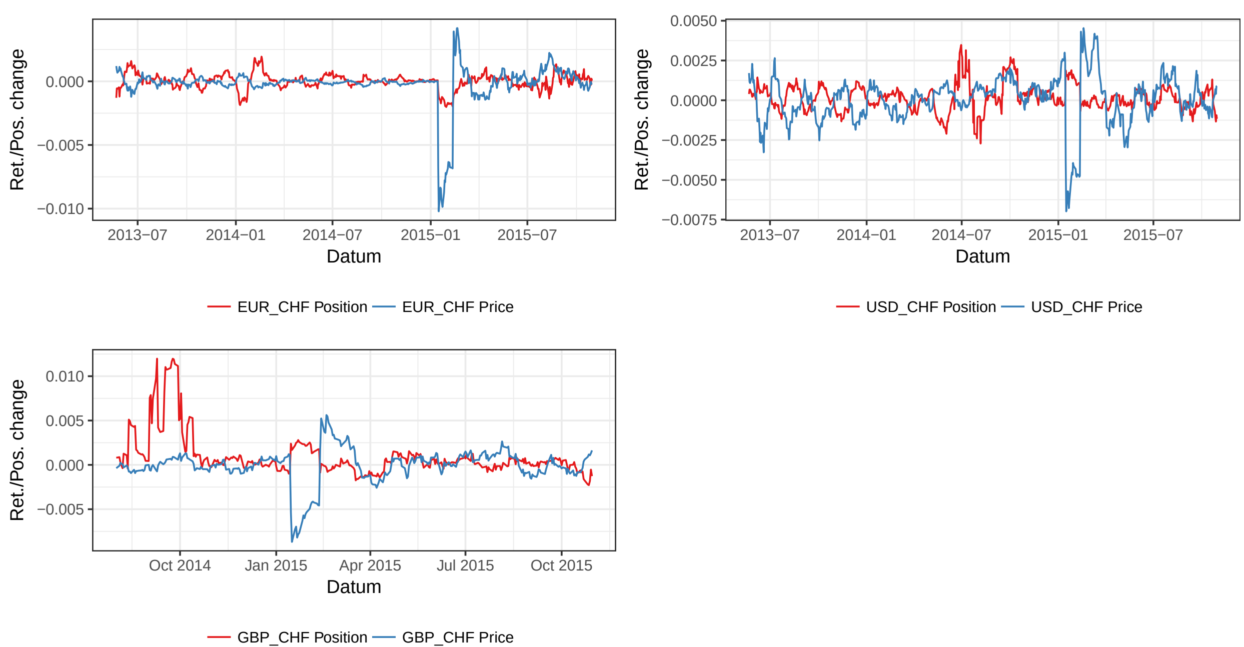

Figure 4: 20-day average log price change and change in positioning (rescaled) for CHF currency pairs

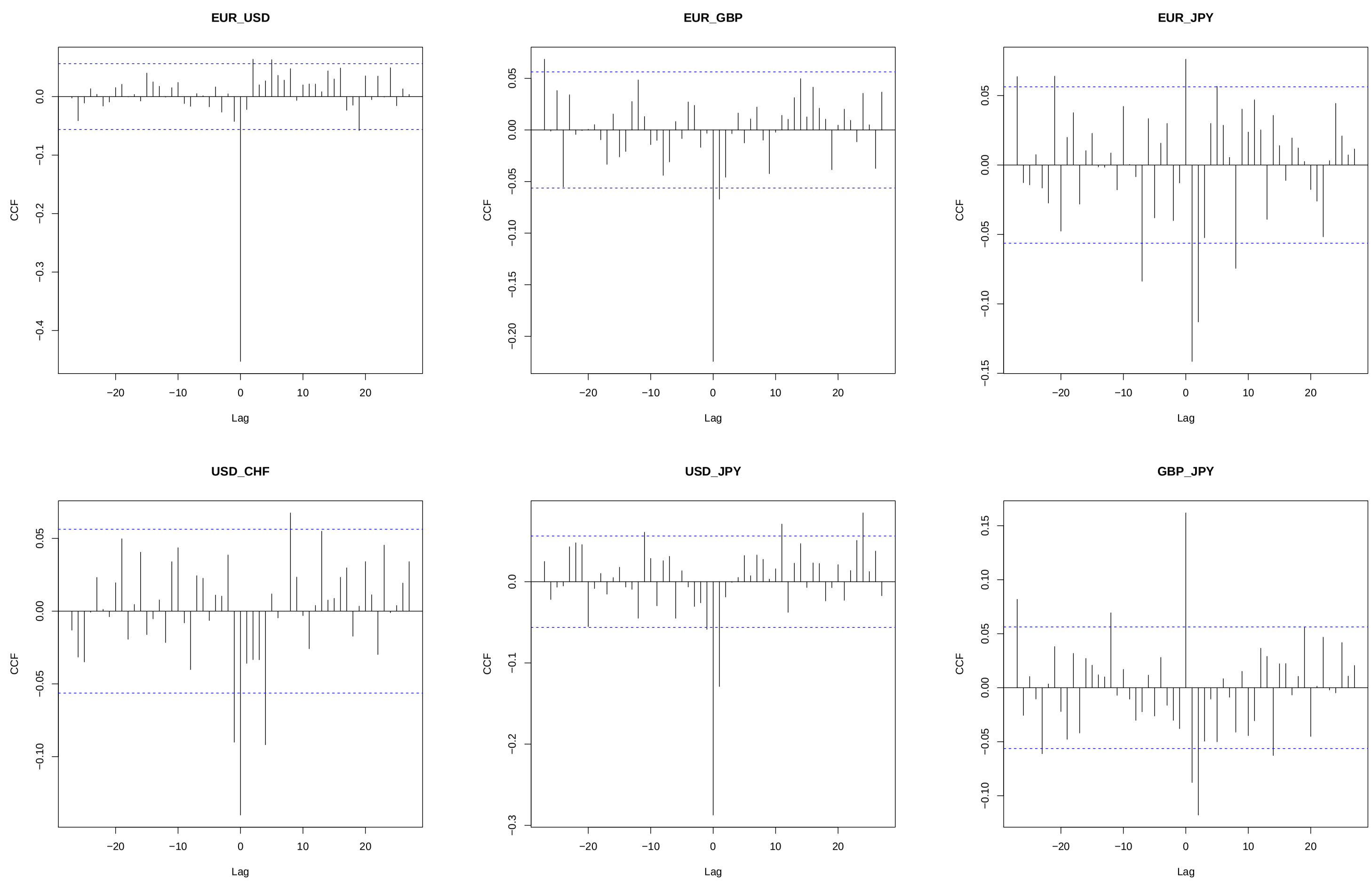

Figure 5: Cross correlation functions for return and positioning change for different currency pairs.

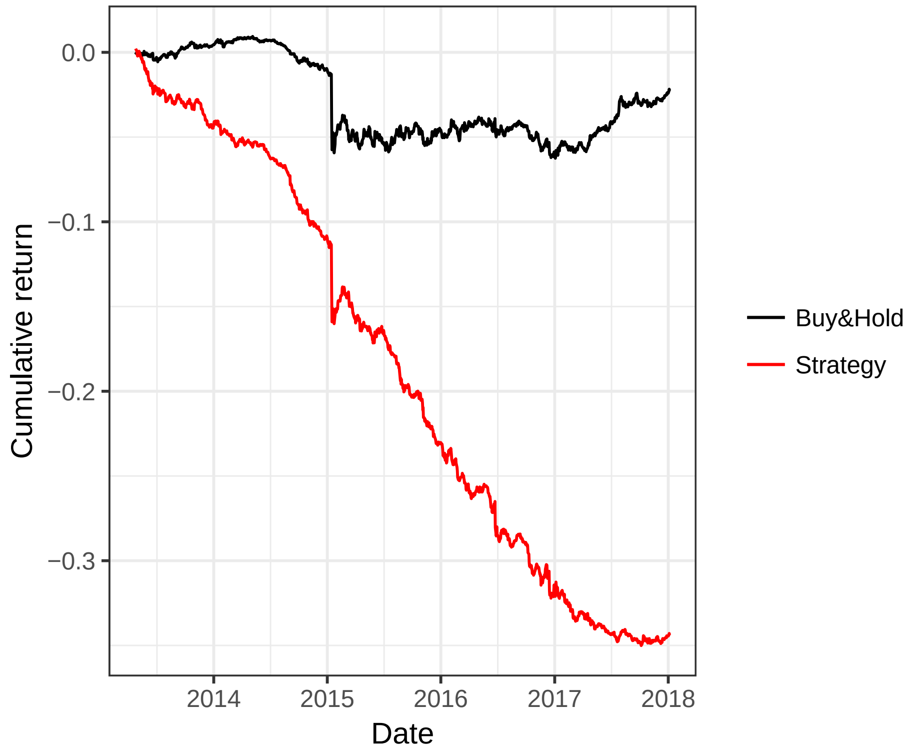

Figure 6: Cumulative return of naive strategy and buy&hold.

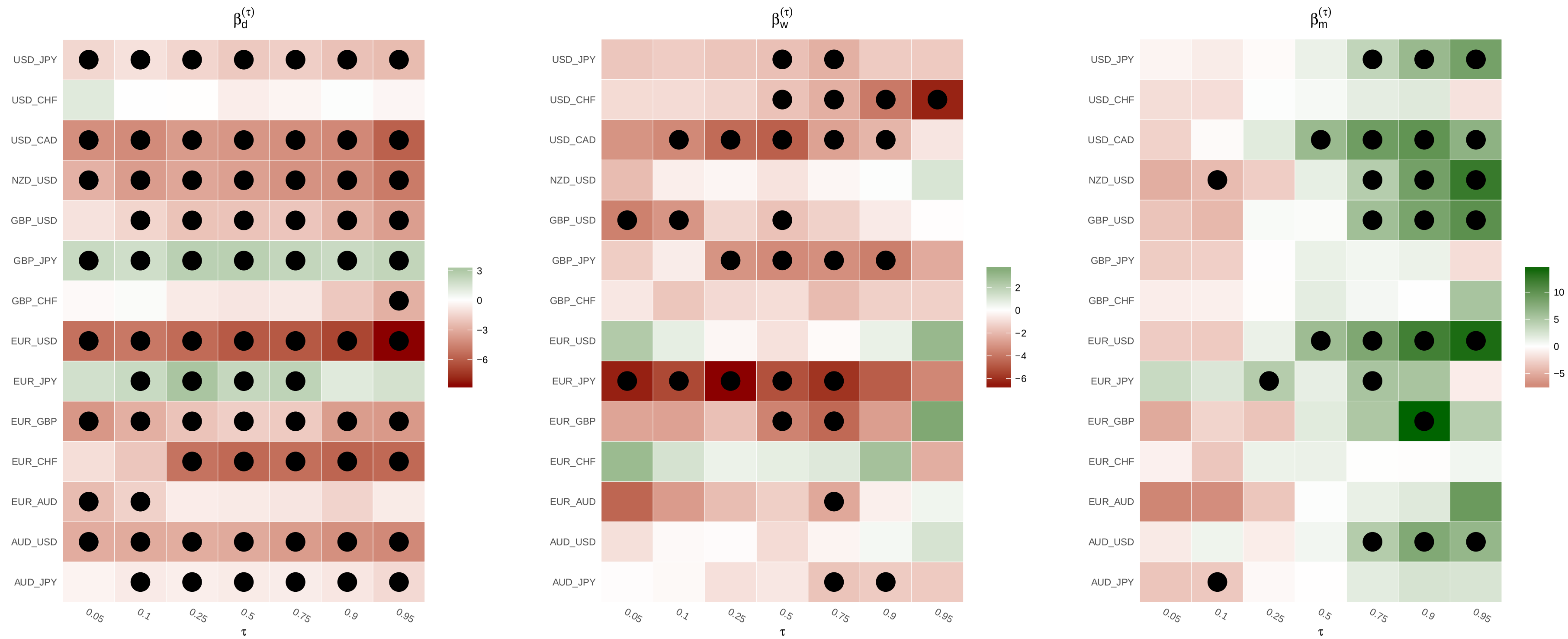

Figure 7: Quantile regression estimates for the daily ($\beta_d^{(\tau)}$), weekly ($\beta_w^{(\tau)}$) and monthly ($\beta_m^{(\tau)}$) regressors for all currency pairs and quantiles τ on the x-axis from 0.05 to 0.95. Black dots mark parameters which significant at a 5% level.

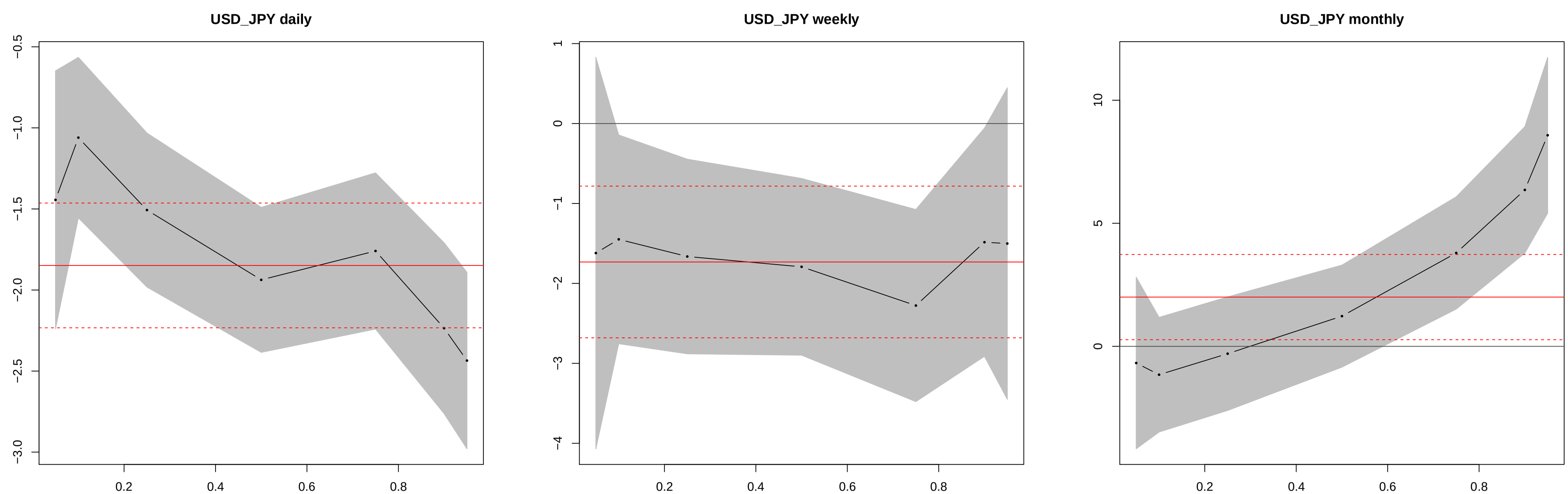

Figure 8: Quantile regression estimates (black) and standard deviations (grey) for the daily ($\beta_d^{(\tau)}$), weekly ($\beta_w^{(\tau)}$) and monthly ($\beta_m^{(\tau)}$) regressors for the USD/JPY and quantiles τ on the x-axis from 0.05 to 0.95. Red solid and dotted line are the estimates and standard deviations for a corresponding linear regression.

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