

Momentum and trend following trading strategies for currencies and bitcoin [☆]

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Abstract

Momentum trading strategies are thoroughly described in the academic literature and used in many trading strategies by hedge funds, asset managers, and proprietary traders. Baz et al. (2015) describe a momentum strategy for different asset classes in great detail from a practitioner's point of view. Using a geometric Brownian Motion for the dynamics of the returns of financial instruments, we extensively explain the motivation and background behind each step of a momentum trading strategy. Constants and parameters that are used for the practical implementation are derived in a theoretical setting and deviations from those used in Baz et al. (2015) are shown. The trading signal is computed as a mixture of exponential moving averages with different time horizons. We give a statistical justification for the optimal selection of time horizons. Furthermore, we test our approach on global currency markets, including G10 currencies, emerging market currencies, and cryptocurrencies. Both a time series portfolio and a cross-sectional portfolio are considered. We find that the strategy works best for traditional fiat currencies when considering a time series based momentum strategy. For cryptocurrencies, a cross-sectional approach is more suitable. The momentum strategy exhibits higher Sharpe ratios for more volatile currencies. Thus, emerging market currencies and cryptocurrencies have better performances than the G10 currencies. This is the first comprehensive study showing both the underlying statistical reasons of how such trading strategies are constructed in the industry as well as empirical results using a large universe of currencies, including cryptocurrencies.

Keywords: Momentum, Currency Markets, G10, Emerging Markets, Cryptocurrencies, Bitcoin, Moving Average Crossover, Cross-Sectional Momentum, Time Series Momentum, Trend-Following

JEL: C40, C50, G00, G10, G15, G17, F17, F30, F31, F32

1. Introduction

Momentum is a traditional strategy for currency trading. Past winners are likely to continue to perform well, and past losers are likely to continue to do badly. To execute this strategy, one buys currencies that performed well and sells currencies that performed badly in the past. Momentum returns contradict the efficient market hypothesis. There exist various theories that try to explain the existence of these returns (Asness et al., 2013).

We use an algorithm presented by Baz et al. (2015) to generate the momentum signal, based on three crossovers of exponential moving averages with different time horizons. The three different crossovers identify short-, intermediate-, and long-term trends respectively. A signal is generated for each time horizon. The three signals are then combined to build the trade signal. Baz et al. (2015) showed that

this approach works well for various asset classes. We set the focus on foreign exchange markets and detail how the algorithm works by applying it to normally distributed returns. The algorithm is then used to conduct a backtest on real data, divided into three different currency categories. The investigated currency categories are the G10 currencies, the emerging market currencies, and the cryptocurrencies. For each category, we show in which periods the strategy worked and in which periods it did not.

This paper examines a strategy that is used in practice. In contrast to other papers about momentum strategies, daily data is used instead of monthly data. The strategy is an extension of simple traditional strategies that are usually analyzed in academic papers.

2. Related literature

Multiple academic studies focus on momentum strategies in the foreign exchange market. Okunev and White (2003) argue that the profitability of momentum strategies in foreign exchange markets was particularly strong during the second half of the 1990s. They claim that it holds for 2001 as well.

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On the contrary, Olson (2004) uses 18 exchange rates to test whether trend following overlay profits diminished over the period from 1971 to 2000. His results show that profits based on risk-adjusted trading rules have indeed dropped over time.

Pukthuanthong-Le et al. (2007) examine futures contracts of the leading currencies of the last 30 years as well as contracts on different currencies. They conclude that the markets are adapted so far that it is not possible anymore to make easy profits by trading with a simple moving average strategy in the main foreign currencies. On the contrary, momentum trading strategies seem to work better on new trading currencies.

Neely et al. (2009) analyze the profitability of technical trading rules in the foreign exchange market over time. They conclude that these easy profits vanished in the early 1990s due to filter and moving average rules. They argue that the returns of less-studied rules have also declined but have not completely disappeared.

Burnside et al. (2011) review three possible explanations for the apparent profitability of the carry trade and the momentum strategy. The first explanation shows the returns as compensation for bearing risk. The second one explains the returns with the vulnerability of carry and momentum strategies to crashes and peso problems. The third explanation is the pricing pressure in currency markets.

Kroencke et al. (2011) take a look at the characteristics and behavior of trend following overlay based currency investments in a portfolio context. They show statistically significant and economically convincing enhancements and claim that an internationally diversified stock portfolio augmented with a foreign exchange investment generates up to 30% higher returns per unit of risk compared to a benchmark portfolio.

Gyntelberg and Schrimpf (2011) analyze the downside risk properties of momentum and other multi-currency investment strategies and show their performance during historical financial market turbulences.

Pojarliev and Levich (2012) take a new look at currency management by applying an established methodology to currency funds and answer fundamental questions such as: Do style factors explain currency returns? Is managerial performance or management style persistent? Do currency managers add value to well-diversified global equity portfolios?

On the basis of the convex relation between momentum and market returns, Kent et al. (2012) develop a hidden Markov model to identify periods in which large losses are more likely. They claim that their estimated model beats alternative models in predicting tail events of moving average trading strategies.

Moskowitz et al. (2012) examine the momentum strategy across all asset classes based on a time series portfolio. They state that a diversified portfolio delivers extraordinary returns with little exposure to standard asset pricing factors and performs best during extreme markets. Additionally, they find that speculators profit from time series

momentum at the expense of hedgers.

Menkhoff et al. (2012) find excess returns of up to 10% per annum (p.a.). They also find that returns positively correlate with idiosyncratic volatility.

Amen (2013) shows that a combination of trend and carry, can be used as a risk indicator for the foreign exchange market and analyze the relationship between bank indices and generic foreign exchange trading styles.

Olszwecki and Zhou (2013) analyze the combination of carry and momentum trading and find evidence that it enables a substantial improvement in risk-adjusted returns. They underline the possible profits of a strategy diversification with their analysis using data of a period of 20 years.

Asness et al. (2013) examine eight different market and asset classes and find substantial profits with the value and the momentum strategy. In the process, they recognize a strong common structure in their returns. Furthermore, they developed a three-factor model which represents the global risk. The financing illiquidity risk is a part which can only be identified if both strategies are examined simultaneously.

Accominotti and Chambers (2014) apply simple technical trading rules like momentum to the market in the 1920s and 1930s. They analyze the excess returns and find that they are also present in this early period.

Raza et al. (2014) examine a sample of 63 currencies of emerging and developed markets and analyze if there is momentum or reversal in weekly returns. They find that momentum appears to be the dominant phenomenon in short horizon (one- to four-week) foreign exchange rate returns rather than reversal.

Geczy and Samonov (2015) analyze the returns of the momentum strategy across and inside of multiple assets from 1800 until 2014. They confirm significant premiums for this 215-year long period.

Goyal and Jegadeesh (2015) concentrate on the return difference of the time series and the cross-sectional strategy in momentum. They find that the difference is mainly due to the time-varying long positions that the time series strategy takes in the market.

Barroso and Santa-Clara (2015b) find that one has to manage the highly volatile risk of the momentum by predicting it. Once the risk is managed, the crashes of the strategy are eliminated, and the Sharpe ratio is nearly doubled.

Barroso and Santa-Clara (2015a) compose currency portfolios and test the relevance of technical and fundamental variables. They argue that carry, momentum and value investing generate returns that are not explained by risk. Exposure to currencies diversifies a portfolio of stocks and bonds. They show an increase in the Sharpe ratio of 0.5 on average while reducing the risk of a crash. They assert that besides risk, currency returns mirror the scarcity of speculative capital.

Orlov (2016) examines the excess of currency momentum and carry trade strategies on the effect of equity market

illiquidity. His results show that the profits of the currency momentum strategy are low after months of high equity market illiquidity. He asserts that their development is therefore explained by the equity market illiquidity.

Bae and Elkamhi (2016) explain the excess returns of the carry and the momentum trading speculation strategy on a risk-based theory. They create a global equity correlation factor and reveal that this explains the variation in average excess returns of the momentum and the carry trading strategy as well.

Orfanakos (2016) shows that overweighting and underweighting momentum according to a function of volatility leads to significant improvements in Sharpe ratio and skewness.

Osterrieder (2016), Osterrieder and Lorenz (2016) and Osterrieder et al. (2016b) provide a statistical analysis of the returns of the most important cryptocurrencies. Their findings show that cryptocurrencies exhibit strong non-normal characteristics, large tail dependencies, and heavy tails.

Osterrieder et al. (2016a) fit parametric distributions to the exchange rates of the most important cryptocurrencies versus the US Dollar and characterize them. They find that, depending on the cryptocurrency, the most suitable fits are given by the generalized hyperbolic distribution, the Normal inverse Gaussian distribution, the Generalized t distribution and the Laplace distribution.

Daniel and Moskowitz (2016) indicate that despite the persistent returns, momentum strategies suffer occasional crashes.

Filippou et al. (2016) and Grobys et al. (2016) observe that the global economic risk can partially explain momentum returns. The investor is compensated for the exposure to global economic risk when holding foreign currencies.

3. Data

In this section, the data that is used for all calculations is described.

Our primary data source was the FRED database provided by the Federal Reserve Bank of St. Louis¹. The database contains daily foreign currency exchange rates of 23 countries (Board of Governors of the Federal Reserve System (US), 2017). The foreign currency was always used as the base currency and the USD as the quote currency. Therefore, all currency pairs describe how many USD one unit of the foreign currency can buy. Currencies that are quoted with the USD as the base currency were inverted to have consistent data.

For the G10 currency category, the currencies of the ten countries known as the G10 were selected. Only nine currency pairs are used, since the USD is included as the quote currency. The currency pairs are AUD/USD,

CAD/USD, CHF/USD, EUR/USD, GBP/USD, JPY/USD, NOK/USD, NZD/USD, and SEK/USD.

For the emerging market currency category, out of the available currency pairs on FRED, the currencies of the countries indexed by MSCI as emerging markets were selected (MSCI, 2017). Those are BRL/USD, INR/USD, KRW/USD, MXN/USD, THB/USD, TWD/USD, and ZAR/USD. The Chinese Renminbi and the Malaysian Ringgit were not included, since those two currencies were pegged to the USD for a long period.

Another source was Eurostat, the statistical office of the European Union². Their database includes the daily exchange rate of ECU/USD. ECU is the European Currency Unit, a weighted bucket of the former currencies of the Euro area (Eurostat, 2017). This exchange rate was used as a proxy for the EUR/USD exchange rate before 1999.

For the cryptocurrencies, the BNC2 data set³ from Quandl (2017) was used. The exchange rates are aggregated from multiple exchanges and weighted by volume. Closing prices were used for all calculations. For the selection of cryptocurrencies, seven out of the fifteen cryptocurrencies with the highest market capitalization as of February 2017 and a data history of at least two and a half years were selected (Coinmarketcap, 2017). Those are Bitcoin, Dash, Dogecoin, Litecoin, Maidsafecoin, Monero and Ripple.

A list of all used data, figures of the time series and histograms of the arithmetic returns as well as annualized volatilities of all currency pairs can be found in Appendix A.

4. Algorithm

This section shows how the algorithm works on the basis of normally distributed returns.

4.1. Normally distributed returns

To simulate an exchange rate with normally distributed returns, a geometric Brownian Motion (GBM) was used. It has the following stochastic differential equation.

$$dP_t = \mu P_t dt + \sigma P_t dB_t \quad (1)$$

where B_t is standard Brownian Motion, μ is the percentage drift, σ is the percentage volatility, and P_t is the generated currency rate. Using Itô's lemma, the following solution is derived.

$$P_t = P_0 \cdot e^{\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma B_t}, \quad t \in [0, T] \quad (2)$$

where T denotes the final time horizon. The exchange rate at $t = 0$ is set to $P_0 = 1$. The expected annual return is set to $\mu = 0$ assuming there is no drift. Therefore, our simulated time series is a martingale.

¹<https://fred.stlouisfed.org/categories/94>

²<http://ec.europa.eu/eurostat/web/exchange-rates/data/database>

³<https://www.quandl.com/data/BNC2>

An annualized volatility of $\sigma = 0.05$ was assumed, corresponding to the historical annualized volatility of EUR/USD.

We simulate 100 years ($t = 1, 2, \dots, 100$) with a step size of $\Delta t = \frac{1}{365.24}$. Note that there is no differentiation between weekdays and weekends. Therefore our simulated time series has 365.24 data points per year instead of 252. One particular path of the exchange rate can be seen in Figure 1.

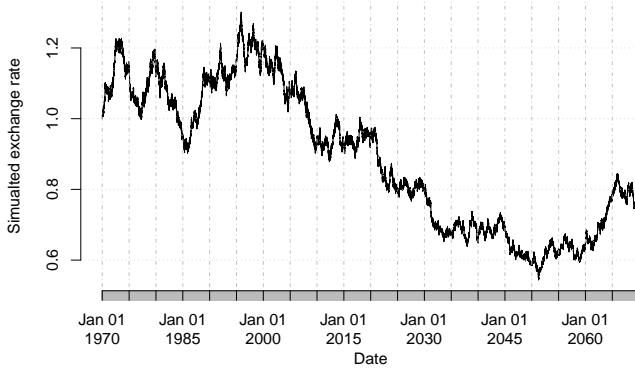


Figure 1: Stochastic simulation of an exchange rate using geometric Brownian Motion.

Figure 2 shows the daily arithmetic returns calculated by $\frac{P_t - P_{t-1}}{P_{t-1}}$.

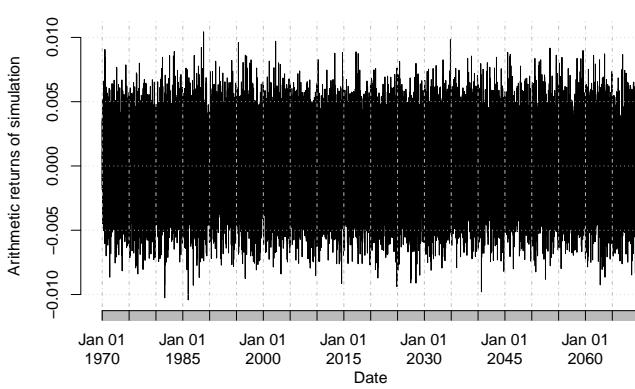


Figure 2: Daily arithmetic returns of the simulation.

The daily arithmetic returns are approximately normally distributed as shown in Figure 3.

4.2. Exponential moving average

The exponential moving average (EMA) is an infinite impulse response filter with exponentially decaying weights. The following formula shows the recursive calculation.

$$EMA_t(P, \alpha) = \begin{cases} P_0 & t = 0 \\ \alpha \cdot P_t + (1 - \alpha) \cdot EMA_{t-1}(P, \alpha) & t > 0 \end{cases} \quad (3)$$

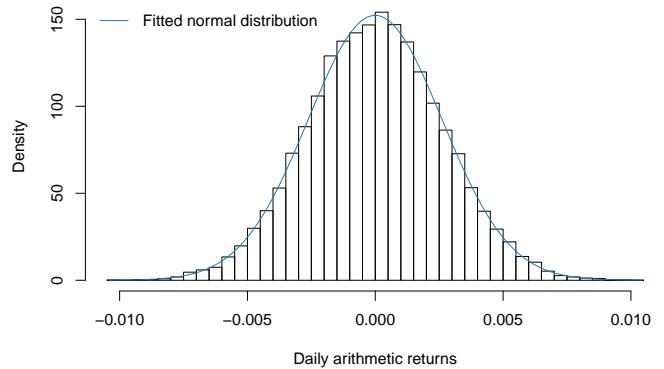


Figure 3: Histogram of daily arithmetic returns.

where $\alpha = \frac{1}{n_k}$ is the exponential smoothing ratio according to Wilder (1978) and n_k is explained in the next section.

4.3. Crossing EMAs for different time-periods

Three different time periods were selected, each with an n_k for a short and a long EMA. We adopt $n_{k,s} = (8, 16, 32)$ for the short EMAs and $n_{k,l} = (24, 48, 96)$ for the long EMAs from Baz et al. (2015).

Note that n_k is not the duration of the filter, and not the half-life time either. The length of the EMA at time t is always $[0, t]$. Equation 4 calculates the half-life.

$$HL = \frac{\log(0.5)}{\log(1 - \alpha)} = \frac{\log(0.5)}{\log(1 - \frac{1}{n_k})} \quad (4)$$

Table 1 shows the half-life for each n_k . Increasing the n_k by factor two results in a half-life that is approximately twice as long. The half-life of our EMAs lies between one week for $n_k = 8$ and about three months for $n_k = 96$.

Table 1: Half-life of the different EMAs.

n_k	HL
$n_{1,s} = 8$	5.2 days
$n_{2,s} = 16$	10.7 days
$n_{3,s} = 32$	21.8 days
$n_{1,l} = 24$	16.3 days
$n_{2,l} = 48$	32.9 days
$n_{3,l} = 96$	66.2 days

To see where the EMAs are crossing, we zoom into the year 2050 of our simulation. Figure 4 shows the two EMAs for $k = 1$. That means $n_{k,s} = 8$ and $n_{k,l} = 24$. In periods where the short EMA lies above the long EMA, a positive trend exists, whereas in periods where the short EMA lies below the long EMA the trend is negative. Figure 5 and Figure 6 show the two EMAs for $k = 2$ and $k = 3$ respectively.

One can see that the EMA-filters are mostly correct. However, there is a delay when the trend changes from positive to negative or the other way around. Notice the

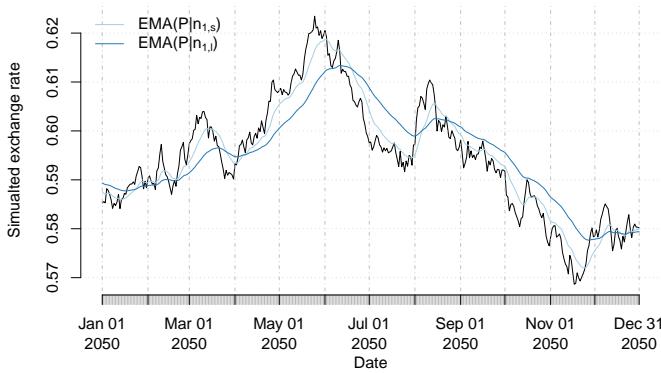


Figure 4: EMA with length 8 (light blue) and 24 (dark blue).

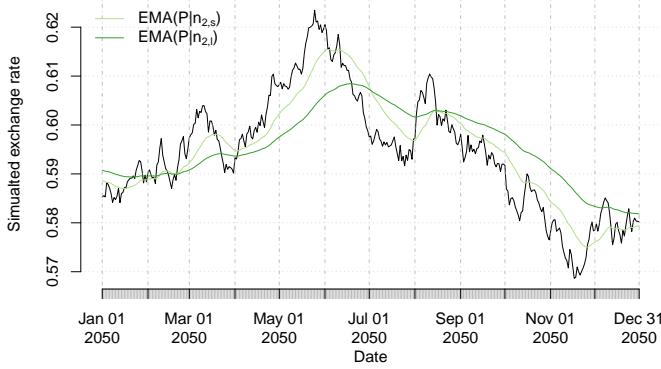


Figure 5: EMA with length 16 (light green) and 48 (dark green).

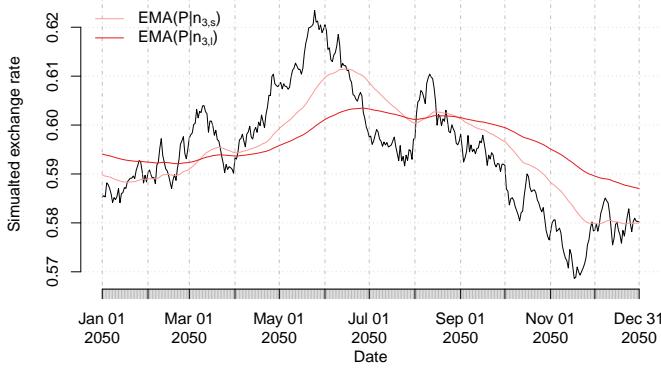


Figure 6: EMA with length 32 (light red) and 96 (dark red).

end of the positive trend at the end of May 2050. Ideally, the short EMAs would cross the long EMAs from the top at the same date. In reality, it takes several weeks for the EMAs to cross. The larger n_k , the longer it takes until the crossing EMAs represent the new trend. On the other hand, a larger n_k is less prone to fluctuations in a larger trend. This can be seen when comparing Figures 4 and 6. The EMAs with length 32 and 96 cross only four times in this one-year period, whereas the EMAs with length 8 and 24 cross nine times.

Using Equation 3, the exponential moving average from

the exchange rate P and the exponential smoothing ratio $\alpha = \frac{1}{n_k}$ is calculated. Again $n_{k,s}$ is the n_k for short EMAs and $n_{k,l}$ is the n_k for long EMAs.

$$x_k = EMA\left(P, \frac{1}{n_{k,s}}\right) - EMA\left(P, \frac{1}{n_{k,l}}\right) \quad (5)$$

where $k = 1, 2, 3$ (Baz et al., 2015).

Figure 7 shows the result of the calculation for $k = 1, 2, 3$. A positive x_k -value indicates a positive trend whereas a negative value indicates a negative trend. x_k is equal to 0 when the short EMA crosses the long EMA and therefore the trend changes its direction. x_k is our first signal. Its sign determines whether one goes long or short in this currency. The further calculation steps simply define the magnitude of the signal and therefore the volume of the investment.

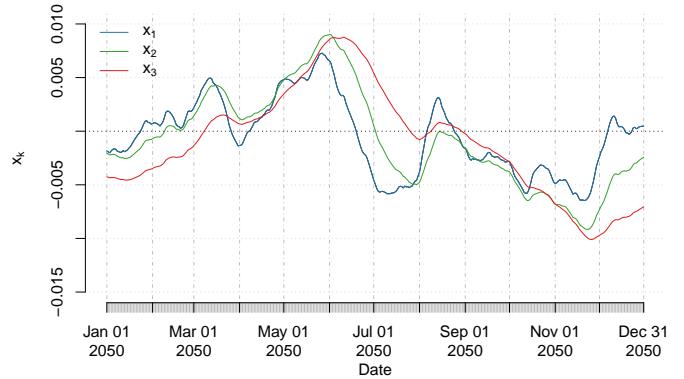


Figure 7: x_k

Table 2 shows the correlation between the three x_k . The correlation between x_1 and x_2 is 0.85. The correlation between x_2 and x_3 is almost the same with 0.86. Similarly one can choose other n_k with another correlation between the x_k . For example, one can choose $n_{k,s} = (8, 23, 66)$ and $n_{k,l} = (24, 69, 198)$, which leads to a correlation of 0.7 between x_1 and x_2 as well as between x_2 and x_3 . Reducing the correlation leads to a longer time window, whereas increasing the correlation results in a shorter time window. We use a factor of three between $n_{k,s}$ and $n_{k,l}$, but any factor is possible. Therefore countless combinations are possible. One can optimize the n_k for each currency, but the risk of overfitting must be considered. Therefore, n_k are chosen such that the signals are sufficiently different from each other, with a correlation of roughly 85%.

Table 2: Correlation between the x_k

	x_1	x_2	x_3
x_1	1.00	0.85	0.55
x_2	0.85	1.00	0.86
x_3	0.55	0.86	1.00

4.4. Normalization

The series x_k is normalized with the three-month moving standard deviation of the exchange rate $sd_{moving(63)}(P)$. This transformation intensifies the signal for periods where the volatility is low. Signals in periods where the volatility is high are lowered.

$$y_k = \frac{x_k}{sd_{moving(63)}(P)} \quad (6)$$

(Baz et al., 2015)

This effect can be seen in Figure 8. It shows the change from x_1 to y_1 as an example. There are two peaks with high volatility at the end of May and July. This can be seen in the upper part of the figure. During these high volatility phases the x_1 is proportionally damped, while the x_1 is proportionally amplified during the low volatility phases before and after the peaks.

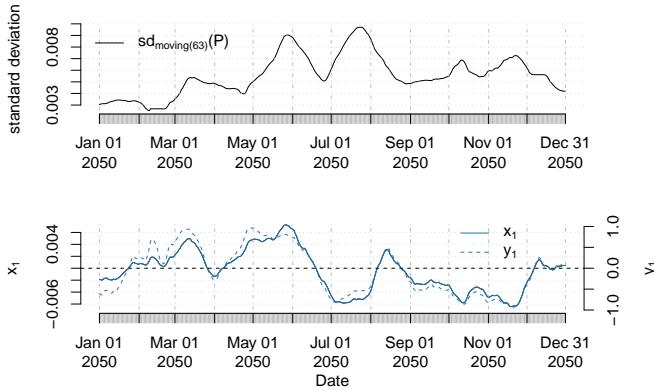


Figure 8: Effect of the normalization with the moving standard deviation on x_k

Figure 9 shows the result of the transformation from x_k to y_k for all k .

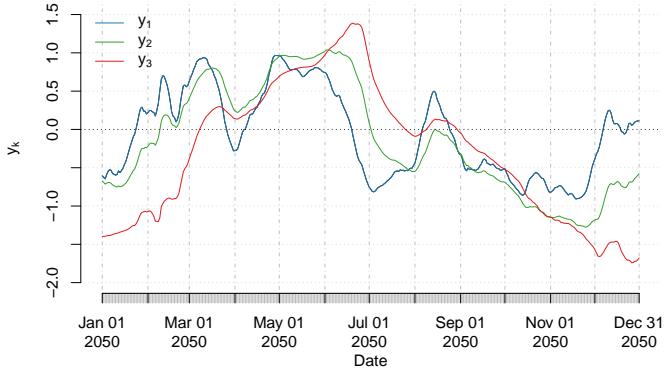


Figure 9: y_k

The resulting time series y_k is normalized again with its moving standard deviation over one year $sd_{moving(252)}(y_k)$. The effect is similar to the one from the first normalization. For this transformation, the rolling standard deviation has

a longer duration and is applied to the y_k instead of P . Figure 10 shows the result.

$$z_k = \frac{y_k}{sd_{moving(252)}(y_k)} \quad (7)$$

(Baz et al., 2015)

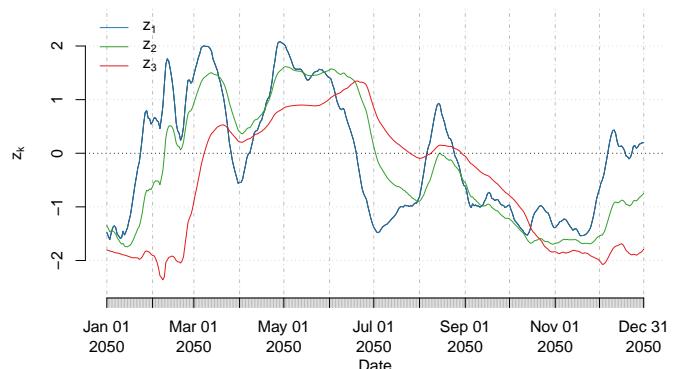


Figure 10: z_k

4.5. Signal generation

We want to scale z_k to take values between -1 and 1. Therefore, the following response function is used to calculate the signal u_k .

$$u_k(z_k) = \frac{z_k \cdot e^{-z_k^2/4}}{\sqrt{2} \cdot e^{-1/2}} \quad (8)$$

This equation is different from the equation used by Baz et al. (2015). Their denominator of u_k is 0.89. In contrast, the denominator used in this paper is $\sqrt{2} \cdot e^{-1/2}$, which is approximately 0.858. In our case, the signal will take values between -1 and 1, whereas the signal in Baz et al. (2015) will take values between -0.96 and 0.96. It is not clear to us how they translate that to a sensible trading signal. They will likely have to make yet another adjustment.

The denominator of $\sqrt{2} \cdot e^{-1/2}$ was derived as follows. We look at the nominator of u_k and call it v_k .

$$v_k(z_k) = z_k \cdot e^{-z_k^2/4} \quad (9)$$

First, the global maximum and minimum of this function is found by setting the derivative to zero and solving the equation for z_k .

$$\frac{d}{dz_k} (v_k(z_k)) = 0 \quad (10)$$

This results in $z_k = \pm\sqrt{2}$, where the slope of v_k is zero. These values are then inserted back into v_k to get the maximum and minimum of this function.

$$v_k(\pm\sqrt{2}) = \pm\sqrt{2} \cdot e^{-1/2} \quad (11)$$

This means that the v_k maps every z_k to a value within $[-\sqrt{2} \cdot e^{-1/2}, \sqrt{2} \cdot e^{-1/2}]$. Since we want u_k to map every z_k to a value within $[-1, 1]$. This can be achieved by dividing v_k by $\sqrt{2} \cdot e^{-1/2}$ which leads to Equation 8.

As shown in Figure 11, the response function now maps every z_k to a u_k within $[-1, 1]$. Therefore, the signal always lies between -1 and 1 . The function has its global minimum in $z_k = -\sqrt{2}$ with $u_k(-\sqrt{2}) = -1$ and the global maximum in $z_k = \sqrt{2}$ with $u_k(\sqrt{2}) = 1$.

Figure 12 shows the resulting u_k from applying the response function to z_k .

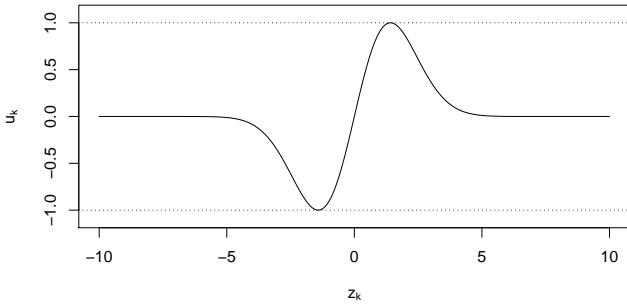


Figure 11: Response function.

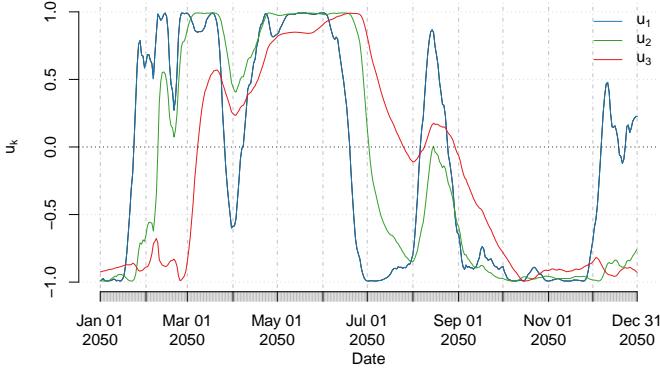


Figure 12: u_k

Taking the weighted sum of all u_k , the final signal is calculated.

$$\text{Signal} = \sum_{k=1}^3 w_k \cdot u_k \quad (12)$$

where $w_k = \text{frac13}$ (Baz et al., 2015). One could also use other weights that sum up to 1. We decided to use equal weights for simplicity. The final signal can be seen in Figure 13.

With the signal, a backtest is performed on the simulated data by multiplying the daily arithmetic returns of the series with the signal lagged by one day. Figure 14 shows the cumulative return over 100 years.

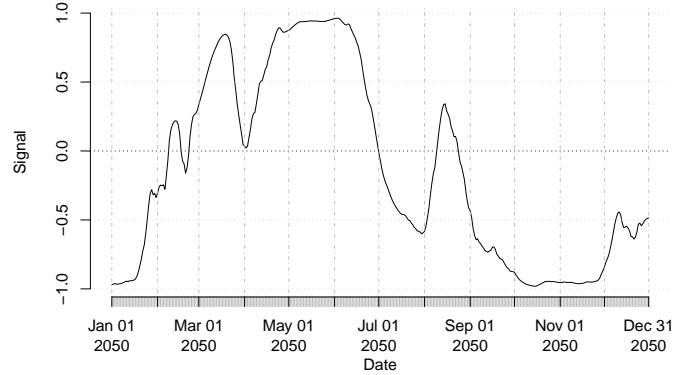


Figure 13: Signal

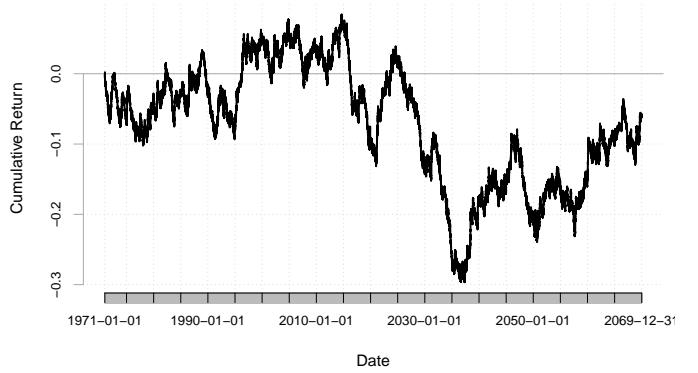


Figure 14: Backtest over 100 years for simulated data.

We now take a look at the histogram of the daily arithmetic returns of our strategy in Figure 15. It becomes apparent that the returns are symmetrically distributed with an average performance of zero. This is what was expected since a geometric Brownian Motion was used for the exchange rate process. The expected cumulative return is also 0. This result shows that the calculations are correct and the same algorithm can now be used on real currency exchange rates.

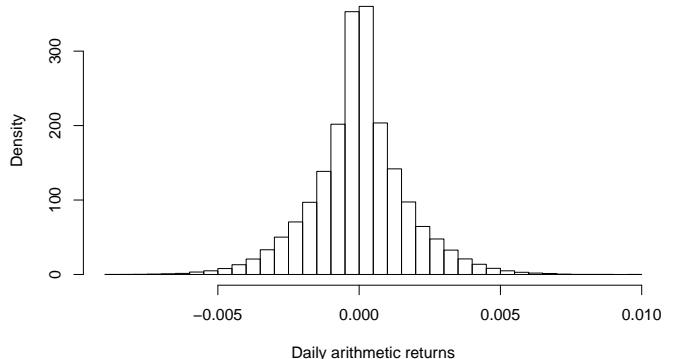


Figure 15: Histogram of daily arithmetic returns.

The histograms of x_k , y_k , z_k , u_k , and the signal can

be found in Appendix B. The transformations deform the normal distribution of the arithmetic returns.

5. Portfolio types

5.1. Time series portfolio

The time series portfolio has a simple composition. On every re-balancing date, one invests in all currencies according to the value of the signal divided by n , the number of currency pairs in the portfolio. For a $signal = 1$ one would invest $\frac{1}{n}$ units of USD in the foreign currency, for a $signal = -1$ one would sell $\frac{1}{n}$ units of USD worth of the foreign currency. For a $signal = 0.5$ one would invest $\frac{0.5}{n}$ units of USD in the foreign currency and so on. Since the signal has a value between -1 and 1, we never buy or sell more than $\frac{1}{n}$ units of USD per currency. Hence we never buy or sell more than 1 unit of USD in the whole portfolio. A unit can be an arbitrary amount of USD that one wants to invest in the momentum strategy.

5.2. Cross-sectional portfolio

When using a cross-sectional portfolio, the signals of all currencies are compared on every re-balancing date. One goes long the three currencies with the largest signal. On the other hand, one sells the three currencies with the smallest (most negative) signal. One always buys or sells exactly $\frac{1}{6}$ units of USD worth of each of the foreign currencies, no matter how small or large the signal is. This method only works if the portfolio contains six or more currencies. Note that a cross-sectional portfolio with six currencies is not the same as a time series portfolio with six currencies. In the cross-sectional portfolio, one always buys or sells $\frac{1}{6}$ units of USD worth of the foreign currency, whereas in the time series portfolio one invests according to the value of the signal. Furthermore, one even purchases a currency with a negative signal provided it is one of the three largest signals. The same applies to selling a currency with a positive signal provided it is one of the three smallest signals. Since we invest in exactly six currencies at any time, the investment in the portfolio is again 1 unit of USD.

6. Backtest

The start of the backtest depends on the currency category. The earliest date for which data is available for all currencies of the category was used. The start date is specified at the beginning of each section. The end of the backtest is always 20 March 2017. Due to the calculation steps with the moving standard deviations (Equation 6, Equation 7), there is a sizable period of data where no reliable signal exists. Equation 6 needs 62 days and Equation 7 needs an additional 251 days for the calculation. Another day is used for the calculation of the arithmetic returns. Therefore, the warm-up period is exactly 313 days long. Considering a year has 252 trading days, roughly fifteen months are needed as a warm-up period where no

trades are executed. This period has to be extended if it includes public holidays where the market is closed, and no data exists. The warm-up period is removed from all graphs, analyses and further calculations. The portfolio is rebalanced on every trading day.

7. G10 currencies

In this section, the algorithm explained in section 4 is used to perform a backtest on the G10 currencies. The data starts on 1 July 1974. The first fifteen months are needed as a warm-up period, therefore the backtest starts on 14 October 1975. Figure 16 shows the exchange rates during the backtesting period. The exchange rates are indexed to visualize the trends and volatility better. CHF/USD and JPY/USD have an upwards moving trend compared to the other currencies which trend sideways.

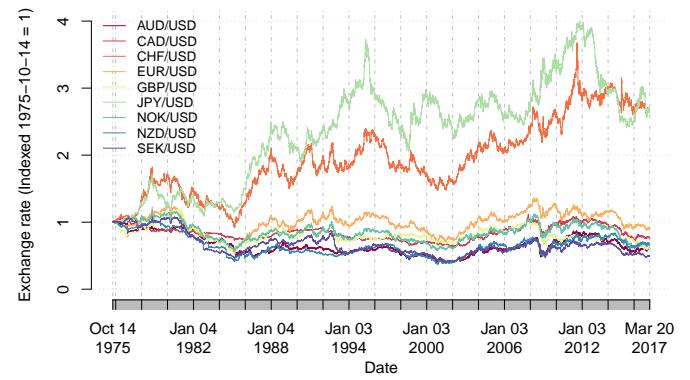


Figure 16: G10 currency exchange rates indexed at the start of the backtest.

Figure 17 shows the correlations between the arithmetic returns of the G10 currencies.

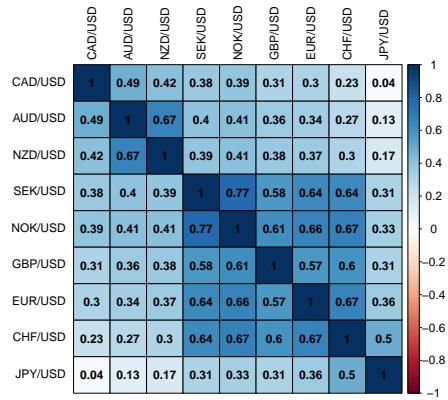


Figure 17: Correlations between the arithmetic returns of the G10 currencies

There is a cluster of correlations above 0.5 between the European countries. The arithmetic returns of AUD/USD and NZD/USD have a correlation above 0.6. The arithmetic returns of JPY/USD and CHF/USD exhibit a

correlation of 0.5, all other currencies in this category have a weak correlation with JPY/USD.

Table 3: Summary of the G10 currencies backtest results for a time series portfolio (TS) and a cross-sectional portfolio (CS).

	TS	CS
Annualized Return	2.45%	0.89%
Annualized Standard Deviation	0.0458	0.0399
Annualized Sharpe Ratio ($R_f = 0\%$)	0.5345	0.2217

With the time series portfolio, an annualized return of 2.45% and an annualized Sharpe ratio of 0.5345 are achieved.

The cross-sectional portfolio achieved an annualized return of 0.89% and an annualized Sharpe ratio of 0.2217.

The annualized return of the time series portfolio is nearly three times the annualized return of the cross sectional portfolio. On the other hand, the annualized standard deviation of the time series portfolio is only slightly higher than the annualized standard deviation of the cross-sectional portfolio. Hence, the Sharpe ratio of the time series portfolio is roughly two and a half times the cross-sectional one.

The cumulative returns, daily arithmetic returns, and drawdowns of both portfolios can be seen in Figures 18 and 19. In Figure 20 the yearly returns of both portfolios are presented for the period from 1975 to 2017.

The largest drawdown of the time series portfolio with a magnitude of 7% started in December 2008 and has not recovered since then. Before 2008 the drawdowns were quite consistent with magnitudes around 4%. The strategy worked well during the financial crisis of 2008, where the value of the portfolio skyrocketed by 13% in a single year.

It is striking that the largest drawdown of the cross-sectional portfolio with a magnitude of 18% started in July 1998 and has still not recovered. The drawdown almost recovered after the early 2000s recession and during the financial crisis of 2008 where the portfolio value soars by 6%, similarly to the time series portfolio. However, the portfolio took another hit and declined ever since. Before this huge drawdown, the drawdowns were quite consistent with magnitudes below 4% before 1990 and maximum magnitudes of roughly 5.5% between 1990 and 2001.

Overall we can say that the strategy worked well for the time series portfolio up to and during the 2008 financial crisis. In fact, the portfolio shows the highest return in the year of the crisis. But since then the returns diminished, and the value of the portfolio stagnated. The cross-sectional portfolio even stagnated as early as 1998 and showed a strong decline since the financial crisis of 2008. For the G10 currencies, the time series portfolio worked much better than the cross-sectional portfolio. The risk-adjusted returns were much higher. But at this point, we conclude that momentum returns in the G10 currencies have vanished.

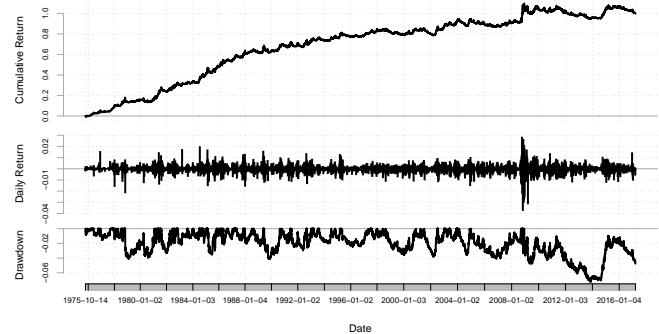


Figure 18: Backtest for G10 currencies, time series portfolio.

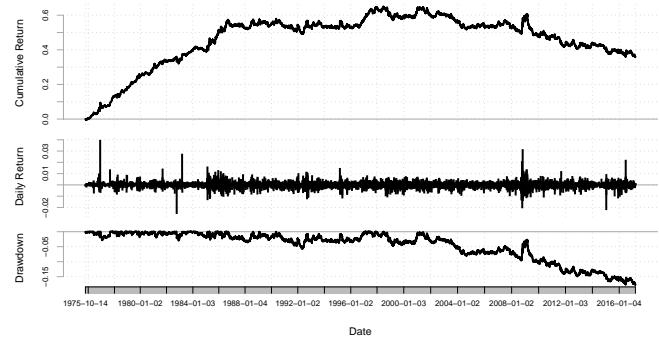


Figure 19: Backtest for G10 currencies, cross-sectional portfolio.

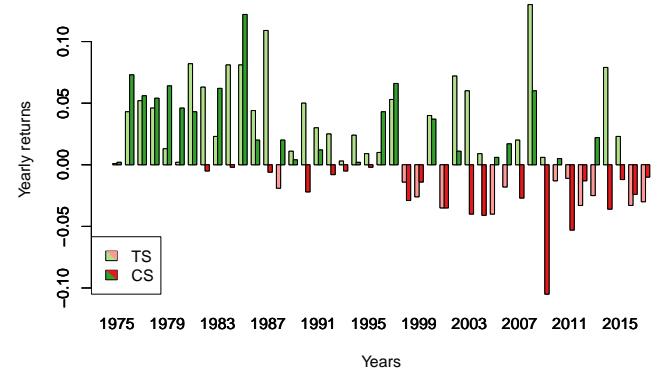


Figure 20: Yearly returns of the G10 currencies for a time series portfolio (TS) and a cross-sectional portfolio (CS).

8. Emerging market currencies

In this section, a backtest is performed on emerging market currencies. These currencies are generally slightly more volatile than the G10 currencies. In this category, the data for the Brazilian Real is only available from 2 January 1995, whereas all other currencies have a longer history. Taking into account the warm-up period, the backtest starts on 10 April 1996 for all currencies. Figure 21 shows the exchange rates during the backtesting period.

The exchange rates are indexed to visualize the trends and volatility better. The impact of the Asian financial crisis after 1997 and the global financial crisis of 2008 are clearly visible. The emerging market currencies devalued against the USD during these periods. All currencies of this category lost value against the USD over the 22 year long period. MXN/USD, ZAR/USD, MXN/USD, and INR/USD decreased by more than 50%. These currency pairs also fell during the last five years, while TWD/USD, THB/USD, and KRW/USD trended sideways during the last five years.

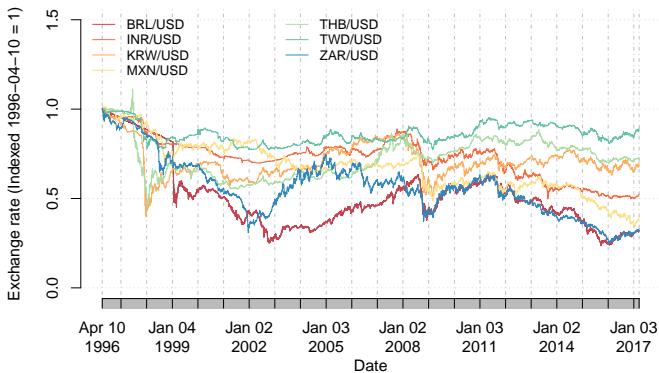


Figure 21: Emerging market currency exchange rates indexed at the start of the backtest.

Figure 22 shows the correlations between the arithmetic returns of the emerging market currencies. There is a cluster of correlations above 0.4 between the South American countries and South Africa. The arithmetic returns of KRW/USD and TWD/USD have a correlation above 0.3. The arithmetic returns of INR/USD and THB/USD seem independent with a weak correlation to all other countries.

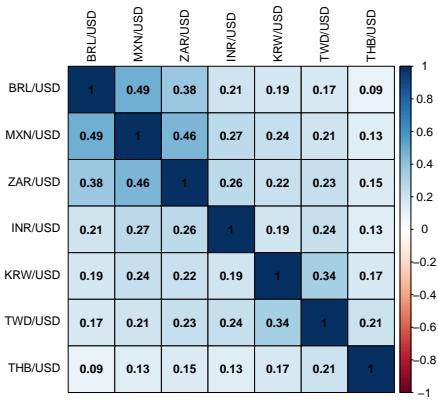


Figure 22: Correlations between the arithmetic returns of the emerging market currencies

The backtest with a time series portfolio results in an annualized return of 2.48% and an annualized Sharpe ratio of 0.5856. The return is similar to the return of the G10 time series portfolio, but the Sharpe ratio is slightly higher.

The cross-sectional portfolio achieved an annualized

Table 4: Summary of the emerging market currencies backtest for a time series portfolio (TS) and a cross-sectional portfolio (CS).

	TS	CS
Annualized Return	2.48%	1.13%
Annualized Standard Deviation	0.0423	0.0445
Annualized Sharpe Ratio ($R_f = 0\%$)	0.5856	0.2533

return of 1.13% and an annualized Sharpe ratio of 0.2533.

While the emerging market currencies are marginally more volatile, both portfolios have an annualized standard deviation of equal height compared to the G10 portfolios. This occurs due to the weaker correlation between the returns of the currencies.

The Sharpe ratio of the emerging market portfolios are slightly better than the ones of the G10 portfolios. Similarly to the G10 currencies, the annualized return of the cross-sectional portfolio is much smaller than the annualized return of the time series portfolio. The standard deviation is almost equal for both portfolio types. This results in a more than twice as large Sharpe ratio for the time series portfolio compared to the cross-sectional one.

The cumulative returns, daily arithmetic returns, and drawdowns of both portfolios can be seen in Figures 23 and 24. In Figure 25 the yearly returns of both portfolios are presented for the period from 1996 to 2017.

One can see that the drawdowns of both types are similar. The first large drawdown with a loss of 5.5% for the time series portfolio started in 1998 and took three years to recover. The cross-sectional portfolio exhibits a similar drawdown with a magnitude of 12.9% around the same time. The drawdown started in 1996 and took five and a half years to recover. This is around the time when the Asian financial crisis hit the Eastern Asian countries, which are well represented in this currency group. For the cross-sectional portfolio, this was the highest drawdown. The second largest drawdown happened during the global financial crisis. This drawdown started in 2008 and took longer to recover for both portfolios. In the time series portfolio, it is the highest and the longest drawdown with a magnitude of 5.8% and a duration of six years. The same drawdown is visible in the cross-sectional portfolio. The magnitude is 10.9% and the drawdown has not recovered yet.

We conclude that the time series portfolio is less susceptible to economic crises, with smaller and shorter drawdowns in comparison to the cross-sectional portfolio. Aside from these two losses, the strategy worked well with the selected exchange rates. The strategy was highly profitable especially in the 2000s. As distinguished from the G10 portfolios we cannot see a decrease in returns to the same extent. At this point in time, the momentum strategy seems to be working much better for emerging market currencies than for the G10 currencies.

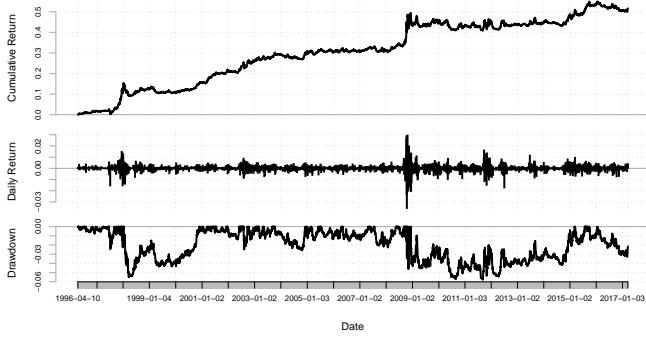


Figure 23: Backtest for emerging market currencies, time series portfolio.

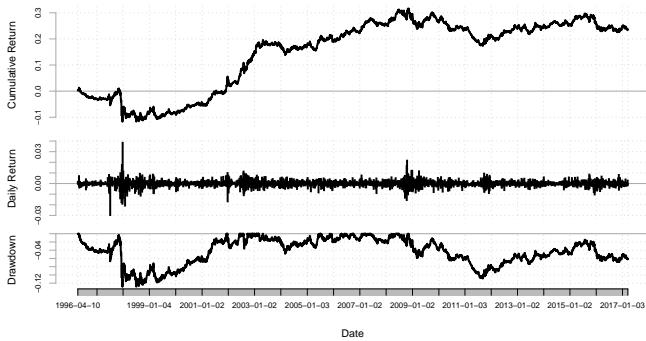


Figure 24: Backtest for emerging market currencies, cross-sectional portfolio.

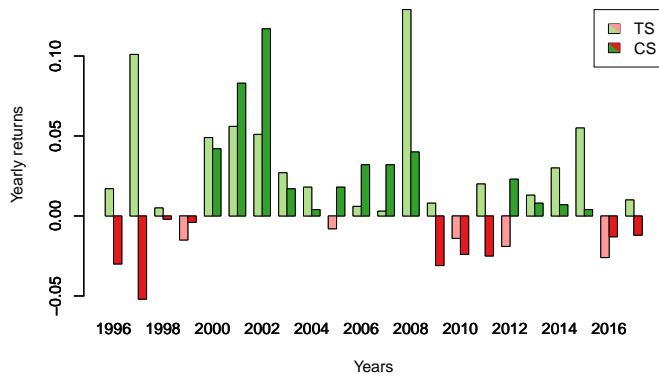


Figure 25: Yearly returns of the emerging market currencies for a time series portfolio (TS) and a cross-sectional portfolio (CS).

9. Cryptocurrencies

In this section, a backtest is performed on cryptocurrencies. Since there are far fewer financial products for cryptocurrencies compared to the well-established fiat currencies, it is questionable whether it makes sense to apply a trading strategy to cryptocurrencies. It is difficult to short sell these currencies. Also, liquidity can be a problem when trading cryptocurrencies. We could only find one ex-

change that allows short selling cryptocurrency/USD pairs (Bitfinex, 2017). The exchange Poloniex (2017) offers shorting cryptocurrency pairs only. The derivatives exchange BitMEX (2017) offers derivatives for cryptocurrencies such as futures and swaps.

From our present point of view, we expect that cryptocurrency trading possibilities will grow for years to come. Hence it makes sense to consider the cryptocurrencies in this paper and to perform a backtest, even if it is just for curiosity's sake. To our knowledge, this is the first paper that considers cryptocurrencies in traditional trading strategies.

Since the cryptocurrencies can be traded even on weekends and bank holidays, a slight adjustment in the algorithm is necessary. The period for the moving standard deviation of Equation 6 has to be extended to 91 days and the moving standard deviation of Equation 7 has to be extended to 365 days. This results in a warm-up period which needs more data. However, there is more data available per year, therefore fifteen months are needed for the warm-up period again. Our cryptocurrency data starts on 22 June 2014. Including the warm-up period the start date of the backtest is the 21 September 2015. Figure 26 shows the exchange rates during the backtesting period. The exchange rates are indexed to better visualize the trends and volatility. The exponential growth of Dash in the first few months of 2017 is striking. BTC/USD, DASH/USD, MAID/USD and XMR/USD are upwards trending. DOGE/USD, LTC/USD and XRP/USD are primarily sideways trending. It is astounding that the currencies Monero (XMR) and Dash increased their value by more than 40 times during this period.

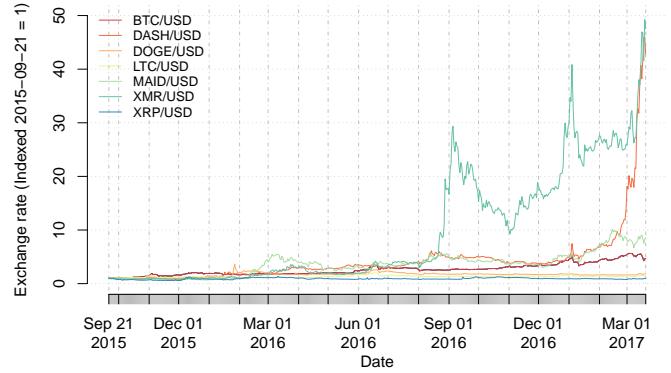


Figure 26: Cryptocurrency exchange rates indexed at the start of the backtest.

Figure 27 shows the correlations between the arithmetic returns of the cryptocurrencies. There is a strong correlation between the arithmetic returns of BTC/USD and LTC/USD. The arithmetic returns of all other cryptocurrencies show a weak correlation.

The result is a 42.02% annualized return and a Sharpe ratio of 1.4843 for the time series portfolio. The cross-sectional portfolio achieves an annualized return of 56.94%

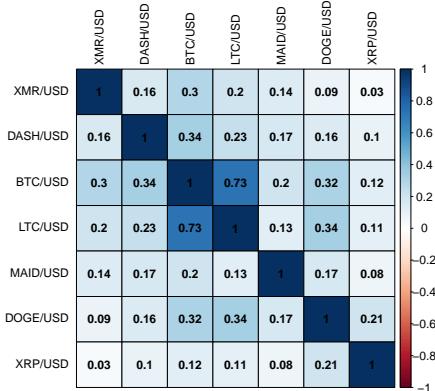


Figure 27: Correlations between the arithmetic returns of the emerging market currencies

Table 5: Summary Cryptocurrencies

	TS	CS
Annualized Return	42.02%	56.94%
Annualized Standard Deviation	0.2831	0.3391
Annualized Sharpe Ratio ($R_f = 0\%$)	1.4843	1.6793

and a Sharpe ratio of 1.6793.

The cumulative returns, daily arithmetic returns, and drawdowns of both portfolios can be seen in Figure 28 and Figure 29. In Figure 30 the yearly returns of both portfolios are presented for the period from 2015 to 2017.

Since cryptocurrencies are still new, we could only do a backtest over a period of 18 months. Osterrieder et al. (2016b) show that the distributions of returns of cryptocurrencies have heavier tails compared to traditional fiat currencies. Our short term backtest likely underestimates this risk, and therefore one should take these results with a grain of salt.

In comparison to the time series portfolios containing traditional fiat currencies, much higher drawdowns were measured. As shown in Figure 28 the largest drawdown in the time series portfolio with a magnitude of 23% occurred between October 2015 and February 2016. There was no event in the financial markets during this period that would explain this behavior. The cross-sectional portfolio shows a similar, but less severe drawdown at the same time. However, there is a significant drawdown with a magnitude of 17% in the cross-sectional portfolio, which started in March 2016 and ended in August 2016.

Aside from the worst drawdowns, there are still significant drawdowns of up to 14% in the time series and the cross-sectional portfolio. Because the returns are remarkably high, the risk/reward ratio is still excellent. In contrast to the traditional fiat currencies where the time series portfolio generates better results, the cross-sectional portfolio seems to be better suited for cryptocurrencies.

We conclude that there is a lot of momentum in cryptocurrencies that can be realized with a momentum strategy. However, at this point, it is difficult to apply a trading

strategy on cryptocurrencies because of the problems mentioned above. In the future, cryptocurrencies are going to become better established and easier to trade. This will be the ideal time to start trading with a momentum strategy.

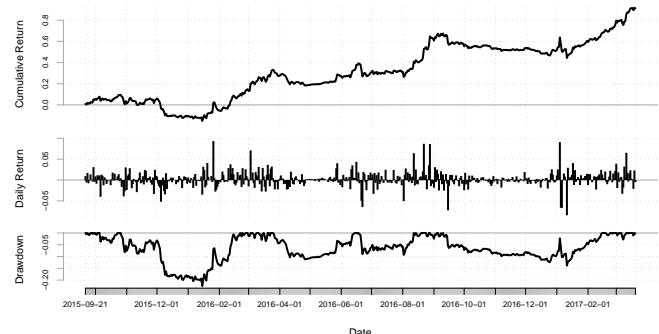


Figure 28: Backtest for cryptocurrencies, time series portfolio.

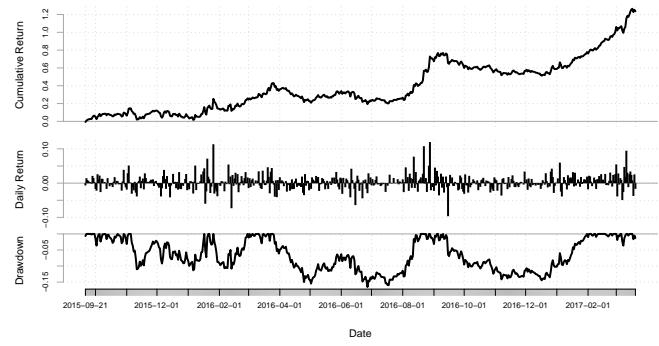


Figure 29: Backtest for cryptocurrencies, cross-sectional portfolio.

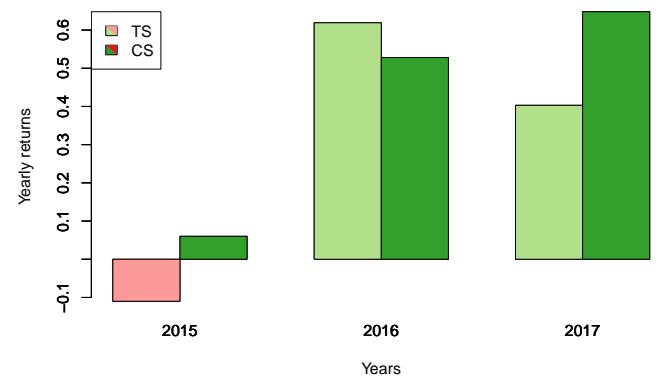


Figure 30: Yearly returns of the cryptocurrencies for a time series portfolio (TS) and a cross-sectional portfolio (CS).

10. Results

The momentum strategy combined with a time series portfolio achieves the highest Sharpe ratios for traditional fiat currencies. For cryptocurrencies, the cross-sectional portfolio offers higher risk-adjusted returns.

In the G10 currencies, the returns diminished in the recent years. It seems that there is no momentum in G10 currencies anymore. Therefore, the strategy is not useful anymore.

When comparing the G10 currencies time series portfolio performance to the FX Momentum USD Index of the Deutsche Bank (2017), one can see a similar performance. The Deutsche Bank (DB) has achieved higher returns, but also suffers higher drawdowns. The index of the DB starts on the 19 June 1989, while our backtest starts in 1975 already. The start of the performance of the DB Index is set to the same value as the performance of our backtest on the 19 June 1989.

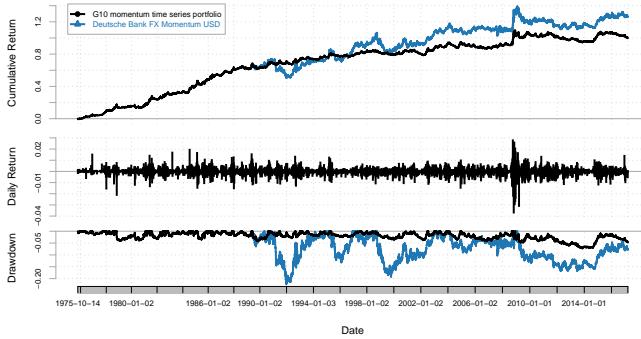


Figure 31: Comparison between our G10 time series portfolio and the Deutsche Bank FX Momentum USD Index

However, in emerging market currencies, a decrease in returns could not be observed. The strategy has worked well for many years up to this day.

In the cryptocurrencies, strong momentum and remarkably high returns can be seen. Trading cryptocurrencies with a momentum strategy could become a very popular trading strategy.

In general, the strategy generates higher risk-adjusted returns for currency types with higher volatility. Drawdowns can usually be explained by unexpected events in the financial markets. During calm periods the strategy works well, but sudden market crashes cause drawdowns of up to 18% in traditional fiat currencies and up to 23% in cryptocurrencies.

11. Conclusion

Momentum is one of the oldest trading strategies. It worked well for the G10 currencies until the 2008 financial crisis hit the financial markets. Since then, the momentum

strategy has not been profitable anymore when trading G10 currencies.

For emerging market currencies, the strategy is effective up to this day, with returns of up to 2.48% p.a and a Sharpe ratio of 0.59. This underpins the findings of Pukthuanthong-Le et al. (2007), who assumed that the profits in the traditional currencies (G10) vanished but investing in exotic currencies (emerging markets) is profitable.

As yet, no one has investigated momentum strategies in cryptocurrencies. We find that the algorithm generates returns of up to 56.94% p.a. and a Sharpe ratio of 1.68 for a cryptocurrency portfolio. However, the backtest only covers a period of 18 months. More data and a long-term backtest are needed to make a more reliable statement about the returns of a cryptocurrency momentum strategy.

Our calculations overestimate the returns, since transaction costs and bid-ask spreads were not considered. The transaction costs could be included in a next step. However, they are comparatively low when one trades in sufficient quantity, hence the results will not change completely.

An explanation for the outstandingly high returns for cryptocurrencies is the strong upward trend during the last year. Similarly, emerging market currencies had strong, long-lasting trends. These trends are easily recognized by the trading algorithm, whereas the G10 currency exchange rates have long-lasting sideways trends with only short up-and downward corrections, which is more difficult for the algorithm to follow.

Filippou et al. (2016) and Grobys et al. (2016) showed that the returns could be seen as compensation for the risk taken to hold these currencies. This explains why the returns rise as the risk rises. G10 currencies are less risky than other currencies, and therefore G10 currencies have lower returns than other currencies. The same applies to cryptocurrencies. Investing in these currencies involves much more risk than investments with traditional fiat currencies. On the other hand, the return of cryptocurrencies is much higher when using the momentum strategy.

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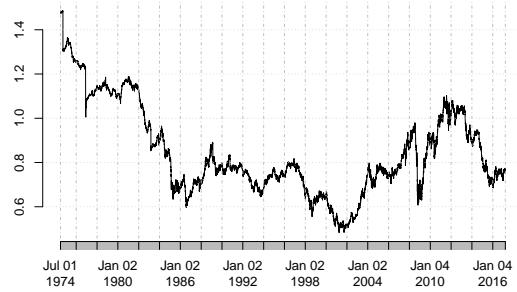
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Appendix A. Data overview

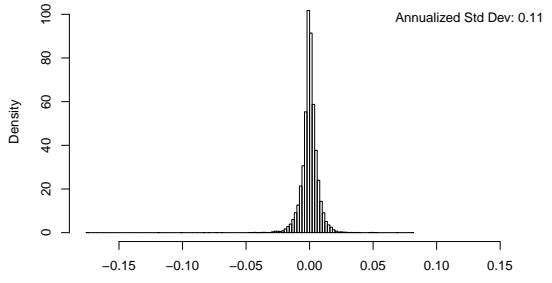
Table A.1 shows an overview of the data used for the calculations and figures in this paper.

Table A.1: Data collection

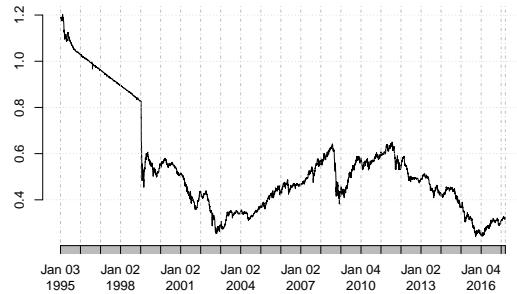
Base currency	Currency pair	Code	Source	Period	Start date	End date
Australian Dollar	AUD/USD	DEXUSAL	FRED	daily	1971-01-04	2017-03-20
Bitcoin	BTC/USD	BNC2_GWA_BTC	Quandl	daily	2014-04-01	2017-03-20
Brazilian Reals	BRL/USD	DEXBZUS	FRED	daily	1995-01-02	2017-03-20
Canadian Dollar	CAD/USD	DEXCAUS	FRED	daily	1971-01-04	2017-03-20
Dash	DASH/USD	BNC2_GWA_DASH	Quandl	daily	2014-04-07	2017-03-20
Dogecoin	DOGE/USD	BNC2_GWA_DOGE	Quandl	daily	2014-04-01	2017-03-20
Euro	EUR/USD	DEXUSEU	FRED	daily	1999-01-04	2017-03-20
European Currency Unit	ECU/USD	ert_bil_eur_d	Eurostat	daily	1974-07-02	1998-12-20
Indian Rupees	INR/USD	DEXINUS	FRED	daily	1973-01-02	2017-03-20
Japanese Yen	JPY/USD	DEXJPUS	FRED	daily	1971-01-04	2017-03-20
Litecoin	LTC/USD	BNC2_GWA_LTC	Quandl	daily	2014-04-01	2017-03-20
Maidsafecoin	MAID/USD	BNC2_GWA_MAID	Quandl	daily	2014-06-22	2017-03-20
Mexican New Pesos	MXN/USD	DEXMXUS	FRED	daily	1993-11-08	2017-03-20
Monero	XMR/USD	BNC2_GWA_XMR	Quandl	daily	2014-05-19	2017-03-20
New Taiwan Dollars	TWD/USD	DEXTAUS	FRED	daily	1983-10-03	2017-03-20
New Zealand Dollar	NZD/USD	DEXUSNZ	FRED	daily	1971-01-04	2017-03-20
Norwegian Krone	NOK/USD	DEXNOUS	FRED	daily	1971-01-04	2017-03-20
Pound Sterling	GBP/USD	DEXUSUK	FRED	daily	1971-01-04	2017-03-20
Ripple	XRP/USD	BNC2_GWA_CRP	Quandl	daily	2014-04-01	2017-03-20
South African Rand	ZAR/USD	DEXSFUS	FRED	daily	1971-01-04	2017-03-20
South Korean Won	KRW/USD	DEXKOUS	FRED	daily	1981-04-13	2017-03-20
Swedish Krona	SEK/USD	DEXSDUS	FRED	daily	1971-01-04	2017-03-20
Swiss Franc	CHF/USD	DEXSZUS	FRED	daily	1971-01-04	2017-03-20
Thai Baht	THB/USD	DEXTHUS	FRED	daily	1981-01-02	2017-03-20



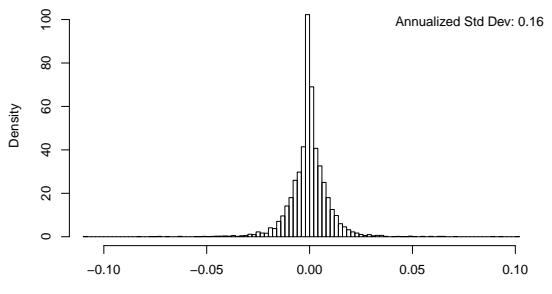
(a) Exchange Rate AUD/USD



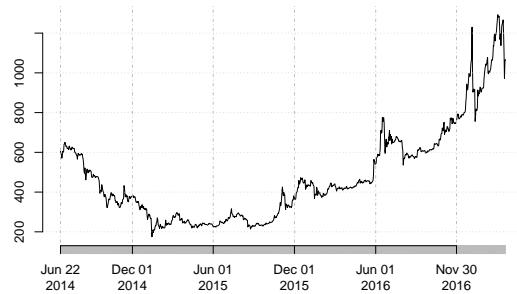
(b) Histogram of AUD/USD arithmetic Returns



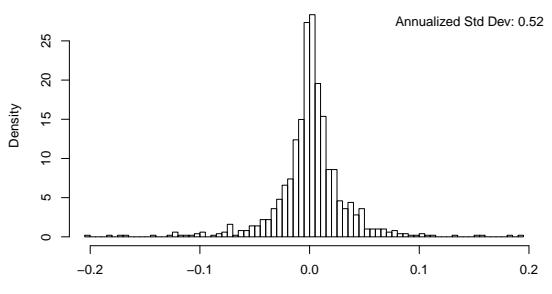
(c) Exchange Rate BRL/USD



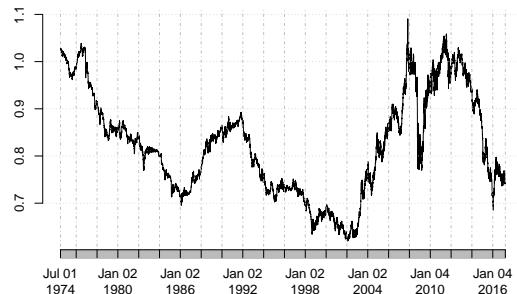
(d) Histogram of BRL/USD arithmetic Returns



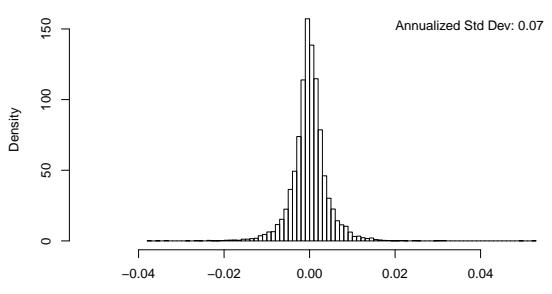
(e) Exchange Rate BTC/USD



(f) Histogram of BTC/USD arithmetic Returns

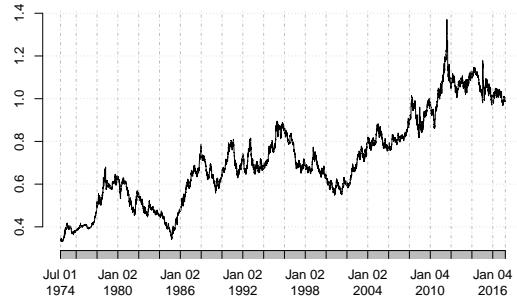


(g) Exchange Rate CAD/USD

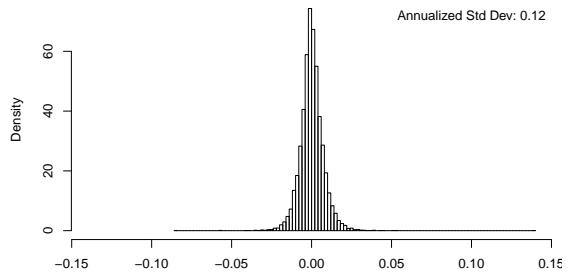


(h) Histogram of CAD/USD arithmetic Returns

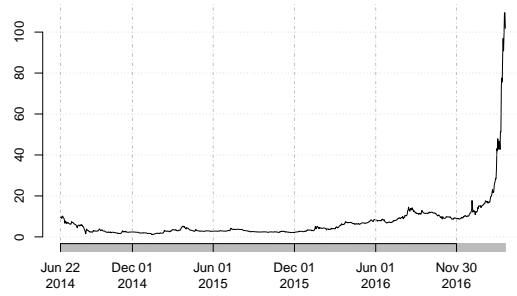
Figure A.1: Exchange rates and histograms of arithmetic returns.



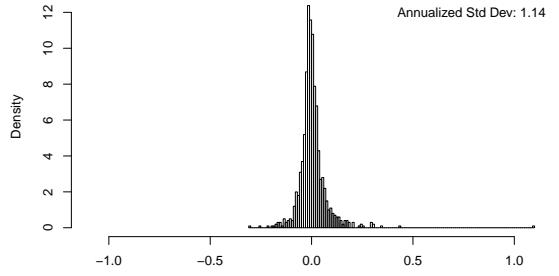
(a) Exchange Rate CHF/USD



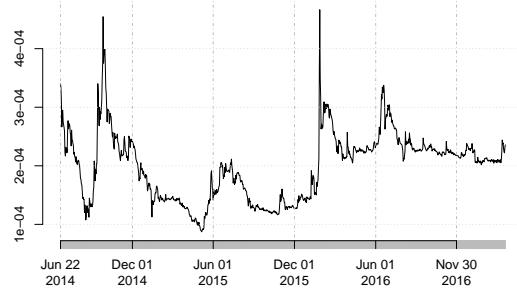
(b) Histogram of CHF/USD arithmetic Returns



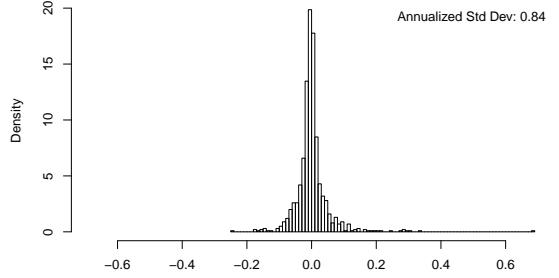
(c) Exchange Rate DASH/USD



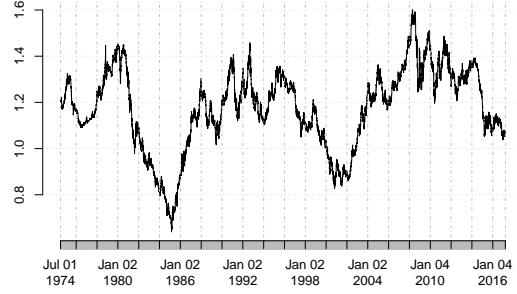
(d) Histogram of DASH/USD arithmetic Returns



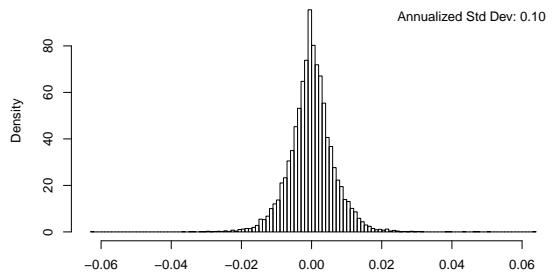
(e) Exchange Rate DOGE/USD



(f) Histogram of DOGE/USD arithmetic Returns

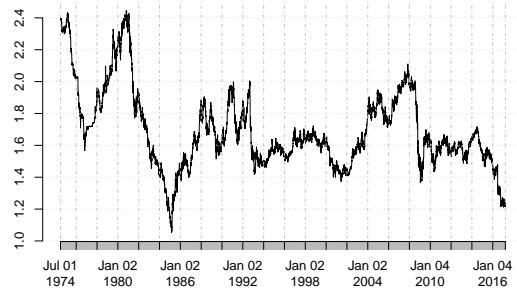


(g) Exchange Rate EUR/USD

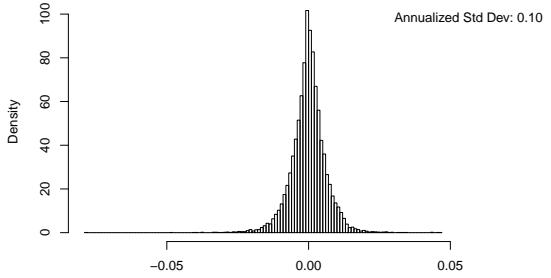


(h) Histogram of EUR/USD arithmetic Returns

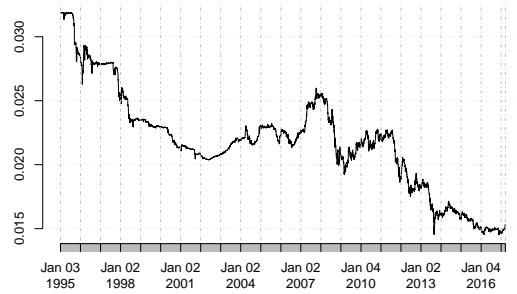
Figure A.2: Exchange rates and histograms of arithmetic returns.



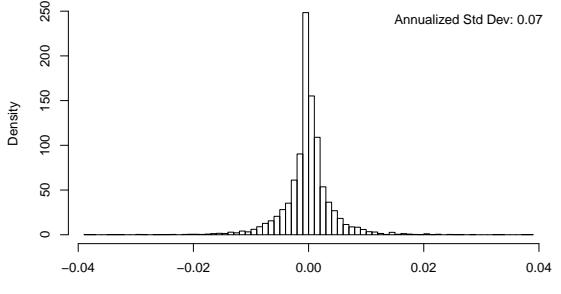
(a) Exchange Rate GBP/USD



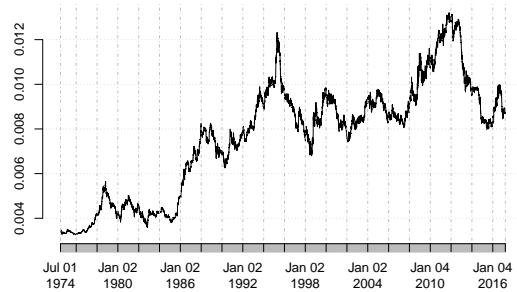
(b) Histogram of GBP/USD arithmetic Returns



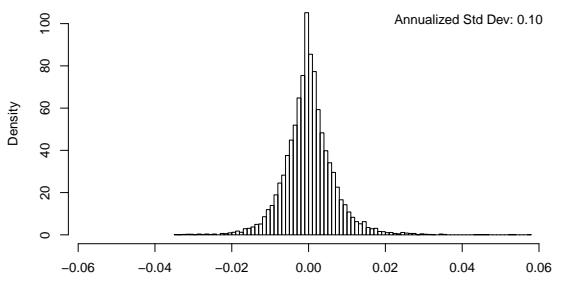
(c) Exchange Rate INR/USD



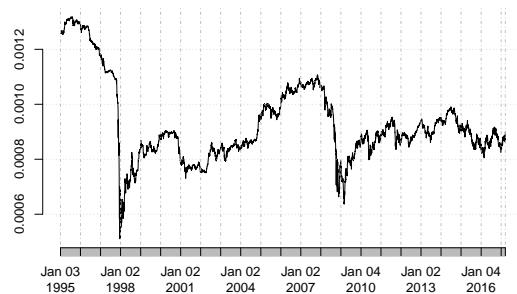
(d) Histogram of INR/USD arithmetic Returns



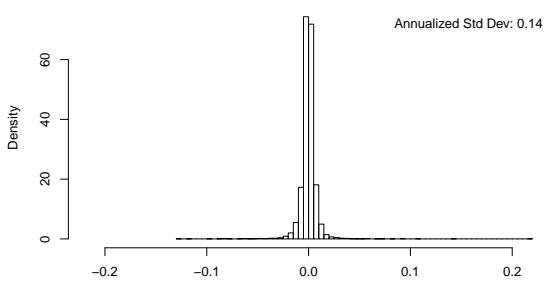
(e) Exchange Rate JPY/USD



(f) Histogram of JPY/USD arithmetic Returns

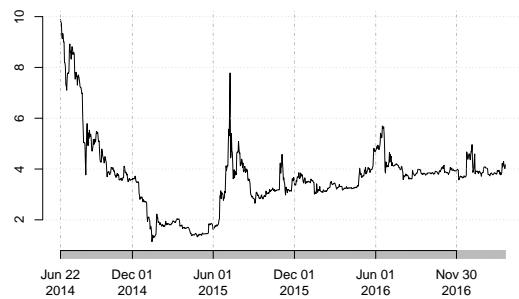


(g) Exchange Rate KRW/USD

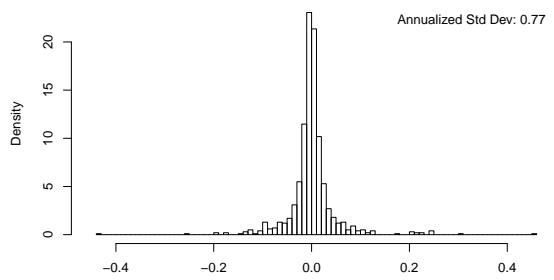


(h) Histogram of KRW/USD arithmetic Returns

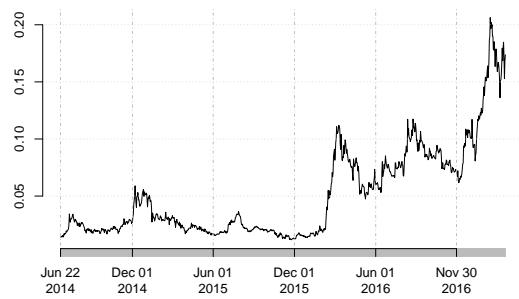
Figure A.3: Exchange rates and histograms of arithmetic returns.



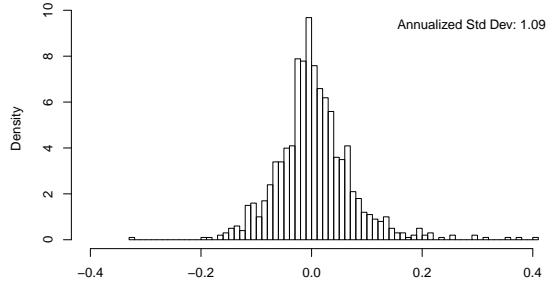
(a) Exchange Rate LTC/USD



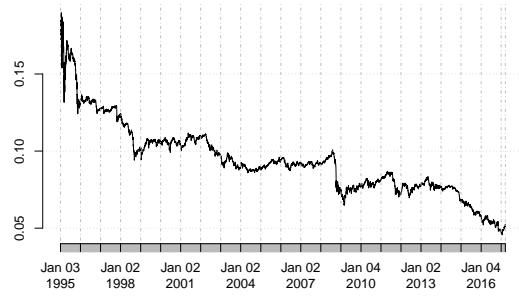
(b) Histogram of LTC/USD arithmetic Returns



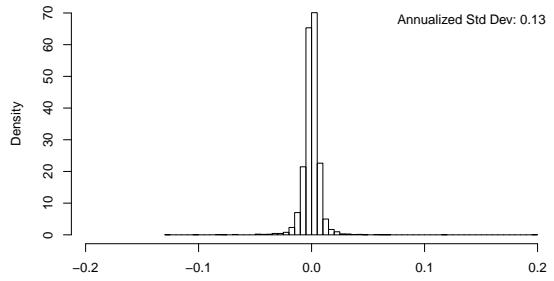
(c) Exchange Rate MAID/USD



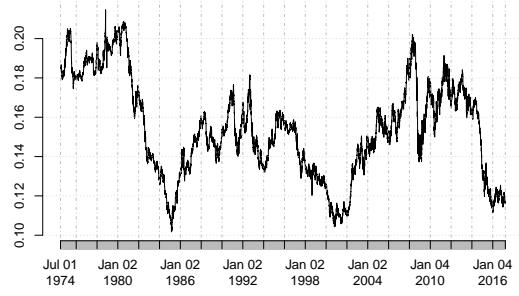
(d) Histogram of MAID/USD arithmetic Returns



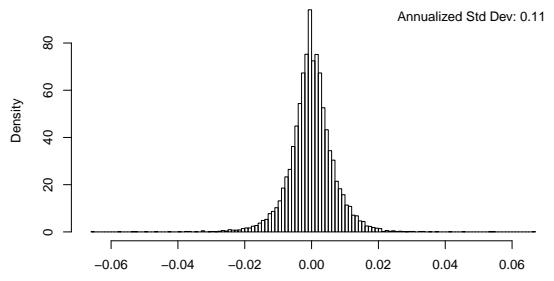
(e) Exchange Rate MXN/USD



(f) Histogram of MXN/USD arithmetic Returns

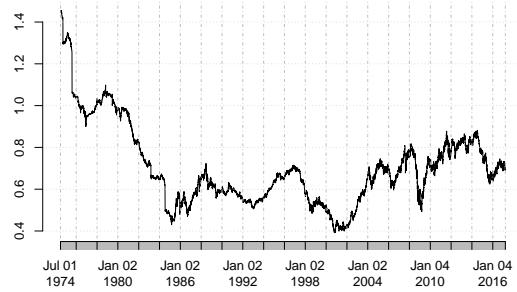


(g) Exchange Rate NOK/USD

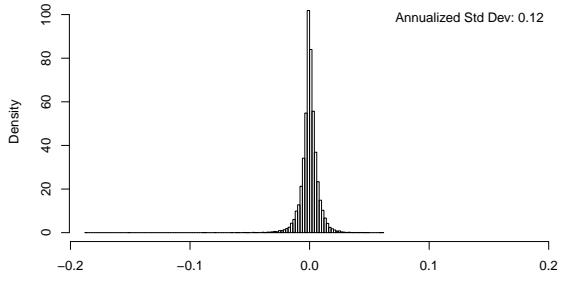


(h) Histogram of NOK/USD arithmetic Returns

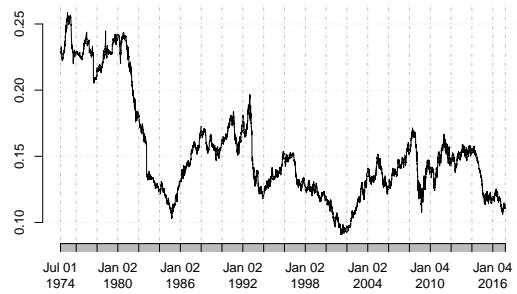
Figure A.4: Exchange rates and histograms of arithmetic returns.



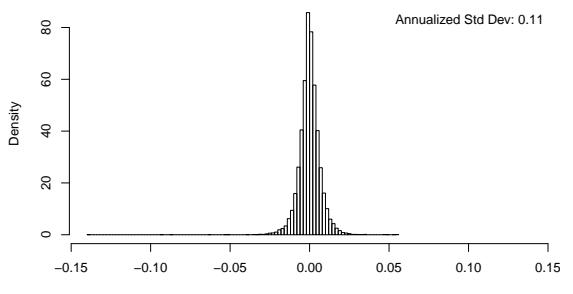
(a) Exchange Rate NZD/USD



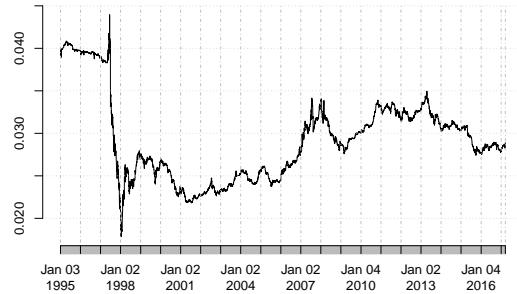
(b) Histogram of NZD/USD arithmetic Returns



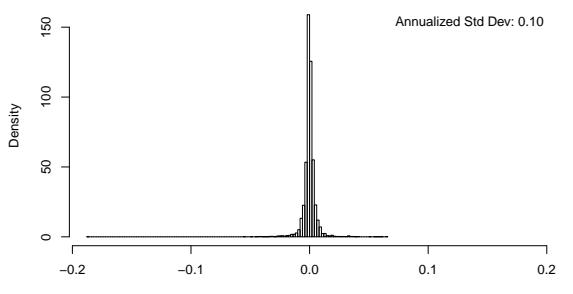
(c) Exchange Rate SEK/USD



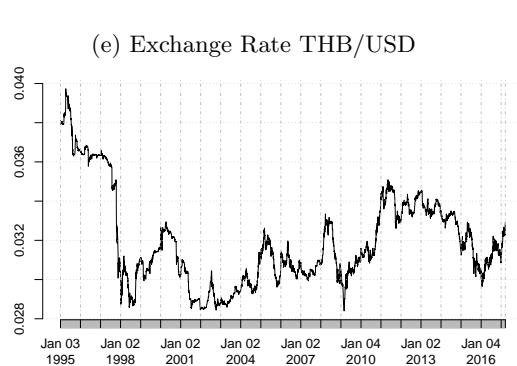
(d) Histogram of SEK/USD arithmetic Returns



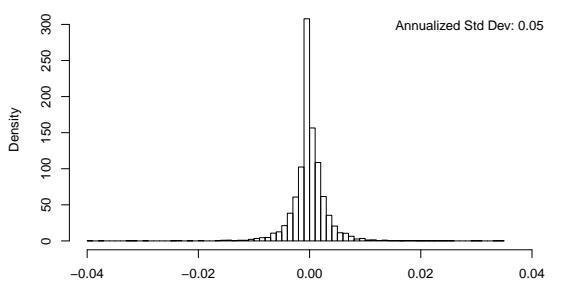
(e) Exchange Rate THB/USD



(f) Histogram of THB/USD arithmetic Returns

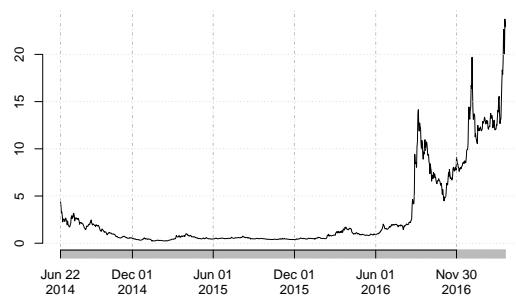


(g) Exchange Rate TWD/USD

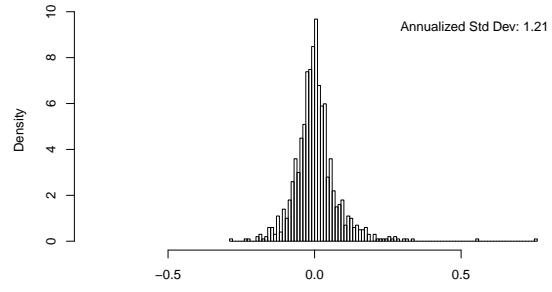


(h) Histogram of TWD/USD arithmetic Returns

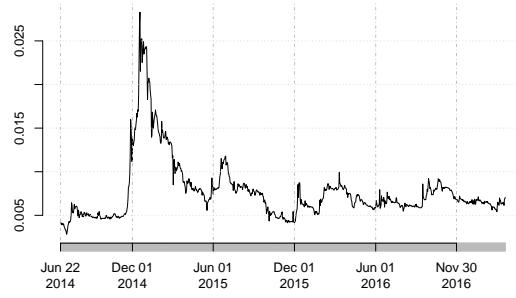
Figure A.5: Exchange rates and histograms of arithmetic returns.



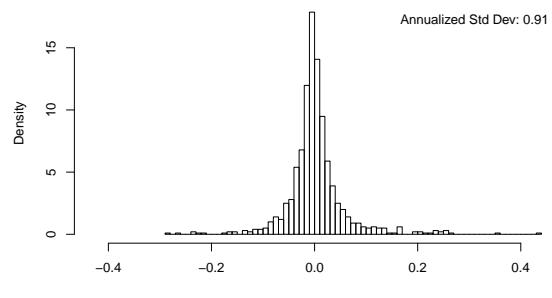
(a) Exchange Rate XMR/USD



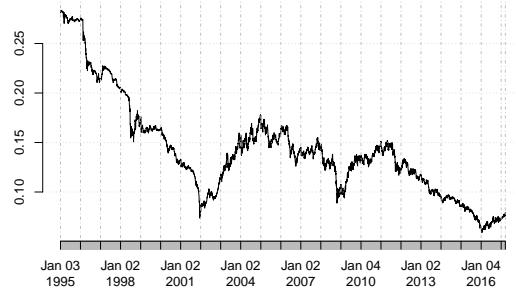
(b) Histogram of XMR/USD arithmetic Returns



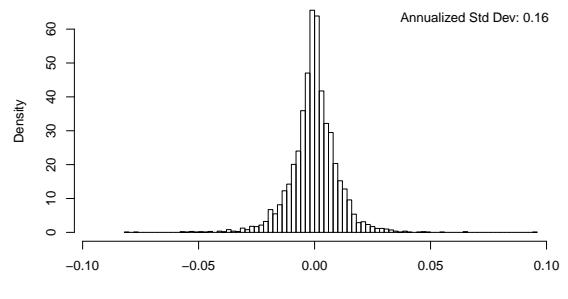
(c) Exchange Rate XRP/USD



(d) Histogram of XRP/USD arithmetic Returns



(e) Exchange Rate ZAR/USD



(f) Histogram of ZAR/USD arithmetic Returns

Figure A.6: Exchange rates and histograms of arithmetic returns.

Appendix B. Histograms of the signal generating steps

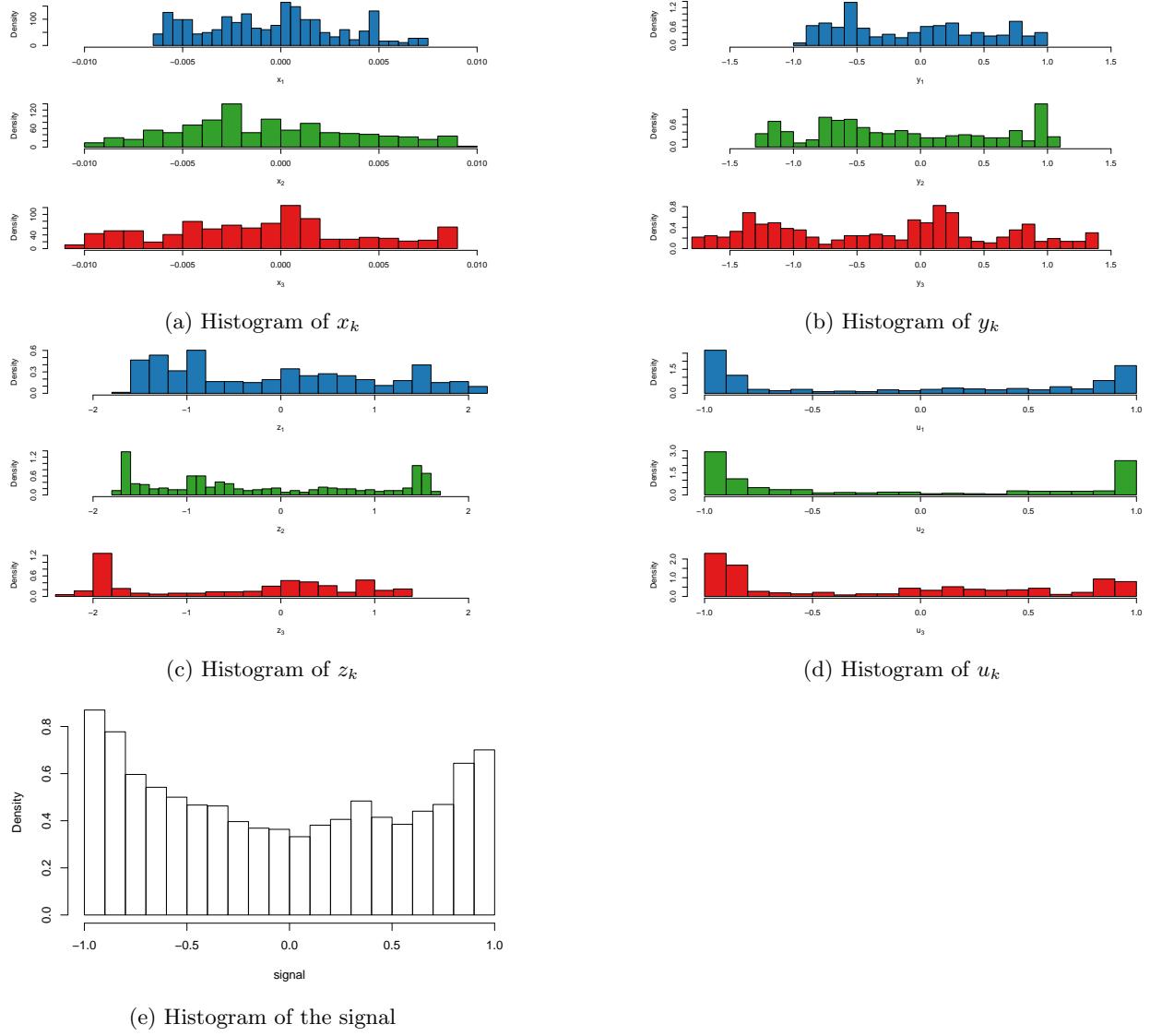


Figure B.7: Histograms of the intermediate steps of the signal calculation