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Ikhlaas Gurrib, Associate Professor, Canadian University of Dubai, United Arab Emirates.

Ikhlaas Gurrib (United Arab Emirates)

PERFORMANCE OF THE AVERAGE DIRECTIONAL INDEX AS A MARKET TIMING TOOL FOR THE MOST ACTIVELY TRADED USD BASED CURRENCY PAIRS

Abstract

The aim of this study is to test a trading system based on the average directional index, which is complemented with the parabolic stop and reverse indicator. The trend-based system is tested onto the most actively traded USD based foreign currency pairs, using both monthly and weekly data set over 2000–2018. Sharpe and Sortino measures are used to track the performance of the currency pairs, based on total risk and downside risk assumptions. Results are robust tested by decomposing the data into pre and post 2008 financial crisis. Using an investment horizon over 18 years, the reliance upon the monthly model produced lower maximum drawdowns and lesser trades than the weekly model. While Swiss Franc had the best (worse) performance in the monthly (weekly) based model, the Chinese Renminbi witnessed the worse (best) performance in the monthly (weekly) based model. Pre and post financial crisis decompositions suggest the weekly-based system is more reliable than the monthly one with relatively more trades and positive performance, where the Chinese Renminbi and Japanese Yen posted the highest Sharpe and Sortino values of 0.996 and 4.452 respectively in the post crisis period. Proportionately high level of negative returns coupled with relatively low positive Sharpe and Sortino values, however, suggest that a trading system relying on the average directional index and parabolic stop and reverse indicator to be further tested and analyzed at higher frequencies.

Keywords average directional index, Sortino, Sharpe, foreign currency markets

JEL Classification G11, G15, G17

INTRODUCTION

Seminal work on the effectiveness of technical analysis can be traced back to Fama (1970) and Ball (1978), where the first study supports the efficient market hypothesis that current market prices reflect all available information, such that reliance on such information would be unprofitable or result in a positive return that is accompanied by an unacceptable risk level. The second study found market timing-based strategies result in negative returns, after adjusting for transaction costs. Park and Irwin (2010), who propelled that technical analysis trading rules were not profitable for U.S. based futures markets, supported findings of Fama (1970) and Ball (1978). Comparatively, Pruitt and White (1988) found their technical based system, which includes variables such as volume, RSI and moving average, outperforming the market after adjusting for transaction costs. In the same line of thought, Menkhoff (2010) found most fund managers in five countries use technical analysis. In support of technical trading, Szakmary, Shen and Sharma (2010) found trend following strategies to be profitable in commodity futures markets and Tsaih et al. (1998) found their trading-based system to outperform a traditional buy and hold strategy in the S&P500 stock index futures market. Similarly, Wong et al. (2003) found the use of RSI and moving average to yield significant positive returns on the Singapore Stock Exchange. Neely et al. (2009) found that both market conditions and profitability, upon using technical analysis techniques, change over time. As described, opposing views exist regarding the success of technical trading in the current literature.

This study bridges the gap by testing the performance of the most actively traded USD based currency pairs, using a trading system built on the average directional index, and backed by the parabolic stop and reverse indicator. This is the first study to test whether such a trend following system works, over both a weekly and monthly horizon, and robust tested over the pre and post financial crisis period. The study covers a broad period of eighteen years, thereby allowing a better understanding how trend following systems work over time. The coverage of the most actively traded USD currency pairs, which includes the Euro, Japanese Yen, British Pound, Australian dollar, Canadian dollar, Swiss Franc and the Chinese Renminbi, allows also the possibility to detect any relationship, in terms of risk, return and performance among these currencies, which are all paired against the USD. The findings have some important implications for regulatory bodies such as Commodity Futures Trading Commission (CFTC) that oversees currency derivatives markets to ensure stability in the currency markets. The use of traditional technical analysis tools like Average Directional Index and Parabolic Stop and Reverse by traders in volatile markets such as leading foreign currency markets can provide information if reliance on a trend following system works for currency markets. The rest of the paper provides some literature review on the performance measure used, some descriptive statistics on the data, the methodology applied to set the trading system, the research findings, before ending with some conclusive remarks.

1. LITERATURE REVIEW

Market timing ability models can be traced back to Treynor and Mazuy (1966) where the market player has the ability to change his or her exposures based on future market movement expectations. Prior to the market going up, the trader takes on more exposures and capitalizes on gains, and prior to the market going down, the trader moves to safer assets and reduces losses. To measure the performance of portfolios based on market timing techniques, performance measures such as Sharpe, Treynor, M^2 and Jensen's alpha were developed and used until now in the investment industry. In line with the development of performance measures, asset-pricing models were developed to explore which aspect of a portfolio should lead to lower or higher expected returns. For instance, the capital asset pricing model (CAPM) proposed by Sharpe (1964) suggests that relying on such a model assumes the portfolio is exposed to market risk. While Jensen's alpha (Jensen, 1968) is based on the difference between CAPM's expected return and the actual returns and remains a popular measure, it does not control firm specific risk which could be important for investors (Fama, 1972). Similarly, Treynor's ratio proposed by Treynor (1965) looks only at the excess return per unit of systematic risk, which is similar to Jensen's alpha as discussed in Aragon and Ferson (2006).

The Sharpe ratio introduced in Sharpe (1966) captures the degree to which a portfolio is able to yield an excess return per unit of risk, where excess return is the difference between return and the risk-free rate. The Sharpe ratio is traditionally used for a portfolio compared to a single investment, since a portfolio excess risk and return would consider the benefits of diversification, as opposed to the Sharpe of a single asset, where correlation cannot be calculated. While various applications exist regarding the use of Sharpe (see Argon & Ferson (2006) and Gurrib (2016) for a good review), the Sharpe ratio does not make any distinction between downside and upside risk. This is particularly relevant, since foreign currency markets tend to display non-normal distributions. For instance, Leland (1999) suggests the need to look into higher moments of distributions to capture investors' utility functions. For positively (negatively) skewed distributions, a portfolio would have a higher (lower) mean than for a normally distributed function, resulting in a relatively lower (higher) risk and higher (lower) excess return per unit of risk. To consider the issues related to distributions and Sharpe performance measure, Sortino and Van der Meer (1991) proposed the Sortino ratio that adjusts the Sharpe measure by looking at downside risk, where downside risk relates to returns falling below a defined target rate. Harry Markowitz, the founder of Modern Portfolio Theory, also discussed the importance of downside risk in his seminal paper (Markowitz, 1959), despite using standard deviation in his portfolio theory model. Various studies used the Sortino, including Sortino (1994), Ziemba (2003), and Chaudhry and Johnson (2008) where the latter found the Sortino ratio to be superior to the Sharpe when distribution of excess returns is skewed.

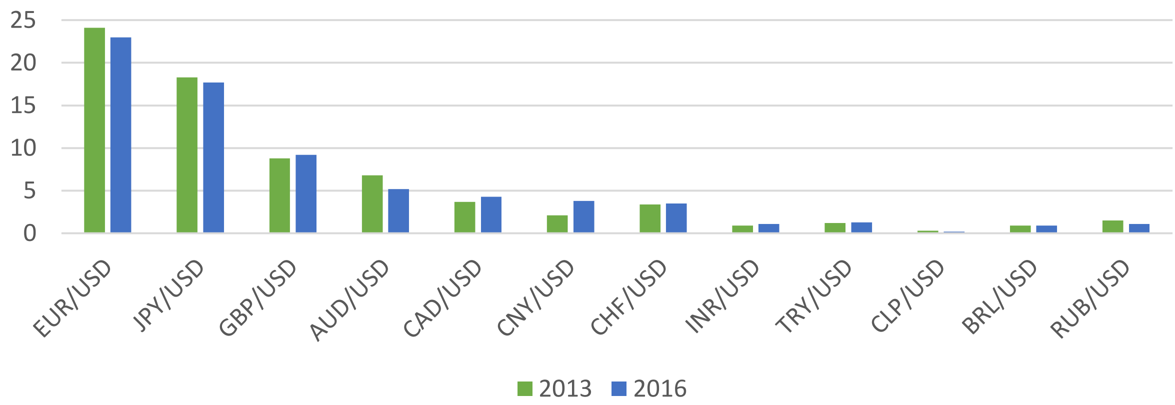
The survey of literature by Menkhoff and Taylor (2007) on foreign exchange markets mostly found evidence of excess return when using technical analysis. While studies like Sweeney (1986) adjusted for transactions costs, others like Cornell and Dietrich (1978) adjusted for interest rates in generating excess returns. Despite the fact that most studies looked at the application of several technical analysis tools, they, however, lacked in three common aspects. Firstly, some studies like Dooley and Shafer (1976) and Logue, Sweeney, and Willett (1978) covered only about three years of data, such that the effect of any major global event like the 2008 global financial crisis might not have been captured in the technical analysis application. Secondly, some studies like Cornell and Dietrich (1978), and Logue and Sweeney (1977) made use of a broad variety of technical analysis techniques, without robust testing each of them. While some studies relied on the use of the Relative Strength Index (RSI) model, there was no apparent review of the assumptions underlying the model. For instance, Gurrib and Kamalov (2018) found that the RSI model can be oversensitive relative to minor price movements and can display asymmetric behavior as to the relative strength values. Thirdly, some studies like Schulmeister (2010), and Logue and Sweeney (1977) looked at only one exchange rate, thereby reducing the generalization of the success or non-success of applying technical analysis tools in other exchange rate markets.

The current study contributes to existing literature on various grounds. It is the first one to test the use of a trading system built on the directional index and parabolic stop and reverse indicators, on the most actively traded USD based currency pairs, over both the pre and post financial crisis, using both weekly and monthly data spanning from 2000–2018. The study over various years, broken down into pre and post financial crisis periods, reduces the sample period issue observed by Dooley and Shafer (1976), and Logue, Sweeney, and Willett (1978). Similarly, robust testing the model over both weekly and monthly frequencies helps in understanding whether such a trend following system acts as a more reliable market timing tool over a longer frequency period such as monthly and avoids potential issues observed in Cornell and Dietrich (1978) and Logue and Sweeney (1977). The inclusion of different currency pairs avoids the issue of generalization present in Schulmeister (2010). Finally, but not least, the use of both the Sortino and Sharpe performance measures provides an additional layer of information by analyzing the effect of both total risk and downsize risk on the performance of any currency pair, within the trading system.

2. DATA

Bank for International Settlements (BIS) (2016) reported that the US dollar (USD) is the dominant trading currency with an involvement of 88% of all trades. As compiled in Figure 1, the seven most actively traded currency pairs based on over the counter (OTC) transactions, were found to involve the USD on one side of the currency pair. These include the EUR/USD, JPY/USD, GBP/USD, AUD/USD, CAD/USD, CNY/USD, and the CHF/USD. This is in line with BIS (2016), which reported that the top five most active currencies during 2013 and 2016 were the USD, EUR, JPY, GBP and the AUD. The USD shared 87 and 87.6 per cent of all OTC foreign exchange transactions during 2013 and 2016. Despite that CNY/USD is relatively less important compared to the leading currency pairs, it is included as part of the leading emerging market economies.

The inclusion of emerging markets such as China in the study is backed by the fact that the small group of emerging economies represented only 1% of world market capitalization in the late 1990s and grew in 2017 to be 24 economies with



Note: Figure 1 reports the foreign exchange market turnover of the most actively traded USD based currency pairs over 2013 and 2016. Euro, Japanese Yen, British pounds, Australian dollar, Canadian dollar, Chinese Renminbi and Swiss Franc were the leading currencies when paired against the US dollar. Emerging markets like India, Turkey, Chile, Brazil and Russia are included only for comparison purposes.

Figure 1. Foreign exchange market turnover of USD based currency pairs

13% of world market capitalization (MSCI, 2017a). Compared with the MSCI World Index that represents the performance of large and mid-cap stocks across 23 developed economies, the MSCI Emerging Markets Index had a Sharpe value of 0.47 compared to 0.30, based on monthly net returns over the 2000–2017 period (MSCI, 2017b). The higher volatility in the returns of the MSCI emerging markets is expected to be more beneficial in the use of market timing tools such as RSI compared to using the RSI tool in more developed and stable markets. The analysis of emerging economies is further backed by the increase in market share of various emerging market currencies over the counter (OTC) turnover as per BIS (2016).

For the purpose of this study, weekly and monthly data for Euro (EUR), Japanese Yen (JPY), British Pound (GBP), Australian dollar (AUD), Canadian dollar (CAD), Swiss Franc (CHF), and Chinese Renminbi (CNY) is compiled from the Federal Reserve Bank of St Louis (FRED). Daily data, as opposed to weekly and monthly data, is not used in this paper for four main reasons. Firstly, due to the foreign currency markets being one of the most volatile markets, trading on a high frequency data would potentially lead of whipsaws and unreliable signals in the trend following based system. As discussed in Gurrib (2016), the shorter the data frequency, the higher the number of whipsaws which can potentially result in more false signals and accumulated losses. Secondly, studies like Faber (2013) applied monthly-based indicators over the 1901–2012 period and found the market timing strategy to outperform a buy-and-hold strategy relative to risk, return and Sharpe performance measures. The same author also pointed out that the maximum drawdown is lower as the data frequency is increased from daily to monthly. Thirdly, studies like Siegel (2013) made use of daily based models which resulted in increasing transaction costs. Lastly, Coppes (1995) found exchange rate changes to be more normally distributed when sampled on monthly rather than daily basis.

In the spirit of looking into pre and post financial crisis robust testing, the data sample is set over 2000–2018, where the crisis breakpoint is assumed to occur in September 2008 with the Lehman Brothers crash. Although not reported here, all the series are tested for normality using the Jarque-Bera test statistic. Only the GBP, EUR and AUD were found to be normal. While the EUR and GBP were found to be normally distributed at 1% level, the AUD was found to be normally distributed at 5% significance level. Further, Augmented Dickey-Fuller (ADF) stationary test shows all currency pairs are stationary after 1st order differencing. This is in line with Gurrib (2018) who found net positions in currency derivatives to be stationary using weekly data from 2007 to 2018. An average 3-month treasury bill of 1.59%, obtained from the Federal Reserve Bank of St Louis (FRED), is used as the risk-free rate. The use of an average treasury bill rate helps to evaluate the performance of different currencies over different periods of time, when based on the Sharpe or Sortino measures. All currencies are paired against the USD. Due to the scope of study, transaction costs are ignored.

3. RESEARCH METHODOLOGY

Before laying down the skeleton of the trading system, for brevity and ease of readability, the rationales behind the use of the Average Directional Index (*ADX*) and Parabolic Stop and Reverse (*PSAR*) indicators are explained. The *ADX* is essentially an index-based indicator which helps to determine the strength or weakness of a trend. It is used together with an up directional indicator (*DI+*) and a down directional indicator (*DI–*) which identify if there is a trend. In layman's terms, when the up directional index is above (below) than the down directional index, a bullish (bearish) trend is in place. In analyzing any trend's strength, *ADX* is used, where high (low) readings indicate a strong (weak) trend. Similarly, PSAR allows the trader to have an entry or exit point, by providing information whenever the price is changing direction. In short, when the PSAR moves from below (above) to above (below) price line, a potential price change is expected. To avoid whipsaws, PSAR works better with trend-based settings like those captured in the *ADX* system.

Developed by Wilder (1978), *ADX* is essentially a technical analysis indicator which measures the magnitude or strength of a trend, but not the actual direction of the latter. The direction is rather captured through the directional movement which is based on the comparison of the difference between two consecutive lows with the difference between their related highs. Directional movement (*DM*) is positive when the current high minus the prior high is greater than the prior low minus the current low. Provided it is positive, *DM* (+) then equals the current high minus the prior high. A negative value is entered as zero. Similarly, directional movement is negative when the prior low minus the current low is greater than the current high minus the prior high. Provided it is negative, *DM* (–) equals the prior low minus the current low. A negative value is entered as zero. This is illustrated as follows:

$$DM_t = DM_t(+) = (High_t - High_{t-1})$$

$$\text{if: } (High_t - High_{t-1}) > (Low_{t-1} - Low_t); \quad (1)$$

otherwise *DM* (+) is zero.

$$DM_t = DM_t(-) = (Low_{t-1} - Low_t)$$

$$\text{if: } (Low_{t-1} - Low_t) > (High_t - High_{t-1}); \quad (2)$$

otherwise *DM*(–) is zero.

In line with Wilder (1978), *DM* is then extended to 14 periods using the True Range (*TR*) to find the 14 period *DM* as follows:

$$True\ Range\ (TR_t) = Max \begin{vmatrix} High_t - Close_{t-1} \\ Low_t - Close_{t-1} \end{vmatrix}, \quad (3)$$

$$High_t - Low_t,$$

where

$$\left\{ \begin{array}{l} 1st\ \ 14 period\ \ \ TR = \sum_{(t=1)}^{14} TR_t \\ Subsequent 14 period TR = \\ = Previous 14 period TR - \\ -average(Previous 14 period TR) + \\ +Current TR \end{array} \right\}. \quad (4)$$

Similar in calculating the 14 period *TR*, the 14 period directional movements (+ and –) are computed by substituting TR_t for $DM_t(+)$ and $DM_t(-)$ in equation (4). The Directional Indicator (*DI*) can then be obtained by smoothing the 14 period $DM_t(+)$ and 14 period $DM_t(-)$ to the 14 period true range values and represented in a matrix form as follows:

$$\begin{bmatrix} Positive\ Directional\ Indicator\ (DI_t(+)) \\ Negative\ Directional\ Indicator\ (DI_t(-)) \end{bmatrix} = \quad (5)$$

$$= \frac{100}{14\ period\ TR_t} \begin{bmatrix} 14\ period\ DM_t(+) \\ 14\ period\ DM_t(-) \end{bmatrix}.$$

The Directional Index (*DX*) can then be calculated by taking the ratio of the difference between the positive directional indicator and negative directional indicator relative to the absolute sum of both the positive and negative directional indicators as observed in equation (6). When the positive *DI* is greater (smaller) than the negative *DI*, this suggests the market is bullish (bearish). The strength of the bullishness or bearishness is captured through the *ADX* as an exponential moving average. Similar to the construction of exponential moving average series (EMA), the average directional index (*ADX*) is calculated in a similar fashion as per equation (7).

$$DX_t = \left| \frac{DI_t(+) - DI_t(-)}{DI_t(+) + DI_t(-)} \right|, \quad (6)$$

$$ADX = \left\{ \begin{array}{c} 1\text{st } ADX = \frac{1}{14}\sum_{t=1}^{14} DX_t \\ Subsequent\ ADX = \frac{1}{14}((ADX_{t-1} \cdot 13) + DX_t) \end{array} \right\}. \quad (7)$$

The ADX indicator can be used to construct a trading strategy based on cross over and cross under rules as follows:

Trading signal:

$$\begin{Bmatrix} Buy \\ Sell \end{Bmatrix} if \begin{Bmatrix} (DI_t(+)\ crossover\ DI_t(-) \mid ADX_t > \partial) \\ (DI_t(+)\ crossunder\ DI_t(-) \mid ADX_t > \partial) \end{Bmatrix}. \quad (8)$$

For the purpose of this study, ∂ is set to 20 as mostly adopted by traders or used as default in trading software. To add robustness to the trading system setup, PSAR is included in the trading strategy. The benefit of PSAR is that it follows prices, and acts as a trend following indicator by helping to confirm any continuation and reversal of trends. For instance, when a downtrend ends, the PSAR acts like a trailing stop below the price, where the stop constantly rises while the uptrend is in effect. The PSAR never decreases in an uptrend and consistently protects profits as prices increases further. Alternatively stated, the indicator acts as a safety net against the tendency to lower a stop loss. Similarly, if prices stop increasing and reverse below the PSAR, a downtrend is in effect with PSAR above the price. Since PSAR never increases in a downtrend, it endlessly protects gains on short selling positions. Due to the scope of the study, where the *ADX* is the main technical analysis decision tool, the PSAR indicator is mainly used to ensure that any buying (selling) signal from *ADX*, at a specific time, is backed by the closing price being higher (lower) than the PSAR value. To be consistent in the analysis, descriptive statistics such as the total number of trades and maximum drawdown are reported, where the maximum drawdown measures the maximum loss in the portfolio value, from a peak to a trough, before a new peak is attained. To be consistent in the risk and return calculations, all returns are based on either a buy followed by a sell, or vice versa. Returns are based solely on the holding periods. Any previous purchase or sale not followed by a subsequent sale or purchase is closed on January 1st, 2018 to ensure no open positions at the end.

As part of evaluating the performance of the different currency pairs, both the Sharpe and the Sortino risk-adjusted performance measures, as discussed earlier, are used. The Sharpe ratio is the excess return per unit of risk, and assumes total risk (upside and downside) is considered. The Sortino ratio assumes only downside risk is considered. In line with Sortino and Van der Meer (1991), the Sortino ratio can be decomposed as follows:

$$Sortino\,ratio = \frac{\overline{R_A} - MAR_A}{\sigma_A^d}, \quad (9)$$

where $\sigma_A^d = \sqrt{\frac{\sum(R_A - MAR_A)^2}{n}}$

and represents the target downside deviation. R_A represents the average return of the financial asset, n is the number of returns, and MAR_A represents the minimum acceptable return. If $(R_A - MAR_A) > 0$, the resulting value is substituted to zero, otherwise, the value is set as $R_A - MAR_A$. This ensures that the model captures only downside risk. For the purpose of this study, the minimum acceptable return is set as the risk-free rate. Future studies can analyze the effect of setting a targeted return instead of the minimum acceptable return.

4. RESEARCH FINDINGS

Table 1 displays the performance of a trading system based on the Average Directional Index and Parabolic Stop and Reverse Indicators. The period under analysis spreads from January 2000 to January 2018. Both weekly and monthly based trading systems results are provided. All positions are closed as at January 1st, 2018, in case the trading models still have open positions. Total number of trades, maximum drawdown, total return, average return, average risk, and average downside risk, including Sharpe and Sortino performance values, are reported. For the monthly-based trading system, CAD, JPY, and CHF had their positions closed at the end to be able to compute the return and risk. GBP and CNY had no standard deviation involved since there was only one buying and one selling signal, resulting in the total returns being the same as the average return. This led to neither a risk value nor a Sharpe value. However, the Sortino value is reported since both currencies had downside risk and the Sortino is not based on the deviation from the average return but rather from the targeted return or minimum acceptable return. CAD had the lowest total return of –32%, accompanied by the highest average downside risk of 22.48%. The Sharpe ratio did not account for the highest downside risk in the CAD where the Euro reported the most negative Sharpe value, despite a negative total return of –10.9%. The monthly-based trading system also produced the highest number of trades for the Canadian dollar. The maximum drawdown was found in the GBP, where the currency lost nearly one third of its value against the USD. The Sortino measure, which adjusts exclusively for downside risk, suggests the Swiss Franc had the highest Sortino value of 28.212. This could be explained by the highest positive total returns of 20.45% for the CHF, accompanied by an average total risk of 14.90% and average downside risk of 0.31%. The relatively better performance of the CHF over this whole period is attributed to one short selling signal in 2006, followed by a buying signal in 2016, where a positive total return of 20.76% was made. This was followed by one sell and one buy trade, with a loss of –0.31%.

For the weekly-based trading system, maximum drawdown for the Chinese Renminbi and Japanese Yen does not include the effect of closing the position at the end, to be able to observe the real drawdowns witnessed by the trader. The highest drawdown was observed with the CHF where the currency lost nearly 50% of its value. The CHF fell mostly during the first ten years post 2000. Compared to the monthly-based trading system, the reliance on weekly data resulted in relatively higher number of trades, with the Euro leading with 28 trades and Chinese Renminbi with 6 trades. With only positive returns, the Chinese yuan reported no downside risk and the second smallest average total risk after the Swiss Franc. While reporting an average risk of 2.28%, the Swiss Franc had the lowest return of –43% that was explained by the second highest downside risk among all other currencies. This resulted in the least performing currency against the USD with a Sharpe of –2.123 and a Sortino value of –0.317. While the highest total return was found when trading on the JPY with a return of 20.13%, this was also accompanied by the highest average total risk, which led to a Sharpe value of 0.079. Based on the Sharpe measure, which accounts for both sides of risk, the CNY had the highest Sharpe value of 0.996. Non-negative returns, however, prevent the calculation of the Sortino, which is based on downside risk. The CAD, with 16 trades, had an average return of 14.73%, an average total risk of 12.75%, average downside risk of 9.21%, and the highest Sortino value of 0.143. The highest average downside risk being compensated by a positive return, well above the risk-free rate, suggests that trading the CAD under the trading model resulted in a performance based not purely on risk premium, but superior market timing ability. This was also observed for JPY, which produced a return of 20.13%, an average total risk of 14.61% relative to an average downside risk of 9.73%. While higher average risk value suggests higher expected risk premium, a higher average downside risk value suggests the need for superior market timing models in order to achieve excess positive returns. Alternatively stated, a higher Sortino value is preferred as a measure of market timing skills, but only possible when the financial asset is subject to returns being lower than the minimum acceptable return or risk-free rate.

Various studies have identified the investment horizon as an important factor affecting the performance measures. For instance, Chen and Lee (1981), Levy and Samuelson (1992), Gunthorpe and Levy (1994) and Sharpe (1966) found performance measures such as the Sharpe to have less persistence over time, suggesting the need to as-

Table 1. Performance of trading strategy (2000–2018)

	CAD	CNY	JPY	CHF	AUD	EUR	GBP
Monthly-based trading system							
Total number of trades	8	2	6	4	4	4	2
Maximum drawdown	–0.138	–0.133	–12.726	0.000	–0.099	–0.146	–0.298
Total return	–32%	–2.07%	–8.82%	20.45%	1.54%	–10.90%	–15.64%
Average return	–8.04%	–2.07%	–2.94%	10.23%	0.77%	–5.45%	–15.64%
Average total risk	9.09%	–	5.39%	14.90%	19.40%	2.46%	–
Average downside risk	22.48%	2.07%	8.79%	0.31%	12.95%	8.09%	15.64%
Sharpe	–1.059	–	–0.841	0.580	–0.042	–2.860	–
Sortino	–0.429	–1.769	–0.515	28.212	–0.063	–0.870	–1.102
Weekly-based trading system							
Total number of trades	16	6	24	20	20	28	22
Maximum drawdown	–0.192	0.000	–22.940	–0.528	–0.314	–0.135	–0.333
Total return	14.73%	12.73%	20.13%	–43.03%	–7.05%	2.05%	11.23%
Average return	1.84%	4.24%	1.68%	–4.30%	–0.71%	0.15%	1.02%
Average total risk	12.75%	3.73%	14.61%	2.28%	13.31%	5.06%	9.19%
Average downside risk	9.21%	0.00%	9.73%	15.22%	16.84%	8.97%	9.93%
Sharpe	0.103	0.996	0.079	–2.123	–0.093	–0.075	0.054
Sortino	0.143	–	0.118	–0.317	–0.073	–0.042	0.050

Note: Table 1 displays the performance of a trading system based on the Average Directional Index and Parabolic Stop and Reverse Indicators. The period under analysis spreads from January 2000 to January 2018. Both weekly and monthly based trading systems results are provided. All positions are closed as at January 1st, 2018, in case the trading models still have open positions. Total number of trades, maximum drawdown, total return, average return, average total risk, average downside risk are reported, including Sharpe and Sortino performance values.

sess the performance of the trading strategy over the pre and post financial crisis. Table 2 displays the performance of a trading system based on the Average Directional Index and Parabolic Stop and Reverse Indicators, based on the pre-financial crisis period ranging January 2000 to October 2008. Both weekly and monthly based trading systems results are provided. Total number of trades, maximum drawdown, total return, average return, average risk, average downside risk are reported, including Sharpe and Sortino performance values. All currencies had open positions if they relied on the trading system, except for the Japanese Yen which had closed positions, and the Chinese Renminbi had no trade. To allow for comparison between pre and post crisis, all open positions were closed on October 1st, 2018. The British Pound experienced the lowest returns of –11.50%, explained by the highest average downside risk of 11.50%. It is important to note that the maximum number of trades were two, resulting in no deviations from the average return. This resulted in no Sharpe calculation, since there was only one buy and one sell transaction at most, which allow the calculation of only one return. While the Sortino values could be calculated, it is important to stress that these are based on one return value, and not reliable for generalization purposes.

Compared with the monthly-based trading system, which resulted in zero to two trades at most, the reliance on weekly data allows for more trades. The Japanese Yen and British Pound had each fourteen and twelve trades, respectively. While the Japanese Yen appears to have the highest drawdown of –19.150, it is in fact the British Pound which witnessed the maximum drawdown of –0.3333 against the dollar. The Japanese Yen also observed the highest total return of 16.13%, with an average return of 2.30% due to the relatively higher number of trades involved in the currency. There were no negative returns observed for the Japanese Yen. The Swiss Franc had the highest average return of 3.85% with 8 trades over the 2000–2008 period. The Australian dollar had the highest average risk, complemented with the high-

Table 2. Pre 2008 financial crisis performance

	CAD	CNY	JPY	CHF	AUD	EUR	GBP
Monthly-based trading system							
Total number of trades	2	0	2	2	2	2	2
Maximum drawdown	0.000	–	–9.890	0.000	0.000	0.000	–0.122
Total return	–6.54%	–	–8.17%	7.60%	–10.39%	3.34%	–11.50%
Average return	–6.54%	–	–8.17%	7.60%	–10.39%	3.34%	–11.50%
Average total risk	–	–	–	–	–	–	–
Average downside risk	6.54%	–	8.17%	0.00%	10.39%	0.00%	11.50%
Sharpe	–	–	–	–	–	–	–
Sortino	–1.243	–	–1.195	–	–1.153	–	–0.138
Weekly-based trading system							
Total number of trades	8	0	14	8	10	8	12
Maximum drawdown	–0.074	–	–19.150	–0.235	–0.134	–0.117	–0.333
Total return	–6.28%	–	16.13%	15.38%	5.43%	–2.22%	–4.75%
Average return	–1.57%	–	2.30%	3.85%	1.09%	–0.56%	–0.79%
Average total risk	5.99%	–	1.65%	2.96%	14.18%	6.09%	7.30%
Average downside risk	10.55%	–	0.00%	0.00%	11.48%	7.82%	8.73%
Sharpe	–0.350	–	1.078	1.121	0.039	–0.178	–0.181
Sortino	–0.199	–	–	–	0.049	–0.139	–0.151

Note: Table 2 displays the performance of a trading system based on the Average Directional Index and Parabolic Stop and Reverse Indicators. The analysis is based on the pre financial crisis period ranging January 2000 to October 2008. Both weekly and monthly based trading systems results are provided. All positions are closed as at October 1st, 2008, in case the trading models still have open positions. Total number of trades, maximum drawdown, total return, average return, average total risk, average downside risk are reported, including Sharpe and Sortino performance values.

est average downside risk of 11.48%. The performance of the different currencies, when measured in terms of total risk resulted in Sharpe values ranging from –0.350 for the Canadian dollar to 1.121 for the Swiss Franc. With no trade for the Chinese Renminbi, no performance measures could be implemented for the currency. With no negative returns observed for the Japanese Yen and Swiss Franc, the Australian dollar had the only positive Sortino value of 0.049, compared with the Canadian dollar and the British Pound which both shared negative total returns, explained by relatively high average downside risk values.

Table 3 reports the performance of the trading strategy based on a monthly and weekly trading system. In regards to the monthly-based system, except for the Chinese Renminbi and Swiss Franc which had closed positions based on the trading system rules, all other currencies had open positions, which had to be closed as at January 1st, 2018 to compute risk and return measures. Following the global financial crisis of 2008, the trading system produced only few trades across all currencies. British Pound had the highest positive total return of 11.04% and the Euro witnessed the biggest negative return of –8.09% over the same period. Due to a maximum of two trades, i.e. one purchase followed by one sale or vice versa, this resulted in no standard deviation measure from the mean. This meant the Sharpe ratio could not be used to assess the performance of investing in these currencies, post crisis. On the other hand, various currencies like CNY, JPY, CHF, AUD, and Euro witnessed negative returns, which was captured in the Sortino ratio.

The weekly-based system reports that, except for the Japanese Yen, Euro and British Pound, all other currencies had open positions at the end of the sample. To be able to compare risk and return with the whole period and post crisis period, all open positions were closed as at January 1st, 2018. The highest maximum drawdown value was observed with British Pound which witnessed a drop of –0.332 in the currency value. The Euro had both the highest number of trades, and the highest total return of 19.92% over the 2008–2018 period. The

Table 3. Post 2008 financial crisis performance

	CAD	CNY	JPY	CHF	AUD	EUR	GBP
Monthly-based trading system							
Total number of trades	2	2	2	2	2	2	2
Maximum drawdown	0.000	–0.133	–10.371	–0.060	–0.017	–0.121	0.000
Total return	2.87%	–2.07%	–7.24%	–5.85%	–0.77%	–8.09%	11.04%
Average return	2.87%	–2.07%	–7.24%	–5.85%	–0.77%	–8.09%	11.04%
Average total risk	–	–	–	–	–	–	–
Average downside risk	0.00%	2.07%	7.24%	5.85%	0.77%	8.09%	0.00%
Sharpe	–	–	–	–	–	–	–
Sortino	–	–1.769	–1.220	–1.272	–3.067	–1.197	–
Weekly-based trading system							
Total number of trades	10	6	10	12	10	18	14
Maximum drawdown	–0.104	0.000	0.000	–0.135	–0.038	0.050	–0.332
Total return	–3.47%	12.73%	11.07%	–11.17%	1.41%	19.92%	–0.45%
Average return	–0.69%	4.24%	2.21%	–1.86%	0.28%	2.21%	–0.06%
Average total risk	4.00%	3.73%	6.13%	8.04%	5.62%	6.90%	9.11%
Average downside risk	5.21%	0.00%	2.76%	15.53%	6.91%	4.45%	9.58%
Sharpe	–0.305	0.996	0.275	–0.297	–0.044	0.245	–0.065
Sortino	–0.420	–	4.452	–0.311	–0.327	–0.251	–0.799

Note: Table 3 displays the performance of a trading system based on the Average Directional Index and Parabolic Stop and Reverse Indicators. The period under analysis is based on the post financial crisis period ranging October 2008 to January 2018. Both weekly and monthly based trading systems results are provided. All positions are closed as at 1st January 2018, in case the trading models still have open positions. Total number of trades, maximum drawdown, total return, average return, average risk, average downside risk are reported, including Sharpe and Sortino performance values.

Chinese Renminbi had the highest average return of 4.24% due to only six trades. While Swiss Franc had the highest average risk value of 8.04%, the Chinese Renminbi had the highest Sharpe value among all other currencies. The Swiss Franc had the lowest total return of –11.17%, which was explained by the highest average downside risk among other currencies. While the Chinese Renminbi had no negative returns, which resulted in no Sortino based value, investing in the Japanese Yen yielded the highest positive Sortino value of 4.452. This could be explained with Japanese Yen sharing the second downside risk value of 2.76%.

5. EVALUATION OF THE TRADING MODEL

A closer analysis of the earlier findings helps to shed light on various grounds. First, using the whole 18-year period as sample size, the maximum drawdown from the monthly based system is lower than the weekly based system. This is in line with Faber (2013) who found daily based models to be more prone to higher drawdown values than monthly based ones. Further, while it is clear that the number of trades is higher with the weekly based model, the relative performance of each currency pair changes based on the frequency of the model, i.e. weekly or monthly. Swiss Franc witnessed the highest return, a relatively high average total risk, the lowest downside risk, and consequently the highest Sharpe and Sortino values under the monthly based model. However, under the weekly model, the same currency underperformed with the lowest return (negative), lowest average total risk, relatively high downside risk, with resulting negative Sharpe and Sortino values. This suggests initially that the weekly performance is more susceptible to more trades, higher maximum drawdown, and higher downside risk compared to a monthly based model. A higher (lower) positive total return tends to be accompanied with a higher (lower) average total risk and a lower (higher) average downside risk. With relatively higher drawdown values and a broader range of returns and risk values, the weekly model is more likely to have variations in the Sharpe and Sortino performance values as observed with the CHF.

When robust tested over pre and post financial crisis periods, the number of trades and maximum drawdown were again consistent in that a monthly based model would have relatively less trades and lower maximum drawdown than the weekly based model. Compared to the pre-crisis period, the number of trades in post-crisis period was relatively higher. If a longer investment horizon such as 2000–2018 is opted, the trader relying on the monthly model would have more trades, compared to a maximum number of two trades noted in the distinct pre and post crisis periods. The same analogy can be applied to the trader who would have a longer investment horizon (2000–2018) where adopting the weekly based system would result in relatively more trades than just investing in the distinct pre or post crisis periods. The relatively low number of trades in the monthly based model in both pre and post crisis periods, suggest that reliance on the monthly based model, in a short time investment horizon, is not warranted. Further, despite the fact that trading the CHF over 2000–2018 would have resulted in positive Sharpe and Sortino values, a Sharpe value of 0.518 is quite low compared to the pre-crisis weekly based Sharpe value of 1.121. The Sortino value of 28.212 is due to the relatively low average downside risk. Based on the above, the weekly model is more likely to have more trades, with higher maximum drawdowns than the monthly model. More importantly, the performance of the USD based currency pairs in post crisis period, was more closely related to that observed under the whole period analysis, compared to the pre-crisis period. While the most noticeable example is the CNY, which had the highest return coupled with the lowest risk, this could be explained by the fact that there was no trade signal from the model in the pre-crisis period for the CNY. The highest Sharpe values of 1.121 and 1.078 were observed in the pre-crisis period for CHF and JPY. Excess return per unit of risk deteriorated, however, in post crisis with the highest Sharpe value being 0.996. Sortino values as well deteriorated during post crisis period, with the only positive value of 4.452 obtained when trading Japanese Yen. Higher maximum drawdown values upon using sampled periods (pre or post crisis) and relatively low performance values like Sharpe or Sortino over the weekly model, point to the need for regulatory bodies to oversee the currency markets on a continual basis, particularly, when currency traders like speculators are investing on shorter investment horizons and relying on weekly based models.

CONCLUSION

In the same spirit as regulatory institutions such as the Bank of International Settlements, which is continuously working on promoting monetary and financial stability internationally, this study analyzes whether major foreign currencies can actually be used to trade successfully under a trend based system. For the purpose of this study, the most actively traded USD based currency pairs are tested over an average directional index model backed by the parabolic stop and reverse indicator. As expected, the weekly-based system produced relatively more trades and higher maximum drawdowns than the monthly-based system. However, the relative performance of a particular currency pair is also subject to the frequency of the model as observed with the Swiss Franc, which experienced both the best and worst performance under the monthly and weekly model, respectively. A weekly-based model tends to produce higher total return and varying levels of total and downside risk. When defragmented over the pre and post crisis period, post crisis performance was found to be closer to the whole period analysis model, with, however, lower number of trades, with higher maximum drawdown values, and positive yet low Sharpe and Sortino values under the weekly based model. The relatively low number of trades under the monthly model also suggests that relying on a monthly dataset is more effective over a longer investment horizon. Despite producing some positive Sharpe and Sortino values, the weekly based model points to the need, as a future research avenue, to consider higher frequencies data model, to benefit potentially from volatile markets such as foreign currencies. This would allow banks, which are the biggest players in the foreign currency markets, to fine-tune their banking system further towards understanding the risk and return characteristics of the most actively traded foreign currency pairs.

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