ANALYSIS OF THE PREDICTIVE ABILITY AND PROFITABILITY OF AN ANALYTICALLY DERIVED TRADING ALGORITHM IN THE INTRA-DAY SPOT FOREIGN EXCHANGE MARKET

by

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Abstract

This paper examines the predictive power and profitability of an analytically derived, technical trading algorithm in the intraday spot foreign exchange market, using over nine years of hourly data. This trading rule, the reservation price policy (RPP), stems from the computer science literature and, based on certain assumptions, is shown to be efficient under the worst-case scenario criterion. The results indicate the existence of significant information content in the trading rule, which is robust to the parameter choice and consistent across the eleven currencies examined. But, the nonparametric, bootstrap analysis shows that the rule does not capture any incremental information above what is accounted for by the seasonal GARCH(1,1)-MA(1) model. Under the assumption of zero transaction costs, the trading rule yields risk-adjusted profits superior to a number of investment alternatives. However, breakeven transaction cost analysis shows that for the trading strategy to be profitable for any of the examined currencies, costs need to be significantly lower than the empirically observed transaction costs. Thus the results are consistent with the efficiency of the foreign exchange market.

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1 Introduction

The state of theoretical modelling of short term exchange rate dynamics is well summarised by Backus *et al* (2009, p. 9) who remark: "Decades of work has left us with the opinion that short and medium-term fluctuations are inexplicable, both before and after the fact." Economic fundamentals are particularly impotent in the intraday realm, which often forces economists to invoke the random walk model in order to explain intraday currency fluctuations (Goodhart, 1988, p.438). It is not surprising that survey evidence reveals technical analysis (which is, essentially, the prediction of asset price movements from the inductive analysis of past movements) to be the most widely used form of short term forecasting technique by both foreign exchange dealers and fund managers in the foreign exchange markets across the globe. Moreover, there is strong evidence that its relative importance has been rising in recent years, largely at the expense of fundamental analysis (Taylor and Allen, 1992; Gehrig and Menkhoff, 2006; Menkhoff and Taylor, 2007). Indeed, Menkhoff and Taylor (2007, p. 967), in their comprehensive survey of the literature on technical analysis in foreign exchange markets, go as far as to say that "technical analysis remains a passionate obsession of many foreign exchange professionals". This makes the FOREX market an ideal avenue for testing the performance of the new, analytically derived, technical trading rule: the *reservation price policy*.

As succinctly summarised by Neftci (1991, p. 549), technical analysis is "a broad class of prediction rules with unknown statistical properties, developed by practitioners without reference to any formalism". In fact, there exists a plethora of available technical trading rules which range from simple moving averages to the very exotic Ichimoku Clouds[1]. Moreover, because it is a relatively simple task, new technical indicators are being created every day. This is mainly due to the extensive, and often arbitrary, parameter choice of the existing rules as well as the possibility of combining old rules to form new ones. It is perhaps this ad-hocness that led to technical analysis traditionally being viewed with a degree of distrust by academic literature, despite its longstanding popularity in practice. However, what makes the *reservation price policy* (RPP) rule unique is that it stems from a formal, analytical derivation. The RPP rule constitutes a well-defined form of a technical trading rule as it meets the condition suggested by Neftci (1991, p. 555) of being a Markov time.In other words, buy and sell signals at time t are generated based on the data available at time t (trading signals are $I_t - measurable$). In addition, under certain assumptions, it can

[1]According to *Investopedia* it is a multi-faceted indicator designed by a Japanese newspaper journalist to give support/resistance levels, trend direction, and entry/exit points of varying strengths.

analytically be shown to be superior to a set of widely-used simple, technical trading rules based on a worst-case performance metric.

The RPP rule's foundations lie in the body of research on non-Bayesian analysis of financial problems that has been developed (mainly independently from the influence of financial economics literature) within the academic, computer science community (El-Yaniv, 1992; El-Yaniv *et al* 1998; El-Yaniv *et al*, 2001; Schmidt and Mohr, 2008; Schmidt *et al*, 2010). The focus of these studies was the development of efficient trading algorithms (trading rules), using the competitive-ratio optimality criterion. The competitive-ratio optimality criterion is a worst case performance measure; i.e. with the minimum use of assumptions, an algorithm is developed so as to yield a predefined (acceptable) relative performance even in the worst case scenario. The advantages of algorithms developed in the analytical competitive-ratio framework is that there are mathematical reasons attached to each algorithm's formulation rather than it being simply a concoction of "time-tested" market heuristics. But the analysis of these "competitive" trading algorithms, although robust and precise, was often solely analytical. There has been some recent effort of empirical examination of the rules developed within the competitive ratio optimality framework using historical market data. Mohr and Schmidt (2008) and Schmidt *et al* (2010) examine a number of rules, including RPP, using daily XETRA DAX data.[2] But the analysis revealed in the two aforementioned papers was carried out within the formalistic framework that, though well suited for testing the efficiency of algorithms, makes the results difficult to coincide with either existing finance literature or real trading applications.

In this paper, we provide the first cross-pollination of the two fields by empirically examining the performance of one of the competitive trading rules [the adjusted *reservation price policy* (RPP) rule] in the spot foreign exchange market with the use of the empirical methodology for testing technical trading strategies which have been well established in the financial economics literature.[3] As foreshadowed by the first paragraph, the empirical investigation is carried out in the context of intraday trading (using eleven spot foreign exchange rates sampled hourly). This makes this study more consistent with the practice of

[2] Another avenue where some of the trading rules developed by finance "outsiders" (such as computer science researchers) were given an opportunity to be tested was the Penn-Lehman Automated Trading (PLAT) Project. PLAT was a broad investigation of algorithms and strategies for automated trading in financial markets [for an example one can see Yu and Stone (2003)].

[3] Although recent research has tended to examine large selections of rules and variations thereof, the approach adopted in this paper (of narrowly focusing on a single rule) is not new in the literature and is consistent with for example Chang and Osler (1999).

technical trading because intraday traders' operations account for more than 90% of the FOREX market volume (Dacorogna et al, 2001, p. 14) and most technical traders, who survey evidence shows are strongly represented in the FOREX market (Gehrig and Menkhoff, 2006), are known to transact at a high frequency (Neely and Weller, 2003, p. 223). This paper investigates separately the incremental, informational content (*predictability*) of the signals generated by the reservation price policy as well as the potential profits a trader could realize by following the prescriptions of this trading rule (*profitability*). We examine the predictive power of the RPP trading rule using (1) the Kolmogorov-Smirnov distribution test and (2) the bootstrap approach advocated by Brock *et al* (1992). A central advantage of the bootstrap is that it allows one to determine if any predictive ability of the examined trading rule could instead be explained by an econometric model that was fitted to the data, thus evaluating whether the RPP trading rule adds any incremental information over the information provided by a fitted exchange rate model. Essentially, this approach allows one to get closer to the source of any potential forecasting ability.

In summary, the results show that the RPP rule has a significant predictive power that appears robust across different spot exchange rates and parameters. However, on average, the RPP signals add no incremental value above a GARCH(1,1)-MA(1) model with seasonal intraday volatility. Indeed, our analysis rigorously shows that the reported predictive ability of contrarian technical trading rules (essentially rules that profit from mean reversion such as the RPP rule) in the intraday foreign exchange market, is likely simply to be an artefact of the negative serial correlation inherent in the high frequency currency data. Finally, the examination of potential profitability shows that, on average, the RPP rule cannot generate positive profits in the presence of realistic transaction costs. Nevertheless, we argue that the reservation price policy may be an effective heuristic which could be of value to foreign exchange dealers.

The rest of the paper is organised as follows: In the next section we provide a brief literature review and discuss the contributions of the paper. In Section 3, a comprehensive description of the reservation price policy trading rule is provided. In Section 4, we present an overview of the data used in this study. The methodology, together with the empirical results of the analysis of predicative ability, is presented in Section 5. An evaluation of the profitability of the reservation price policy trading rule is presented in Section 6. We then offer a brief explanation and discussion of the empirical results in Section 7, after which we then conclude.

2 Literature Review

The attitudes of many orthodox financial economists towards technical analysis are epitomised by the words of Malkiel (1981 cited in Brock *et al*, 1992, p. 1732), who describes it as an "anathema to the academic world". Yet, despite the initial scepticism, a considerable number of researchers have ventured into the murky waters of technical analysis. This then leads to a development of a voluminous literature on the subject which, driven by the current availability of immense and inexpensive computational power in conjunction with the development of electronic databases of prices, appears to have ballooned in recent years.[4] In spite of its size, the literature on technical trading rules is neither complete nor does there appear to be a true consensus; this leaves the field open to contributions, especially in the sparsely researched area of intraday technical trading within the foreign exchange market.

There are a few studies focusing solely on the theoretical underpinnings of technical trading [some examples are Treynor and Ferguson (1984), Brown and Jennings (1989) and to an extent Neftci (1991)], but the majority of research has been done in the form of empirical analysis. Most empirical studies have investigated the profitability of technical trading rules in a range of financial markets (with disproportional focus on foreign exchange and equity markets) for the purpose of either uncovering profitable trading rules or testing market efficiency, or both. A number of classic empirical works are Sweeney (1986)[5] as well as Levich and Thomas (1993) who examine technical analysis in the foreign exchange market and the seminal paper by Brock, LeBaron and Lakonishok (1992) which looks at the performance of technical analysis in the stock market. A few others notable examples are Lee and Marthur (1996), Kho (1996), Curcio *et al* (1997), LeBaron (1999), Sullivan *et al* (1999), Chang and Osler (1999), Osler (2000), Kwon and Kish (2002), Neely and Weller (2003), and Olson (2004).[6] Park and Irwin (2007) as well as Menkhoff and Taylor (2007) provide excellent surveys for all asset markets and the foreign exchange market respectively.

Park and Irwin (2007) report that among a total of 95 studies done between the years 1988 and 2004, 56 studies find positive results regarding the profitability of technical trading strategies, 20 studies

[4] Park and Irwin (2007) count 137 technical trading studies (with 44 studies focusing on foreign exchange markets) in the period 1960-2004.

[5] Richard Sweeney's research has led to a co-authorship with Patchara Surajaras of a book titled "Profit-Making Speculation in Foreign Exchange Markets".

[6] Due to the immense volume of available literature it is difficult to do all the contributors justice, thus many other excellent and important papers were in all probability, unintentionally omitted but a comprehensive evaluation is provided in the literature surveys by Park and Irwin (2007) as well as Menkhoff and Taylor (2007).

obtain negative results and 19 studies indicate mixed results. However one should be wary of drawing the conclusion that on average the evidence supports the notion of technical trading profitability because that would imply the equal weighting of each study which would be erroneous (because empirical studies differ significantly in terms of the number of technical trading systems considered, treatment of transaction costs, risk, data snooping problems, parameter optimization, out-of-sample verification, and statistical tests adopted). Similarly, Menkhoff and Taylor (2007, p. 944) conclude that the evidence concerning the profitability of technical analysis tends to be inconclusive. A telling picture is painted by the contradictory results of recent research that empirically tests the performance of very broad sets of technical trading rules. For instance recent work by Qi and Wu (2005), Schulmeister (2009), Marshall *et al* (2008), Marshall *et al* (2010) and Kuang *et al* (2010) test the profitability of 2127, 2580, 7846, 5000 and 25 988 trading rules respectively, but notwithstanding the supposed comprehensiveness of their analysis the researchers come to dissimilar conclusions.[7]

The lack of consensus on the profitability of technical trading rules is mostly driven by two factors: (1) data snooping issues and (2) the fact that any evidence of statistically significant trading profits are open to the criticism of whether or not such profits are merely the equilibrium rents that accrue to investors willing to bear the risks associated with such strategies (Lo *et al*, 2001 p. 1726). Data-snooping has been an eternal problem of empirical time series analysis, but recently many previously established results have come under a increased scrutiny with the introduction of statistical techniques that explicitly account for data snooping bias (Sullivan *et al*, 1999). However as we explain in the next section the theoretical underpinning of the RPP trading rule as well as other precautions allow us to mitigate the issue in this paper.

To avoid the second criticism, a few notable studies namely Gencay (1997), Osler (2000) and Lo *et al* (2000) choose to investigate exclusively the informational content in technical trading rules (i.e. their predictive power), while Omrane and Oppens (2004) examine both the predictive power and profitability

[7] Qi and Wu (2005) find evidence of past trading rule profitability, but suggest that profitability has weakened significantly in the past periods. Schulmeister (2008) finds evidence of profitability at high frequencies and, similarly to Qi and Wu (2005), suggests that profitability in daily data has decreased in recent years. In contrast Marshall *et al* (2008), Marshall *et al* (2010) and Kuang et al find no evidence of profitability of technical trading rules, with the latter going as far as to claim that technical trading profits are "illusory". What makes the issue even more perplexing is the fact that Schulmeister (2009) and Marshall *et al* (2008) come to different conclusions while analysing the data of the S&P 500 (although at different frequencies and time periods).

of a set of trading rules. A further motivator for such an approach is the fact that exclusive focus on profitability may overlook valuable information because trading profits are often highly sensitive to the level of transaction costs and thus the predictive power of the trading rules could be disregarded as it is often unusable to purely speculative traders, but the rules may still represent important information to the dealers (Neely and Weller, 2003, p. 230). For these reasons we examine separately both the predictive power and the profitability of the trading rule in the foreign exchange market.[8] Despite the substantial attention, academic investigation of technical trading in the foreign exchange market has not been consistent with the practice of technical analysis. Essentially technical analysts could be justified if some inefficiency exists in the form of sluggish response from investors to new information (Kwon and Kish, 2002). Thus intuitively one would expect such sluggishness to be fairly short lived, which would lead to utilising and testing technical strategies at high frequency.[9] It appears to be the case in practice as statistical arbitrage funds that specialise in trying to indentify short-term price reversals by using volume profiles and histories of prices (essentially technical trading rules) focus on high-frequency trading (Brunnermeier, 2009, p. 19). Indeed most technical traders, especially in the currency market, are known to transact at high frequency and aim to finish the day with the net open position of zero (Neely and Weller, 2003, p. 224). In addition, as is mentioned earlier in the paper, more than 90% of the foreign exchange market volume is driven by intraday traders (Dacorogna et al, 2001, p. 14) and intraday trading is prevalent among dealer banks, who account for the disproportionate share of the foreign exchange market transactions (Goodhart, 1988, p. 454; Frankel and Froot, 1990, p.182; Lyons, 1998, p. 97). Yet the vast majority of investigations have been undertaken using daily and weekly data. The literature focusing on the performance of technical trading rules in the intraday foreign exchange market is essentially limited to Curcio *et al* (1997); Olser (2000);

[8] Analysis of profitability of a trading rule can show whether a rule is justified to be a standalone trading system, while analysis of a rule's predictive ability may simply show whether a trader or dealer can receive any incremental value by including a rule's signals in his or her information set. Also, perhaps inadvertently, in examining the profitability of the reservation price policy rule, this paper (similar to all other empirical studies of technical trading rules) offers a comment on market efficiency.

[9] In the recent article Schulmeister (2008) offers strong support to the aforementioned theory. Examining the S&P 500 data he demonstrates that when based on daily data, the profitability of technical models has steadily declined since 1960, and has been unprofitable since the early 1990s. However, when based on 30-minutes-data the same models produce an average gross return of 7.2% per year between 1983 and 2007. Also coincidently Mohr and Schmidt (2008) in their empirical evaluation utilising daily XETRA DAX data show that reservation price policy trading rule performs relatively better the shorter the trading period.

Neely and Weller (2003) and to an extent Gencay *et al* (2002).[10] So by evaluating the performance of the RPP trading rule using hourly spot foreign exchange rate data this paper helps to add to the remedy of the disparity between research and practice.

Curcio *et al* (1997) find that on average technical trading is not profitable in the intraday currency market in the presence of transaction costs, but they point out that that under certain market conditions technical rules may have some forecasting ability. Olser (2000) examines the "support" and "resistance" levels and finds evidence of predictive power. Neely and Weller (2003) find that the examined technical rules have surprisingly stable predictive ability, but similarly to Curcio *et al* (1997) they find that no profits can be made after accounting for transaction costs. However none of the aforementioned studies attempt to pinpoint the impetus behind the uncovered predictive power. The reasons why a technical rule may be informative remain a pertinent question of the literature. Menkhoff and Taylor (2006, p. 955) provide a summary of commonly cited explanations such as "not-fully-rational" behaviour of investors (which could lead to self fulfilling predictions) and central bank foreign exchange intervention, however both hypothesis are not well supported empirically. A weaker but less theoretically onerous explanation is that technical rules may be exploiting certain known characteristics of the price-generating process such as for example significant negative first order autocorrelation that has been established as one of the stylised facts of high frequency data (Dacorogna *et al*, 2001, p. 123).[11]

The bootstrap approach initially popularised by Brock *et al* (1992) allows one to test if the information captured by technical trading rules could be accounted for by well-known statistical processes (for example an autoregressive or a moving average process) for the price generating process. Therefore this approach assists one in zeroing in on the source of a trading rule's predictive ability. This technique has been used at daily frequencies in the foreign exchange market (Levich and Thomas, 1993) and at intraday frequency in equity market (Marshall *et al*, 2008). However to the best of our knowledge Gencay *et al* (2002) remains the only work that applies the bootstrap approach to high frequency foreign exchange data. But the work of Gencay *et al* (2002) is not easily categorised as a test of technical trading rule performance because they investigate the performance of a commercial real time trading model (the details of which are proprietary)

[10] There may of course be other studies that we have overlooked; however firstly Neely and Weller (2003) arrive at a similar conclusion and secondly it appears based on a casual examination of citations and the strength of publishing journals that these four studies form the main body of empirical research in this field.

[11] Of course such an approach leaves the fundamental causes behind the certain characteristics of the data (for example serial correlation) an open question.

and use the bootstrap approach more as specification test of the statistical models for the data generating process rather than as a means to uncover the basis for a trading rule's predictive ability. This paper, thus, adds to the literature by applying the bootstrap methodology to a well defined technical trading rule in the intraday currency market and in doing that, rigorously examines whether any predictive ability of the trading rule is an artefact of known characteristics of the data generating process.

Finally, the paper deals with the subject that has recently received substantial public attention. Since the introduction of electronic execution mechanisms many market players have rapidly shifted to the use of fully electronic trading engines (algorithmic trading engines) that submit orders without human interaction based on quantitative rules (Gomber and Gsell, 2009).[12] This phenomenon has remained largely unnoticed by the public and mainstream academia, but the 6th of May 2010 "Flash Crash" has put automated high-frequency trading under the spotlight. Despite the fact that exact causes of the crash are still unclear, there has been tremendous backlash against high frequency traders and regulators are considering new restrictions to high-frequency computerized trading although many practitioners are insisting that automated high-frequency trading has helped ameliorate the damage of the crash.[13] Therefore given that high frequency rule-based trading is currently a topical issue our analysis of the performance of the trading rule (which could potentially be used by high frequency traders) in the intraday currency market may shed some light on the processes, risks and potential returns of high frequency algorithmic trading.

[12] There is a common misconception that the terms high-frequency trading and automated trading are synonymous, which is not true. Although many automated trading systems focus on intraday trading, automated trading refers to fully automated trading systems that executes trades based on predefined algorithms, while high-frequency trading simply refers to trades executed intraday.

[13] See for example "High-frequency trading: Up against a bandsaw" from Financial Times, 2 September 2010 ; "High-Frequency Trading Biggest Concern for U.S. Equity Traders" from Bloomberg 6 January 2011; and "Jim Simons on Flash Crash: High Frequency Traders Saved the Day" from Wall Street Journal Blogs 13 September 2010.

3 Trading Rule

One can imagine a financial decision problem in which a trader is faced with a conundrum of whether to buy/sell an asset or wait for a better price. Assuming the trader has a limited time to trade, he or she could buy/sell the asset "too early" and miss out on a lower/higher price. Alternatively, the trader could buy/sell the asset "too late", thus foregoing a more advantageous price by having chosen to wait. The question is whether there exists an algorithm that would allow the trader to achieve a *satisfactory* performance no matter what the path of prices may be. Competitive analysis is concerned with minimizing a relative measure of performance and, when applied to financial trading strategies, it leads to the development of trading algorithms with minimum relative performance risk, i.e. the satisfactory performance a trader may be seeking (al-Binali, 1999, p. 99). One such trading algorithm, the empirical performance of which is the focus of this paper, is the RPP. This section provides the foundations for the empirical analysis to follow. In this section, we begin with carefully developing the theoretical underpinnings behind the RPP algorithm. Following this, the justification for the choice of the RPP trading rule is presented and its details formalised. In addition, certain contentious issues in empirical analysis of trading rules, such as data snooping, are addressed. The section concludes with detailed illustration of the practical implementation of the RPP trading rule.

3.1 Theoretical Preliminaries[14]

In a time series *search problem* an online player is searching for a maximum (or a minimum) price in a sequence that unfolds sequentially one price at a time. Once during the game the player can decide to accept the current price p in which case the game ends and the player's payoff is p. For example a player could be searching to sell an asset within a time frame of one week. The player then observes daily prices and makes a daily decision of whether to accept a given price on a particular day or wait for the next day in the hopes of finding a better, higher price. An online player makes decisions under uncertainty. More precisely a player's algorithm computes online if for each $j = 1, \ldots, n-1$, it computes an output for j before the input for $j+1$ is given. A player's algorithm computes offline if it computes a feasible output

[14]The following section is grounded in the computer science literature and thus may seem slightly at odds with the usual paradigm of economics and finance; however it is highly applicable and useful to the study of trading rules and serves an important purpose in this paper as will become evident later. The length of the section is the side-effect of the effort made to make it self-contained and accessible to the reader unfamiliar with the topic.

given the entire input sequence$j = 1, \ldots, n$ (i.e. in a time series context the player can be thought as being clairvoyant).

Competitive analysis has been used in the computer science industry for over 30 years, and it is a popular performance metric of online algorithms. Following El-Yaniv (1998) let an optimal offline algorithm be denoted as OPT and an online algorithm as ON. Then in the case of a maximisation problem (i.e. searching for a maximum price) an online algorithm ON is *c-competitive* if for any input set I,

$$ON(I) \geqslant \frac{1}{c} \times OPT(I) \tag{1}$$

Similarly in the minimisation problem (searching for a minimum price) an online algorithm ON is *c-competitive* if for any input set I,

$$ON(I) \leq c \times OPT(I) \tag{2}$$

The smallest c such that ON is *c-competitive* is called ON's competitive ratio. The competitive ratio is a worst-case performance measure. For example in a search problem for a maximum price any *c-competitive* online algorithm is guaranteed a value of at least the fraction $1/c$ of the optimal offline payoff $OPT(I)$, no matter how unfortunate or uncertain the future will be. Similarly in a minimisation problem any *c-competitive* online algorithm is guaranteed a payoff no larger than c times the smallest possible price achieved by an optimal offline algorithm , $OPT(I)$, under all eventualities. As argued by El-Yaniv et al (1992, 2001) given the uncertain nature of strategic financial decision making problems, competitive analysis applies well to these problems. The advantage of competitive analysis over traditional probabilistic models is the ability to devise a robust trading strategy, which guarantees (under the maximisation formulation of the problem) at the very least performance equal to $1/c$ of the clairvoyant (best possible performance) benchmark, with the minimal assumption regarding the future distribution of prices. For example, instead of knowledge about the distribution of future exchange rates, an online strategy might be based only on the knowledge of the bounds on possible exchange rates over the period in question, and should work well no matter how erratically the rates vary during the investment horizon (El-Yaniv, 1992).

In a universe with costless trading and in which prices are bound by the interval $[m, M]$ where $0 < m \leq M$, El-Yaniv (1998) and El-Yaniv et al (2001) introduce an optimal, competitive online search strategy known as the *reservation price policy*[15] under the assumption that both m and M are known to the

[15] Although the algorithm examined in this paper is also called the *reservation price policy* it is defined in a different context. Thus to avoid confusion we save the acronym (RPP) only for the exact trading rule analysed in the paper, and continue to use the full title in describing the earlier versions of the rule.

player. The reservation price policy in a search problem is to accept the first price greater than or equal to $p^* = \sqrt{M \times m}$, where p^* is labelled the reservation price. It is easy to see why the *reservation price policy* is the optimal competitive policy. As the competitive analysis concerns itself with the worst case performance, the optimal reservation price should balance the return ratios (offline/online) resulting in the following two events: (i) the maximum price encountered, p_{max} is $\geq p^*$, in which case the worst-case return ratio $[OPT(I)/ON(I)]$ is $\frac{M}{p^*}$ and (ii) p_{max} is ¸$\leq p^*$ in which case the worst-case return ratio is $\frac{p_{max}}{m}$. Therefore, the optimal reservation price p^* is the solution of $\frac{M}{p} = \frac{p}{m}$, yielding a competitive ratio of $c_s = \sqrt{M \times m}$. Moreover the *reservation price policy* remains optimal for both an infinite and finite time horizon as well as with known and unknown duration (investment horizon) (El-Yaniv, 1998).

Given that search problems and trading problems are closely related (El-Yaniv, 1998), Mohr and Schmidt (2007) derived a natural extension to the reservation price policy search algorithm that includes both buying and selling. Their extension allows the *reservation price policy* to be used in bi-directional search problem (trading problem), which is suited for modelling problems faced by a currency speculator (for example Sweeney (1986) in one of the first rigorous studies of technical trading, examines the profitability of technical trading rules in the currency market using essentially a bi-directional trade problem formulation). Bi-directional or two way trading allows the player to convert asset D (for example US Dollars) into asset Y (for example Japanese Yen) and asset Y back into asset D during a time interval. The underlying assumption is that the objective of a player is to maximize the amount of D at terminal time T, i.e. the player has the objective to maximize his personal wealth in terms of asset D, at time T.[16] Given a sequence of asset prices which are revealed online in a universe with costless trading where prices are bound by the interval $[m, M]$ where $0 < m \leq M$, the optimal deterministic bi-directional algorithm is the following *reservation price policy*:

Buy the asset at the first price smaller or equal and sell the asset at the first price greater or equal to reservation price $p^* = \sqrt{M \times m}$

[16] The discussion is restricted to bi-directional non pre-emptive algorithms. In a bi-directional non pre-emptive search the player has a restriction to convert the whole amount of wealth at one point during a conversion, however assuming that the player trades at least once during the trading period, he or she is not restricted in the amount of trades he or she can make. For example if the trader's wealth is \$1000/Y1000 he or she has to convert the entire amount into the other currency each time he or she makes a trade, but, as long as the player makes at least one roundturn trade, the player is not restricted in the number of trades he or she makes during the trading period.

In order to derive the competitive ratio Mohr and Schmidt (2007) use the following logic. In a single trade problem one searches for the minimum price m and the maximum price M in a time series of prices for a single asset in order to make one roundturn trade at which point the game ends. At best one buys at price m and sells later at price M. If one buys and sells (trades) assets k times it is labelled the k-trade problem with $k > 1$. In order to adopt the search strategy, *reservation price policy*, to the single trade problem one simply has to carry out the search twice. In other words assuming the player enters the market with cash, then following the reservation price policy the player buys at the first price less than or equal to his reservation price. Then the player searches for the price to sell the asset and accepts the first price greater than or equal to his reservation price. One can assume, for the purpose of worst case/competitive analysis, that if the player fails to buy the asset, subsequently sell the asset or both during the given, trading time period, he is forced to execute all his remaining transactions, if any, at terminal time T. Thus in the worst case we get a competitive ratio of c_s (derived earlier) for selling and given equation 2 and the symmetry of the problem the same competitive ratio of c_b for buying. What is left is to derive a total competitive ratio for the single trade problem.

Even though competitive analysis is new to economic literature, it is not dissimilar to the strategic analysis one may see in game theory. Competitive analysis of an (online) problem can be viewed as a two-person game between the online player and an adversary (the offline player). The online player chooses an online algorithm ON and informs the adversary of his or her choice. The adversary then chooses an input sequence I. The payoff to the adversary is the resulting performance ratio $\frac{OPT(I)}{ON(I)}$. The competitive ratio, c, can thus be interpreted as the rate of return. In light of this and given that the competitive ratios for buying and selling, whilst following a reservation price policy, are shown earlier to be the same and equal to c_s, then intuitively an overall competitive ratio for the single trade problem is equal to $c_t = c_s c_b = \frac{M}{m}$.

Mohr and Schmidt (2007) establish the upper bound for the competitive ratio of their modified *reservation price policy* in a more general k-trade problem. The proof will be replicated for completeness of the argument and as it will be a useful later on in the paper. One can assume that for each k trades the online player that is operating under a *reservation price policy* rule is faced with the time series of prices that constitutes the worst possible case for the player. In a universe where prices are bound by the interval $[m, M]$, and the online player knows the values of m and M, a sequence of prices $(M, \sqrt{M \times m}, m, m, \sqrt{M \times m}, M)$ represents such a time series. OPT always buys at price m and sells at price M resulting in a return rate of M/m; ON buys at price $\sqrt{M \times m}$ and sells at price $\sqrt{M \times m}$ resulting in a return rate of 1, e.g.

$\frac{OPT}{ON} = \frac{M}{m} = c$ for $k = 1$. Therefore for a k-trade problem the worst case, competitive ratio is $c = \left(\frac{M}{m}\right)^k$, if M and m are constant. Otherwise if for each i-th transaction $(i = 1, ..., k)$ different upper bounds $M(i)$ and lower bounds $m(i)$ are assumed, then $c = \prod_{i=1}^{k} \left(\frac{M(i)}{m(i)}\right)$.

Although the upper bound of the competitive ratio is exponential in k the measure may be somewhat misleading and one should bear in mind two issues when interpreting the results. Firstly the competitive ratio is the worst case measure and should not be understood as the expected value. For example Mohr and Schmidt (2007) analyse the performance of the adjusted reservation pricy policy algorithm on a year of XETRA DAX data and show that on average the experimental ratio $\frac{OPT}{ON}$ reaches 57.07% of the analytical worst case/competitive ratio. Secondly the optimal offline returns in a k-trade problem are exponentially large so the high competitive ratio does not necessary exclude the possibility of substantial returns for the online player.

3.2 Trading Rule Validation and Definition

Unlike the technical trading rules that are often empirically examined in the literature the adjusted reservation price policy rule of Mohr and Schmidt (2007) stems from an analytical derivation rather than simply being something that is observed to be used by market participants. Moreover Ahmad, Mohr and Schmidt (2010, hereafter Ahmad *et al*)[17] show the *reservation price policy* rule to be efficient based on the competitive ratio framework.

Ahmad *et al* (2010) examine three heuristic trading rules that have been of major interest in the literature. The comparable rules are Moving Average Crossover (MA), Trading Range Breakout (TRB), and Momentum (MM). These rules have been popular in the literature due to their wide usage in practice and have been investigated in the work of Brock *et al* (1992) as well subsequent research. Ahmad *et al* (2010) suggest that all three of the technical rules can be interpreted as a form of a reservation price trading rule. For example according to the Moving Average Crossover (MA) rule buy and sell signals are generated by two moving averages of the level of the index – a long-period average and a short-period average. In its simplest form this strategy is expressed as buying (or selling) when the short-period moving average rises above (or falls below) the long-period moving average, thus making the point of intersection of the two moving averages an implicit reservation price of the player. Of course due to vast choice of parameter values even for a simple rule such as Moving Average Crossover, deducing any truly general analytical

[17] The paper is in the process of publication, but can be made available upon request.

results is an unworkable task. However with the aid of some simplifying assumptions Ahmad *et al* (2010) calculate the theoretical competitive ratios for the three rules. They show that the competitive ratio of the heuristic conversion algorithms MA, TRB, and MM equal $c = \prod_{i=1}^{k} \left(\frac{M(i)}{m(i)}\right)^2$, which is a square of the competitive ratio achieved by the reservation price policy.

The reservation price policy rule is both grounded in theory and is found to be analytically superior to a number of popular technical rules, which arguably warrants an empirical examination. However the bi-directional search framework within which the rule is defined is limiting as it precludes short selling. The issue is especially pertinent for analysis of currency trading as traders can easily establish short or long positions on a specific currency. To illustrative the point one can think of a US investor, in a bi-directional conversion setting, converting US Dollars into South African Rand when he or she expects the dollar to depreciate and then converting back to US Dollars either when it is optimal to do so or at the end of the investment horizon. The limitation of this framework is that if the investor is holding dollars and expects the US Dollar to appreciate (perhaps due to a trading single), he or she cannot trade on that expectation within a bi-directional conversion framework. Thus before proceeding with the empirical investigation, we firstly expand the definition of the rule provided by Mohr and Schmidt (2007) and then slightly modify the framework in order to derive the competitive ratio for the new rule and demonstrate that the general theoretical results still hold.

We redefine the *reservation price policy* rule as follows (hereafter both the *reservation price policy* and RPP will refer only to the rule defined below):

Go long the asset at the first price smaller or equal and go short the asset at the first price greater or equal to reservation price $p^* = \sqrt{M \times m}$

Simply for the purpose of deriving the competitive ratio for the redefined *reservation price policy* rule let us assume an investor that begins the conversion problem with non-zero wealth denominated in both US Dollars and South African Rand respectively. The investor then engages in two separate bi-directional conversion problem, attempting to maximise the Dollar account and the Rand account, separately (one can rationalize this assumption if one assumes a holding company with equal split of South African and American shareholders controlling two equal sized firms in USA and South Africa respectively).Within this framework an investor always has the ability to trade on any expectation.[18] We assume that the investor

[18]It is important to bear in mind that these details are only necessary for the purposes of deriving the competitive ratio

follows the reservation price policy trading rule for each of the bi-directional conversion problem, then the competitive ratio for each problem (in a case of known bounds and k transactions) is known to be equal to $c_{\$} = c_R = \prod_{i=1}^{k} \left(\frac{M(i)}{m(i)}\right)$. Given that essentially the investor is engaged in two bi-directional search problems, we may use the logic of the previous subsection and treat each competitive ratio as a rate of return; therefore the final (aggregate) competitive ratio is equal to $c_t = c_{\$} c_R = \prod_{i=1}^{k} \left(\frac{M(i)}{m(i)}\right)^2$. Essentially the competitive ratio, $c < \frac{M(i)}{m(i)}$, holds for every trade, thus in the setting with both long and short positions the only alterations is the increase (doubling) of the number of trades, k. In a similar vein we can show that under the above framework the competitive ratios for the heuristic trading rules (MA, TRB and MM) are simply the square of the competitive ratio under the bi-direction framework i.e. $c_t = \prod_{i=1}^{k} \left(\frac{M(i)}{m(i)}\right)^4$. Thus the reservation price policy remains the analytically optimal trading rule among the four trading rules under competitive ratio optimality criterion.

Although the algorithm has been developed under the assumption of known upper and lower bounds, for the purposes of empirical examination, the bounds need to be estimated. Estimation of m and M from past prices is a natural starting point and has been adopted by Mohr and Schmidt (2007) who use static estimators of the bounds. Of course it is vital to note that, the derivation of the reservation price policy is done in an abstract setting; however when one attempts to estimate the bounds from past data, one immediately falls into the realm of technical analysis. The underlying assumption of all technical trading rules, which we are forced to make, is that past prices carry some information about the future path of prices (or in our case at the very least their bounds). However we would like to point out that the assumption of incremental information in past price data although may be contradictory to the Random Walk Hypothesis (or the assumption that prices follow martingales) is not immediately in conflict with the existence of efficient markets. Indeed Lo and MacKinlay (1999, p. 14) point out that there is often a common misconception that the Random Walk Hypothesis is equivalent to the Efficient Market Hypothesis, hence efficiency in a sense of price changes, properly weighted by aggregate marginal utilities, being unpredictable can still hold even if prices do not follow a random walk (Lo, 2004, p. 16). So in line with other technical rules we propose rolling or moving estimators of M and m (and implicitly for p^*), which are better able to incorporate new information into the estimator.

The dynamic/rolling estimators of p^*, m and M at specific time, t^*, are as follows:

as in the empirical domain especially if one considers derivative contracts such as CFDs, the trader can easily "bet" on any direction of the market.

$$p_t^* = \sqrt{\widehat{M} \times \widehat{m}} \quad (3a)$$

$$\widehat{M}_t = [p(t)|t = t^*, t^* - 1, \ldots, t^* - h] \quad (3b)$$

$$\widehat{m}_t = [p(t)|t = t^*, t^* - 1, \ldots, t^* - h] \quad (3c)$$

Thus on transition from t to $t+1$, the approximation of M and m is updated by adding a new observation p_{t+1} and deleting the oldest one p_{t-h}.[19] Where h is the number of periods considered by the estimator. Given that the empirical analysis is carried out on hourly spot currency data, ten periods (h) that ought to be representative of the currency trader's choice set are examined: 3, 4, 5, 6, 7, 8, 10, 12, 20 and 24 hours.[20] We then define the *reservation price policy* rule that utilises a parameter h in estimating the reservation price as RPP (h).

3.3 Data-snooping issues

Arbitrariness in the choice of parameters is an inherent weakness of the empirical studies of trading rules; similarly our choice of h has an inescapable degree of subjectivity. This shortcoming is openly acknowledged in Brock *et al* (1992, p.1736) and Curcio *et al* (1997, p. 271). Jagadesh (2000, p. 1767), in his discussion of the work of Lo *et al* (2000) on technical analysis, sums up the issue in saying that certain subjective choices are the prerogative of the researchers and cannot be entirely avoided. Fortunately, the reservation price policy trading rule is holistic in the sense that it generates both trade entry and exit signals and thus, apart from the choice of a single parameter, does not require further ad-hoc impositions such as

[19] A suggestion for future research is to try different estimators for M and m, for example utilising a Koyck lag structure.

[20] To gauge a typical time range that may be used in practice by intraday, technical traders we consult two technical analysis manuals. For example Lien (2006, p. 118) suggests looking at a 14-period Average Directional Index (ADX) indicator and 14-period Relative Strength Index (RSI) that measure the strength of the trend. Schlossberg (2006, p.79-99) also claims that 14 periods is a typical length for certain indicators, namely Stochastics, RSI and Commodity Channel Index (CCI). Another example is the momentum indicators called Moving Average Convergence/Divergence (MACD). It is defined as the difference between two different period exponential moving averages (EMAs) of closing prices. The typical period for the two exponential moving averages is 12 and 26 periods (Schlossberg, 2006, p.87). Given that day traders are looking at price data sampled hourly or more frequently, we thus believe that our set of possible values for h represents a reasonable sample of parameters used in practice

"take-profit" levels.[21]

However, the biggest concern, which can be further reinforced by ad-hoc parameterisation, is the data snooping biases. Data snooping occurs when a given set of data is used more than once for purposes of inference or model selection and is endemic in time series research (White, 2000). Indeed, it is not difficult to imagine that the more scrutiny and subjective tweaking a dataset receives, the more likely one is to find "interesting" spurious patterns. Hence, empirical studies of technical trading rules have been increasingly more strict regarding any potential data snooping [especially since the publication of the seminal work of Sullivan *et al* (1999) which examines the robustness of the results of Brock *et al* (1992) with White's Reality Check for data snooping and comes to the conclusion that their results were, surprisingly, corroborated]. However, we argue that the approach adopted in this paper sufficiently mitigates the data snooping problem.

Firstly, we focus on a single rule, the reservation price, which was developed in an abstract, academic setting with no reference to any financial data (unlike other technical trading rules, are developed by practitioners). In order to make the rule empirically testable we only need to choose a value for a single parameter (h) and in choosing the value of parameter h, no optimisation is carried out, but rather we choose a small, representative set of possible values of h which are deemed to be in line with a priori expectations about trader behaviour (with no direct influence from the examined dataset). Additionally, we report the results for all values of h. Finally, we utilise a relatively lengthy data set and check the robustness of certain results across various non-overlapping subperiods. Therefore, although a complete remedy for data-snooping biases is not viable, it is unlikely to be a concern in this study.

3.4 The practical implementation of the reservation price policy trading rule

In closing this section, we retreat from the abstract foundation and representation of the *reservation price policy* rule and present a detailed illustration of how the RPP rule may be deployed in practice, or in our case, in an empirical investigation. In this paper we assume that the trader enters the market with a net position of zero (but with some positive wealth) and we make the assumption that the trader is only allowed to have one open position at any one time (i.e. either a short or a long position).[22] It is

[21] As a contrasting example, the chart patterns examined by Lo *et al* (2000) only provide entry signals; thus for some tests Lo *et al* (2000) choose to record returns during the next 10 days after the occurrence of a pattern.

[22] One could imagine a trader that posts margin collateral (denominated in unspecified currency) with his prime broker and is then free to borrow (at negligible interest rate) in any currency in order to trade on his or her expectations about the

important to note that due to the way the rule is defined the RPP trading rule never provides a neutral recommendation i.e. at each point in time there is always either a "buy" or "sell" signal.[23]

Figures 1 and Figure 2 show a visual representation of the mechanics of the RRP trading strategy. Given that hourly foreign exchange data is used in this paper, the figures show 24 hours on the 9th of January 2001 in the EUR/USD market. Although both the exchange rate and the RPP (h) series are represented by smooth functions in the figures, both are actually discrete functions as exchange rates are sampled hourly. Let us assume the trader begins the trading day at 00:00 with a net position of zero. Then, every hour a trader (either human or machine) compares the exchange rate level to the reservation price (represented by the red line in the figure) where the reservation price is dynamically estimated from past price data. Given that at 00:00 the EUR/USD price is above the reservation price, the trader first opens a long position. At 01:00 the trader again checks the price of EUR/USD relative to the reservation price. In this example the price still remains above the reservation price, thus the trader does nothing as one long position has already been established.

At 02:00, the price of EUR/USD has moved above the reservation price; at this point the trader closes the long position and immediately opens a short position. We assume that both transactions can be made at the same price (given that the foreign exchange market is highly liquid and we sample at an hourly frequency this assumption appears benign).

Figure 1 shows the RPP (4) trading rule, while Figure 2 shows the RPP (10) trading rule during the same period. The key difference is that the RPP (4) rule reacts more rapidly to new information and thus carries out more transactions than the RPP (10) rule [in the twenty-four hour period examined RPP (4) rule generates eight transactions while the RPP (10) rule generates only four transactions]. Of course, while the RPP (10) saves on transaction costs, it is more sluggish in responding to new price information relative to RPP (4) rule. Alternatively, in contrast, it could be thought to be less sensitive to random noise as opposed to a RPP (h) rule with lower values of h. Finally, it is worth noting that in the jargon of technicians, the RPP (h) rule is a contrarian rule. Schulmeister (2009, p. 191) states that a strategy is contrarian if produces sell (buy) signals at the end of an upward (downward) trend. In essence, the rule makes an implicit assumption that there is a degree of mean reversion present in the traded asset.

exchange rate. Alternatively one can assume that the trader simply trades foreign exchange derivatives contracts.

[23] During the empirical investigation in the rare cases where the reservation price was equal to the market price, an assumption was made that the trader would go long. The assumptions of the trader going short; waiting for the next signal and going long and short with equal probabilities were also tested, and the results were qualitatively identical.

However, whether such an assumption has any merit and whether the RPP rule has any predictive power is an empirical matter that is addressed in the sections to follow.

4 Data

The currency data used in this paper are hourly quotes for spot foreign exchange rates and was obtained from www.disktrading.com [this data provider is also used by Koopman et al (2005) and Marcucci (2005)].[24] The hourly transaction price is proxied by the midpoint between bid and ask quote at the end of each calendar hour (midquote). Midquotes are widely used as proxies for transaction prices in analysis of intra-day exchange rates (for example Baillie and Bollerslev, 1991; Dacorogna *et al*, 1993; Curcio *et al*, 1997; Anderson and Bollerslev, 1998). With regard to the choice of frequency, Curcio *et al* (1997) also use hourly foreign exchange quote data to test the profitability of technical trading rules. They argue that the choice of frequency helps to avoid the price uncertainty due to the fact that the data set is made up of only quoted and not transaction prices. This view is further supported by empirical work of Danielsson and Payne (2002), who conclude that measurement errors tend to disappear with aggregation, and that return properties between indicative quotes (as used in this paper) and firm, tradable quotes are insignificant above ten-minute sampling frequencies. In addition recent survey evidence suggests order flow analysis rather than technical analysis is the preferred tool for examination of very high frequency data (Gehrig and Menkhoff, 2006).[25] Finally, using hourly price data as opposed to higher-frequency data limits computation costs and reduces the risk of introducing microstructural artefacts (Lyons, 2001 and Dacorogna *et al*, 2001).[26]

This paper uses eight spot US Dollar exchange rates and three, most liquid spot cross rates. The eight exchange rates vis-a-vis the US Dollar listed in descending order (ranked by traded volume (BIS, 2010)), are the Euro (EUR), British Pound Sterling (GBP), Japanese Yen (JPY), Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Swedish Krona (SEK) and South African Rand (ZAR). The cross rates,

[24] Although some researcher have preferred to use currency forwards and futures, testing the performance of a trading rule on spot currency data is more in line with practice as evidence suggests that banks place most of their speculative positions in the spot rather than the forward market (Goodhart, 1988, p. 457). Finally Levich (1986, p.1029) explains that "It is easily shown that when covered interest rate parity theorem holds [which it does], spot and forward speculation are equivalent investments in that they lead to the same time series of expected profits".

[25] For example in a manual on the use of technical and fundamental analysis for day trading Lien (2006) suggests using hourly charts for determining entry points for intraday trades.

[26] Additionally as has been succinctly stated by Taylor (2007) the fact that exploitation of any dependence is more difficult when expected profits per trade decline as data frequency increases, while costs do not, renders higher frequency data suboptimal for analysis for trading rule profitability.

again ranked by traded volume and listed in descending order (BIS, 2010), are EUR/GBP, EUR/JPY and EUR/CHF. The sample period is from 16:00 on Sunday the 7th of January 2001 to 18:00 on Friday the 23rd of July 2010.[27]

The foreign exchange market is the largest, most liquid and a truly global market with average daily turnover of around $4 trillion with spot foreign exchange market turnover contributing around 40% to the total daily turnover (BIS, 2010). The foreign exchange market is a mixture between automated, electronic order-matching systems and an over-the-counter (OTC) market maker based trading system. The FOREX market participants interact around the clock; however due to lack of liquidity and unreliability of weekend quotes no weekend quote data are supplied by the data provider.[28] The sample contains 497 weeks of data stamped in Eastern Standard Time (EST) with each week's prices usually running from Sunday 16:00 to Friday 18:00, with uninterrupted, homogenous hourly price series in between.[29]

Table I presents the summary statistics for the entire sample period of the distributions of hourly log exchange rate changes. Each exchange rate series contains around 60 000 hourly returns and exactly 497 weekend returns (i.e. log exchange rate change between the first available price on a Sunday at date t and the last available price of a Friday at date $t - 2$). In all the exchange rate series except CAD/USD the results of the Kolmogorov-Smirnov distribution test suggest that one cannot assume that hourly and weekend returns come from the same distribution.[30] Therefore for completeness the summary statistics for the entire sample, hourly returns and weekend returns are presented separately in Section A of the Appendices, however the distributional characteristics of the exchange rate changes do not seem to be affected by the exclusion of the weekend returns.

The average mean return of the sample of 11 exchange rates is close to zero and is equal to 0.000069%, with six currency pairs having a positive mean return and five currency pairs a negative one (the sign of the mean return corresponds to the net depreciation/appreciation of the currency during the sample

[27] The CHF/USD and EUR/YEN series begin at 17:00, while ZAR/USD begins at 20:00 on Sunday, 7th of Jan 2001.

[28] Following Anderson and Bollerslev (1997) most researchers ignore the weekend period regardless of data availability.

[29] However due to issues surrounding daylight savings time conversion, national holidays and simply problems with data availability there a number of weeks that do not start precisely on Sunday at 16:00 and/or end on Friday at 18:00. Thus weekend returns are computed at the first available price on day t and the last available price on day t-2. For example in some weeks the first available price on Sunday is at 17:00 and also in other weeks the last available price on Friday may be the 17:00 price.

[30] The t-test for equal means between weekend and hourly returns rejects the null hypothesis of equal means in seven out of eleven exchange rates. We do not report the results of the tests.

period as is evident in Figure 3). Standard deviations seem quite similar across the series except in the case of South African Rand and Australian Dollar. The two currencies have the two highest standard deviations of the sample of hourly log exchange rate changes, which could be due to South Africa being a developing market and both Australia and South Africa being lucrative carry trade targets (Hassan & Smith, 2010). All exchange rates display very high kurtosis and, under the null of normality, all exchange rate log changes, except the Swedish Krona, are significantly skewed (with significant positive and negative skewness occurring with equal proportions among the exchange rates which possess significant levels of skewness). But as a consequence of these characteristics the Lilliefors test is a two-sided goodness-of-fit test for normality rejects normality in all exchange rates at the 1% level. The results are in line with expectations as the Gaussianity assumption of intraday foreign exchange changes is rejected utilising an array of sophisticated statistical techniques by Drunat *et al* (1998).

There is highly significant negative first order autocorrelation for all currencies, which is in line with the results of Baillie and Bollerslev (1991) who analysed hourly exchange rates; Neely and Weller (2003) who analysed 30-minute exchange rate data and the stylized facts of intraday currency data discussed by Dacorogna *et al* (2001). Likewise the Ljung–Box-Pierce portmanteau test is significant at the 1% level for all three lags tested.[31] Harris and Yilmaz (2009, p.1580) suggest that significant autocorrelation of returns may be a basis of the effectiveness of technical trading rules, thus the topic will be addressed in detail later in the paper.

The Lagrange multiplier test, LM (12), is a test for autoregressive conditional heteroscedasticity (ARCH) effects in OLS residuals from the regression of log exchange rate changes on a constant. Both the ARCH LM test and the corresponding Ljung-Box statistic, Q2(12), on the squared residuals are highly significant for all the exchange rates, suggesting the presence of ARCH effects in the sample of hourly log exchange rate changes up to the twelfth order. The significant dependence among intraday squared returns is in line with other findings such as Baillie and Bollerslev (1991) and the Chang and Taylor (2003) results based on the analysis absolute 30-min DM/USD returns as well as the stylized facts presented by Dacorogna *et al* (2001).

[31] It is worth mentioning that with heteroscedastic and leptokurtic errors as is the case in this sample, the standard chi-squared critical values for the Ljung-Box test may be inappropriate as it often leads to Type I errors. However given the great absolutely size of the test statistic the Ljung-Box tests remain indicative of the presence of serial correlation (Baillie and Bollerslev, 1991).

Similar to Brock *et al* (1992) in addition to the full sample some of the results will be presented for four subsamples: 07/01/2001–07/01/2003, 07/01/2003–07/06/2007, 07/06/2007–01/06/2009 and 01/06/2009 – 23/07/2010. The discretionary choice of periods has been made in order to represents a valid sample of different regimes and the criteria for the choice of subperiods was primarily the risk associated with each period [proxied by the Chicago Board Options Exchange (CBOE) VIX Index] and secondarily the global market performance (proxied by the S&P 500)[32].[33] Figures 4 and 5 display the two series. The first period includes the years 2001 and 2002. The year 2001 was a pivotal year which saw the collapse of the "dot-com" bubble, a brief recession in the US from March to November 2001 (NBER, 2010) and the September 11 attacks, which all contributed to significant increases in volatility. Increased volatility, on average lacklustre global growth and poor performance of the stock markets carried through to the year 2002, thus the two years could be grouped together based on the criteria of elevated volatility and poor market performance. The second subsample period stems from January 2003 to July 2007, and represents the period of incredibly low volatility.[34] The next period was chosen to coincide with the recent recession in the US (NBER, 2010). This subsample incorporates the worst periods of the Credit Crisis and the highest levels of volatility.[35] The last subsample period runs from the end of the most recent US recession to the end of the sample and represents a period of modest volatility similar to the 2001-2002 period, but with relatively robust growth of the stock markets. Evaluating the performance of the trading rule across subperiods that represent different volatility regimes ought to be an appropriate robustness check and a response to potential criticism that profitability or lack thereof of the trading rule may simply be idiosyncrasies of the particular time period.

[32] The S&P 500 has been used as a proxy for the world portfolio in the context of ICAPM models [as in Cornell and Dietrich (1978)]; however in the context of this paper the S&P 500 simply proxies for the global stock market performance. One only needs to examine the historical correlations across equity world markets [for example Engle (2009)] to convince oneself of the fact that the S&P 500 makes a fair proxy.

[33] An alternative and arguably more precise procedure would be to fit a Low Frequency Volatility exchange rate model as in Engle and Rangel (2009) and base one's choice of subperiods on the volatility measure provided by the model, however it appears unnecessary in this case.

[34] In the sample period the lowest value of the VIX was recorded on the 24 of January 2007 at 9.89, which is not dissimilar to the historical minimum reported VIX Value of 9.31 since the year 1990.

[35] The VIX Index reached an all time high on the 20th of November 2008, the day the Dow Jones industrial Average reached its lowest level since 1997.

5 Predictability

The RPP trading algorithm is first analysed in terms of predictive ability. Hence this section aims simply to gauge the information content of the RPP signals, without concern for possible profitability of strategies based on these trading signals. Although informativeness does not guarantee a profitable trading strategy especially when one is faced with significant transaction costs, it still remains a natural first step in a quantitative analysis of technical trading rules. In other words we seek to infer whether the signals generated by the RPP trading rule provide incremental information about future foreign exchange movements or whether such signals are merely random noise that tells us nothing about the future. Given the peculiarity of financial time series data we follow a non-parametric approach, utilising two distinct techniques. The first procedure, motivated by Lo, Mamaysky and Wang (2000), is to use a goodness-of-fit test that compares empirical distribution between returns conditional on RPP rule's Buy and Sell signals respectively. Although it is arguably a weaker test of the effectiveness of the RPP rule, it provides a good starting point and the motivation for more involved procedures. The second approach is to use the bootstrap methodology that Brock, Lakonishok and LeBaron (1992) (hereafter BLL) developed in their seminal paper, and that was subsequently adopted in later studies such as Detry and Gregoire (2001) study of European stock indeces; Kwon and Kish (2002) study of daily NYSE and NASDAQ prices; Metghalchi *et al* (2008) study of daily Swedish stock exchange data as well as Marshall *et al* (2008) study of intraday NYSE data. The bootstrap procedure not only provides a robust method of evaluating the significance of RPP trading rule's effectiveness, but also brings one closer to gauging the source of the rule's predictive ability.

5.1 Methodology

This section presents the methodology of the both the goodness-of-fit test and the BLL (1992) bootstrap analysis, that is used in this paper to make inference about the predictive ability of the RPP trading rule.

5.1.1 Goodness-of-Fit Test

Lo *et al* (2000) utilise the Kolmogorov-Smirnov test in order to compare the unconditional empirical distribution of returns with the corresponding conditional empirical distribution, conditioned on the occurrence of a technical pattern (thus making an inference about the information content in the technical patterns).[36] They argue that if technical patterns are informative, conditioning on them should alter the empirical distribution of returns; if the information contained in such patterns has already been incorporated into returns, the conditional and unconditional distribution of returns should be close. Technical patterns do not occur all the time, in contrast the RPP rule categorises every period as either a "Buy" or a "Sell", thus instead of comparing conditional and unconditional distribution of returns this paper tests whether empirical distributions of returns conditional on Buy and Sell signals respectively are different. In the words of Lo and Hasanhodzic (2009), Lo *et al* (2000) ask the following simple statistical question: do post-pattern stock returns behave any differently from stock returns drawn randomly. In this section we aim to ask and answer a similar question, in other words we want to determine if returns conditional of the RPP Buy signal behave any differently from returns conditional on the RPP Sell signal.

Ignoring any interest rate differential the hourly return at time t is defined as:

$$r_t = log(p_t) - log(p_{t-1}) \tag{4}$$

We also define two indicator variables I_t^b and I_t^s :

$$I_t^b = \begin{Bmatrix} 1 \text{ if } p_t^* < p_t \\ 0 \text{ otherwise} \end{Bmatrix}$$

$$I_t^s = \begin{Bmatrix} 1 \text{ if } p_t^* > p_t \\ 0 \text{ otherwise} \end{Bmatrix} \tag{5}$$

where I_t^b indicates Buy signals, I_t^s indicates Sell signals and p_t^* represent the reservation price defined in equation 3a.[37]

The reservation price algorithm utilises price information up to and including time t, subsequently as was mentioned earlier each hourly period in the sample is classified as either a "Buy" or a "Sell".

Following Taylor (2007, p. 163) we can thus state that a trading rule applied to a stationary stochastic process is uninformative if the conditional density $f(I_t^b \times r_{t+1} | I_t^b = 1)$ and $f(I_t^s \times r_{t+1} | I_t^s = 1)$are identical; the rule is informative is these conditional densities are different. In other words trading rules provide information about future returns if the returns during Buy periods have a different distribution to the

[36] The Kolmogorov-Smirnov is also used by Mailet and Michel (2000) in their study of technical trading rules.

[37] During the empirical investigation only in a few cases was the reservation price equal to the market price. In these indifferent cases we assumed the rule would generate a Buy signal.

return during Sell periods. A goodness-of-fit test such as the Kolmogorov-Smirnov test utilised by Lo *et al* (2000) is used to make the comparison.[38]

Denote by $\{Z_{1t}\}_{t=1}^{n_1}$ and $\{Z_{2t}\}_{t=1}^{n_2}$ two samples that each IID with cumulative distribution functions $F_1(z)$ and $F_2(z)$, respectively. The Kolmogorov-Smirnov test is a nonparametric test that tests the null hypothesis that $F_1 = F_2$ and is based on the empirical cumulative distribution functions $\widehat{F}_i$ of both samples:

$$\widehat{F}_i(z) = \frac{1}{n_i}\sum_{k=1}^{n_i}\mathbf{1}(Z_{ik} \leq z),\ i = 1, 2, \tag{6}$$

where $\mathbf{1}(\cdot)$ is the indicator function. The statisitic is given by the expression

$$\gamma_{n_1 n_2} = \left(\frac{n_1 n_2}{n_1 + n_2}\right)^{1/2} \sup_{-\infty<z<\infty}\left|\widehat{F}_1(z) - \widehat{F}_2(z)\right| \tag{7}$$

Under the null hypothesis $F_1 = F_2$, the statistic $\gamma_{n_1 n_2}$ should be small. And the limiting distribution of the statistic is:

$$\lim_{\min(n_1,n_1)\to\infty} \Pr(\gamma_{n_1 n_2} \leq x) = \sum_{k=-\infty}^{\infty}(-1)^k \exp(-2k^2x^2),\ x > 0 \tag{8}$$

Given the large sample sizes used in this study, the limiting distribution ought to provide reliable p-values. Additionally, using Monte Carlo analysis Lo *et al* (2000) show that for a broad range of sample sizes and size quintiles, subperiods and exchanges, the bootstrap distribution of the Kolmogorov-Smirnov statistic is well approximated by its asymptotic distribution. Thus one can have sufficient confidence in the test.

The sampling distributions of the Kolmogorov-Smirnov statistic are derived under the assumption that returns are IID, which as can be seen by significant autocorrelation and evidence of strong ARCH effects is not a plausible assumption in this dataset. In order to try to attenuate the problem this paper follows Lo *et al* (2001) by normalizing the returns of each exchange rate, that is, by subtracting its mean and dividing by its standard deviation, hence:

$$x_t = \frac{r_t - mean(r_t)}{SD(r_t)} \tag{9}$$

Therefore, by construction, each normalized return series has zero mean and unit variance.

Lo *et al* (2000) also raise the issue of the power of the Kolmogorov-Smirnov test in relatively small sample sizes; however it will not be an issue in this study as samples sizes of the variables examined are in excess of fifty thousand observations.

[38] The description of the Kolmogorov-Smirnov will be following Lo et al (2001) very closely

5.1.2 BLL Methodology

Due to its pedigree and congruency to the analysis of predictive power of trading rules, we adopt the methodology of BLL(1992) in this paper. Although this paper closely follows the methodology of earlier works, in order to make the paper self contained, the method is fully explained in this subsection.

In line with BLL (1992) and Kwon and Kish (2002) the mean return conditional on the buy signal and the mean return conditional on the sell signal as well as their respective variances are defined as follows:

$$\overline{r}_b = E(r_t|I_t^b = 1) = \frac{1}{N_b}\sum_{t=0}^{N-1} r_{t+1}I_t^b \tag{10a}$$

$$\overline{r}_s = E(r_t|I_t^s = 1) = \frac{1}{N_s}\sum_{t=0}^{N-1} r_{t+1}I_t^s \tag{10b}$$

$$\widehat{\sigma}_b = E\left[r_t - \overline{r}_b|I_t^b = 1\right] = \frac{1}{N_b}\sum_{t=0}^{N-1} (r_{t+1} - \overline{r}_b)^2 I_t^b \tag{10c}$$

$$\widehat{\sigma}_s = E\left[r_t - \overline{r}_s|I_t^s = 1\right] = \frac{1}{N_b}\sum_{t=0}^{N-1} (r_{t+1} - \overline{r}_s)^2 I_t^s \tag{10d}$$

where $\overline{r}_b$ and $\widehat{\sigma}_b$ are the mean and variance of returns conditional on the Buy signal, $\overline{r}_s$ and $\widehat{\sigma}_s$ are the mean and variance of returns conditional on the Sell signal, N_b and N_s are the total number of Buy and Sell returns respectively and the indicator variables, I_t^b and I_t^s are defined as in equation 5.

There are then two natural measures of predictability using $\overline{r}_b$ and $\overline{r}_s$ (or $\overline{r}_I$ if we could be refering to either). We can compare mean returns conditional on buy and sell signals to the unconditional mean returns, as well as compare the mean return conditional on buy signal to the mean return conditional on the sell signal. We can thus define two hypothesis tests:

$$H_0 : \overline{r}_I - \overline{r} = 0 \tag{11a}$$

$$H_1 : \overline{r}_I - \overline{r} \neq 0 \tag{11b}$$

And

$$H_0 : \overline{r}_b - \overline{r}_s = 0 \tag{12a}$$

$$H_1 : \overline{r}_b - \overline{r}_s \neq 0 \tag{12b}$$

Traditionally difference-in-means hypothesis are tested using a standard t-test. The conventional t-test methodology assumes normality, stationarity and independent distributions. The concern, however, is that the data examined in this paper reveals substantial evidence of leptokurtosis, skewness, autocorrelation and conditionally heteroscedasticity thus substantially decreasing the reliability of the t-test method. An alternative approach that was pioneered by BLL(1992) and subsequently adopted in by other researchers (Levich and Thomas (1993), Kwon and Kish (2002), and Marshall *et al* (2008)) involves the use of the bootstrap procedure in order to compute reliable rejection probabilities for the hypothesis. The bootstrap is often used as a substitute for analytical asymptotic formulae when the statistics of interest have complicated asymptotic properties, thus the approach saves one from undergoing an onerous task of deriving such formulae (Horowitz, 1997). Also it is relatively robust in terms of accounting for non-normality, autocorrelation, and conditional heteroscedasticity (Kwon and Kish, 2002).

Essentially the bootstrap approach is based on the notion that by sampling from the data one can approximate the sampling variations which produced that data in the first place, and the necessary condition is that the empirical distribution function represented by the sample is a good estimator of the population distribution function (Mooney and Duval, 1993, p. 61). Indeed it is shown that under mild regulatory conditions, the bootstrap yields an approximation of the distribution of an estimator or test statistic that is at least as accurate as the one obtained from first-order asymptotic theory (Horowitz, 1997, p. 188). Given the large data sample (each exchange rate series contains over fifty thousand observations and spans over nine years) as well as the fact that the bootstrap approach was used successfully in similar, prior research we adopt the procedure in this paper.

A formal and an informal description of the bootstrap methodology is provided by BLL (1992). Also Kwon and Kish (2002) as well as Marshall *et al* (2008) provide an excellent description of the bootstrap procedure. For completeness a brief description of the methodology will be provided in this paper, however it may be inadvertently influenced by the eloquent accounts by the three aforementioned sources.

The first step is to fit a null model of hourly exchange rate movements to the data set such that the random realizations of the model replicate the time-series properties of the original date series (the models can vary from naive random walk process to an autoregressive or moving average processes with generalized autoregressive conditionally heteroscedastic errors) . After having estimated a null model we can then obtain a series of estimated standardised residuals. The second step is for estimated residuals to be redrawn with replacement to form a scrambled residuals series which is then used with the estimated parameters to form a new representative exchange rate series for the given null model. The step can be repeated numerous times to create a large number of simulated exchange rate series. The central point to note regarding this process is that because the residuals are resampled from the original series rather than randomly generated, no distribution is assumed for the error term (in effect the distribution of standardized residuals for the new series is the same as that in the original). Following BLL (1992) and Kwon and Kish (2002) we create 500 replications of each exchange rate series.[39] Figure 6 presents a visual illustration of the procedure.

The third step is to evaluate the performance of the trading rule on each of the simulated series and record the values of the statistics of interests (for example the conditional returns). The set of statistics calculated on the 500 simulated series provide a good approximation of their distribution. The final step is to compare the statistics generated by a the trading rule on the original exchange rate series with the same statistics computed on 500 random realizations of the series.

With regard to drawing inference BLL (1992) exclusively use the *percentile* method. The *percentile* method involves directly comparing a statistic of interest (in our case it could be the conditional returns; the difference between conditional returns or the conditional standard deviations) to the 500 statistics of the simulated series. Essentially the null hypothesis of zero informational content of the trading rule is rejected at the α percent level if the statistics of interest (for example conditional returns) obtained from the actual exchange rate series data are greater than the α percent cut-off of the simulated returns under the null model.

Efron and Tibshirani (1993, p. 221) suggest that more accurate testing can be obtained through the use of a "*studentized statistic*" or "*bootstrap-t*" (also known as "*percentile t*").[40] Indeed Kwon and Kish (2002) in their expansion of the BLL(1992) study utilise both the *percentile* and the *bootstrap t* methods. The *bootstrap t* procedure is almost identical to the standard t-test, except in the case of the *bootstrap t* the t-statistic calculated on the actual exchange rate series is compared to the empirical (bootstrapped) distribution of t-statistics rather than a Student's t-distribution. Again, similar to the *percentile* method, the null hypothesis is rejected at the α percent level if the t-statistic obtained from the actual exchange rate series data is greater (or smaller if we are dealing with a one-sided test) than the α percent cut-off of the simulated t-statistics. Kwon and Kish (2002) put forward two such t-statistics to test the two

[39] Both BLL (1992) and Kwon and Kish (2002) conduct sensitivity analysis of statistical inference to the choice of the number of replication. The simulation results show that 500 replications are sufficient and that replication beyond 500 adds little to the reliability of the statistics.

[40] More precisely Efron and Tibshirani (1993, p. 322-325) show that *bootstrap t* confidence intervals are second order accurate.

hypotheses.[41]

The t-statistic for returns of the buy (sell) reservation price policy trading rule over the unconditional returns (essentially the buy-and-hold-strategy) is:

$$t = \frac{\overline{r}_I - \overline{r}}{\sqrt{\frac{\widehat{\sigma}_I^2}{N_I} + \frac{\widehat{\sigma}^2}{N}}} \tag{13}$$

where $\overline{r}_I$ and $\widehat{\sigma}_I^2$ are the mean return and variance conditional on the buy/sell singnals as in equation 10, N_I is total number of conditional returns and $\overline{r}$, $\widehat{\sigma}^2$and N refers to the mean, variance and total number of unconditional returns.

For the buy–sell or the buy–sell spread, the t-statistic is:

$$t = \frac{\overline{r}_b - \overline{r}_s}{\sqrt{\frac{\widehat{\sigma}_b^2}{N_b} + \frac{\widehat{\sigma}_s^2}{N_s}}} \tag{14}$$

where $\overline{r}_b$ and $\widehat{\sigma}_b^2$ are the mean and variance of conditional Buy returns as in equations 10a and 10c, while $\overline{r}_s$ and $\widehat{\sigma}_b^2$ are the mean and variance of conditional Sell returns as in 10b and 10d. N_b and N_s are the total number of conditional Buy and Sell returns respectively.

Another, perhaps key, advantage of the bootstrap method is that it allows one to simulate distributions of the trading rule returns by any specified model. A null model is fitted to the data set such that the simulated realizations of the model replicate a portion of the time-series properties of the original series. In other words unless one is fortunate to fit a model that perfectly mimics the true data generating process, the simulated data series will only possess some of the properties of the original data series. Indeed it is a known limitation of the bootstrap that it may fail for statistics that depend on "a very narrow feature of the original sampling process" (Stine, 1990, p. 286 cited in Mooney and Duval, 1993 p. 60) that the resampling process is unable to reproduce. However utilising this method one can still determine if the predictive ability, if any, of the trading rule is simply the result of a particular null model or if the rule is capturing something outside the scope of the null model. Indeed this is highlighted by BLL (1992, p. 1744) who state that their bootstrap "methodology can be used not only to assess the profitability of various trading strategies, but also as a specification test for alternative models. In light of this, we perform the bootstrap evaluation of RPP trading rule under two null models, one of which is specifically chosen to

[41] The same t-test approach is also adopted by Metghalchi et al (2008) in their study of the profitability of technical trading rules in the Swedish stock market.

partially control for the obvious of the possible sources of any potential predictive power. The two models are discussed in the next subsections.

Null Models

Random Walk Model Given a frequent assumption in the financial theory that exchange rates may be approximated by martingales[42]. the need to stay consistent with BLL (1992) and Kwon and Kish (2002) as well as the need for a reliable benchmark – the first model for bootstrap analysis is a random walk.

The random walk model can be expressed as:

$$\ln p_t = \ln p_{t-1} + \epsilon_t \tag{15}$$

Where ϵ_t is a random disturbance term with an unspecified distribution.

The natural logarithmic difference defined as a return is resampled with replacement (fitting the random walk model amounts to simply scrambling the log difference of exchange rates). The resampled returns will of course have the same unconditional distribution as the original return series. The next step is to create 500 simulated exchange rate series of equal size as the actual exchange rate series. This is done by beginning each series at the level corresponding to the actual exchange rate on the first day and hour of the chosen sample period; subsequent exchange rates are created by exponentiatiating the resampled or bootstrapped returns.[43] Then we simply evaluate the performance of the RPP trading rule on 500 simulated exchange rate series and record the performance statistics, which are subsequently used to draw inference about statistical significance of the RPP's predictive ability under the assumption that hourly exchange rate changes follow a random walk.

[42] A classic reference suggesting that exchange rate changes are well approximated by a random walk is Meese and Rogoff (1983).

[43] Given that the diagnostic tests suggest that the hourly and weekend returns come from different distributions; the hourly and weekend returns are divided into separate sets. We sample with replacement to create 500 simulations of each set. We then merge the two sets in order to create 500 simulations of a return series that exhibit the structure of the actual exchange rate series of 122 hourly returns (on average) followed by a weekend return (with a total of 497 weekend returns in each simulated exchange rate series).

GARCH (1, 1)-MA (1) Model BLL (1992), Kwon and Kish (2002) along with Marshall *et al* (2008) make use of Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models for the bootstrap simulation in their analysis of trading rules. Over the years, the GARCH family of models have not only proven exceptionality versatile and reliable at representing volatility processes (Andersen and Bollerslev, 1998), but parsimonious variations such as GARCH (1,1) have been shown to often outperform more sophisticated models (Hansen and Lunde, 2005). Additionally, as was discussed earlier, sample statistics indicate a strong presence of an ARCH effect in the data. Hence, in this paper the second model for the simulation will stem from the GARCH family. However, the standard GARCH models are not immediately applicable to high frequency volatility modelling.

It is now a well documented, stylised fact that average level of volatility depends on the time of day, i.e. intra-day volatility exhibits significant and persistent seasonality (Muller *et al*, 1990; Baillie and Bollerslev, 1991; Dacorogna *et al*, 2001; Taylor, 2007). Although evidence of periodic behaviour of intra-day volatility has been documented for a number of asset markets in different regions, it is most pronounced in the global foreign exchange market due primarily to its structure (Dacorogna *et al*, 2001). The intraday seasonal patterns of volatility are so distinctive and intuitively credible that there is a strong case for taking them into account before attempting to model the dynamics of volatility. Indeed Dacorogna *et al* (2001, p. 174) state that "seasonality of volatility is a dominant effect that overshadows many further stylized facts of high-frequency data". While Andersen and Bollerslev (1997, p. 125) take this further by claiming that direct ARCH modelling with no regard for intraday periodicity "would be hazardous".

A number of techniques have been developed for dealing with the intraday seasonality. One methodology for removing periodic effects from intraday volatility is time-deformation as endorsed by Dacorogna *et al* (1993, 2001). In this case the timescale is redefined so that the average volatility is the same for all intraday intervals during a given, fixed time period such as a one day. An alternative, and perhaps more intuitive, approach is put forth by Andersen and Bollerslev (1997, 1998), and Taylor and Xu (1997) and is well documented in Matens *et al* (2002). Fundamentally, this method is based on factorization of the volatility into an essentially deterministic, seasonal part and a stochastic part, while actual proposed techniques vary in their sophistication and computation complexity.

The focus of this paper is not an estimation of the most robust intraday volatility model for the purpose of forecasting volatility, as the volatility model employed need only be an adequate, in-sample representation of the underlying process so as to be utilised in the bootstrap procedure. Nevertheless, in light of the overwhelming evidence of strong intraday periodicity, ignoring it would amount to a gross misspecification. However, given this paper's focus we can afford to utilise one of the computationally lighter of the available techniques for dealing with the intraday seasonality.

This paper adopts the method of filtering out the seasonal component from the returns followed by the estimation of the null model on the filtered series. We use the seasonal variance estimator originally introduced by Andersen and Bollerslev (1997, 1998) which utilises the logarithm of the squared returns. This choice is guided by the fact that Martens *et al* (2002) recommend employing the log of the squared returns as opposed to simply squared returns in order to estimate seasonal factors because, based on an empirical investigation, the former appears to not only have a better in-sample fit, but it also improves the out-of-sample forecasting performance. Thus, borrowing the notations of Martens *et al* (2002), the seasonal variance estimator for exchange rate i is given by:

$$s(i)_n^2 = \exp\left[\frac{1}{D(i)}\sum_{d=1}^{D(i)} \ln\left(\left(r(i)_{d,n} - \overline{r}(i)\right)^2\right)\right](n = 1...N). \tag{16}$$

where $r(i)_{d,n}$ is the nth intraday return on day d (we have $D(i)$ days and N intraday periods) and $\overline{r}$ is the mean taken over all returns.One should note that we are choosing to not differentiate intraday seasonality by the day of the week.

Figure 7 shows the seasonal variance estimators for each hour of the day. The pattern is in line with our understanding of the functioning of the foreign exchange market and prior research. The next step we filter the returns using the estimated seasonal terms:

$$\widetilde{r}(i)_t \equiv \widetilde{r}(i)_{d,n} \equiv \frac{r(i)_{d,n}}{s_{(i)n}} \tag{17}$$

The advantage of filtering (deseasonalise) the returns, is that one can then use the standard volatility modelling techniques for modelling intraday volatility of exchange rates. However apart from an adequately representing intraday volatility, the chosen model needs to account the presence of significant autocorrelation in the data. Indeed one of the defining features of high frequency data is the clear evidence of negative first-order autocorrelation and the descriptive statistics of the sample used in this paper confirm it. In order to accommodate for the presence of significant autocorrelation we follow Baillie and Bollerslev (1991) as well Andersen and Bollerslev (1997, 1998) in estimating a MA(1) process for the conditional mean (deseasonalised) returns of hourly exchange rates.[44] Also given that there is evidence of difference

[44] Gencay et al (2002, pp. 486) estimate an AR (4) process for the conditional mean returns of intraday foreign exchange

in distributions between hourly and weekend return we follow Marshall *et al* (2008) and include a weekend dummy, $D(i)$, in both the conditional mean and variance equations in order to account for any difference in the conditional mean level and/or conditional volatility between the hourly and weekend returns.

Thus formally the complete model is defined as follows:

$$\widetilde{r}(i)_t = \mu_0(i) + \theta_1(i)\varepsilon_{t-1} + \phi(i)D(i) + \varepsilon_t \quad (18a)$$

$$h_t = \omega_0(i) + \alpha_1(i)\varepsilon^2_{t-1} + \beta_1(i)h_{t-1} + \psi(i)D(i) \quad (18b)$$

$$\varepsilon_t = h_t^{1/2} z_t \quad (18c)$$

$$z_t \sim N(0,1) \quad (18d)$$

Where ε_t is an independent, indentically distributed normal random variable.[45]

The estimated parameters, together with respective robust standard errors (based on robust procedures of Bollerslev and Wooldridge (1990, cited in Baillie and Bollerslev (1991)) for all eleven exchange rates are presented in Table II. The important result is that for all eleven exchange rates the coefficient on the MA(1) term was estimated to be negative and highly significant. Given the negative serial correlation found in the data the result is in line with a priori expectations (similar result is reported by Baillie and Bollerslev (1991)). The significance of the coefficient and of course the serial correlation could be either spurious or a characteristic of investor behaviour. A more detailed discussion is offered in the later sections of the paper, hence for now we simply assume that the conditional mean follows an MA(1) process.[46] The coefficient

series, which could be another alternative. However the MA (1) model is a slightly more parsimonious representation and based on both the Akaike Information Criterion and Schwarz's Bayesian Criterion appear to be a slightly better fit (the tests are not reported in the paper, but can be made available upon request).

Another alternative is an ARCH-in-mean model as such models have been frequently used in the literature as for example Marshall et al (2008) who employ a GARCH-M model in order to perform the bootstrap analysis on technical trading rules in the intraday equity market. However the theoretical grounding for the use of an ARCH-in-mean type specification on intraday foreign exchange data is very poor. But for experimentation purposes we nevertheless fitted the GARCH-M model to the data. The coefficient on the variance in the conditional mean equation was insignificant and the model failed to remove the autocorrelations in the residuals.

[45] We also tried fitting the GARCH-MA (1) model using Student's t innovations, but the model failed to adequately remove autocorrelation from the residuals in any of the exchange rates, thus it was decided to estimate the model with Gaussian innovations. Interestingly the same peculiarity is reported by Marshall et al (2008, pp.205) in their analysis of intraday US equity data.

[46] Performing a simple Ljung–Box-Pierce portmanteau test on the residuals (not reported), suggests the presence of up to

on the weekend dummy in conditional mean equation is significant in eight out of eleven exchange rates (interestingly the coefficient is insignificant in the case of ZAR/USD and EUR/GBP which is in line with insignificant t-test for difference in means between hourly and weekend returns in those two exchange rates). The sign of the coefficients on the weekend dummy corresponds on average to the differences between hourly and weekend returns as reported in the descriptive statistics.

Once we obtain the model parameters, the next step, as was described earlier, is to generate standardised residuals (i.e. the residuals divided by the conditional standard deviation) and then resample (with replacement) these standardized residuals. Using these resampled residuals in conjunction with the model parameters, we iteratively construct a new time-series of filtered returns.[47] Then we put back the seasonal components into filtered return series: the return for each hour of the day gets adjusted by an appropriate seasonal factor for that hour (i.e. the inverse of equation 17). Finally the time series of simulated returns is used to create a time series of simulated exchange rates. Finally we evaluate the performance of the RPP trading rule on the simulated series.

A few points are worth noting. The residuals are resampled from the actual exchange rate series so the distributions of standardized residuals for the new series are the same as that in the original. Also because we use dummies to flag weekend returns, the new realization will also exhibit the structure of the actual exchange rate series of 122 hourly returns (on average) followed by a weekend return (with a total of 497 weekend returns in each exchange rate series). Finally the simulated return series features both GARCH volatility and intraday seasonality. Figures 8, 9 and 10 offer a visual comparison of an actual EUR/USD exchange rate series with one randomly chosen simulated EUR/USD series. Visually the difference between the simulated and original series is only noticeable when one views the returns time series over the entire sample as the fitted null model is incapable of replicating shifts in long run volatility. Apart from the obvious limitations of the fitted null model, we can assume that both the simulated return and exchange rate series mimic the original series fairly closely. Most importantly we know precisely which features of

20th-order serial correlation in the residuals in nine out of eleven exchange rates (the tests are insignificant only in the case of EUR/USD and CHF/USD exchange rates). Indeed Baillie and Bollerslev (1991) in their examination of hourly exchange rates encounter a similar result, however they argue that due to the leptokurtosis in the data conventional tests are not asymptotically justified. The, thus, perform a robust LM test that show that any serial correlation is well approximated by an MA (1) process. We do not carry out the robust LM tests on our data, so we assume the results of previous research still hold.

[47] As suggested by Taylor (2007, pp206) we use the variance of the complete sample as the value of the conditional variance for the first period.

the original exchange rate series are being mimicked by the simulated series.

5.2 Empirical Results

5.2.1 Goodness of Fit Test Results[48]

Several statistics of the results from the trading strategy based on the reservation price policy trading rule for the full sample period are presented in Table IIIa and Table IIIb. To conserve space in the main body of the paper Table IIIa presents statistics of the results generated by the RPP (4) rule for all the eleven exchange rates analysed, while Table IIIb presents the results of the RPP(h) rule for all h, but only for the EUR/USD exchange rate.[49]

The first two columns of both tables are the number of returns conditional on RPP's Buy and Sell signals respectively (i.e. buy and sell returns).[50] Although no significance tests have been performed one can observe a strong sell bias in the sample.[51] This pattern is consistent with respect to the choice of h and corresponds very closely to the average performance of the currencies during the sample period. As was mentioned in the Section 4, during the sample period the US Dollar experienced significant depreciation against most currencies, while the Euro experienced significant appreciation against most currencies up until 2008. Given that the RPP rule signals are based on the implicit assumption of mean reversion, the results are in line with a priori expectations.[52]

Columns three and four of the tables report the mean buy and sell returns respectively. In Table IIIa, the buy returns are all positive; while the sell returns are all negative (the average buy and sell hourly returns across all the currencies are 0.052 and -0.0049 percent respectively). One can observe in Table IIb that this pattern holds for a large subset of h and only breaks down at h equal to 12, 20 and 24

[48]To simplify the analysis in this section the distinction between weekend and hourly returns is ignored. The results are quantitatively identical if the analysis is performed exclusively on hourly returns. Furthermore explicit controls for weekend returns are introduced in later sections

[49]The full set of results may be found in Section B of the Appendices

[50]The buy and sell returns are the returns during the periods where the RPP algorithm is long, while the sell returns are the returns where the RPP algorithm is short. We, however, label the returns as "buy" and "sell" because that appears to be the established practice in the literature and is, perhaps, more intuitive.

[51]There is a very strong buy bias in the case of SEK/USD, however the dataset reports the indirect exchange rate quotation therefore a buy bias would have been a sell bias if the exchange rate was reported using the direct method.

[52]Only for two exchange rates, the CHF/USD and ZAR/USD, do the results show that the sell bias is sensitive to the choice of h. This is consistent with the fact that both the CHF/USD and ZAR/USD exchange rates experienced mixed performance during the sample period, with no clear and prolonged appreciation or depreciation.

respectively. On average this result holds across all eleven currencies with the pattern breaking at h equal to 20 for GBP/USD, JPY/USD, AUD/USD, CHF/USD and EUR/JPY. The pattern appears immune to the choice of h for CAD/USD, SEK/USD, ZAR/USD, EUR/GBP and EUR/CHF.

The two penultimate columns of the tables present the fraction of buy and sell returns greater than zero. Across the eleven exchange rates, for buy returns this fraction ranges from 0.4996 to 0.5325 and, for sell returns, it ranges from 0.4094 to 0.4674 (the averages across the sample of exchange rates are 0.5167 for buy and 0.4440 sell returns). On average across all the exchanges the fraction of buy returns that are greater than zero is in excess of 0.5 and the fraction of sell returns greater than zero is less than 0.5 across h equal to 3, 4, 5, 6, 7 and 8. While for h equal to 10, 12, 20 and 24 the results are less strong, however there is still a noticeable difference between the fractions of buy and sell returns greater than zero for all h.

Under the null hypothesis that the RPP trading rule does not produce useful signals the fraction of positive returns should be the same for both buy and sell returns. Performing a one-sided binomial test on the faction of buy returns shows that the difference from the null value of 50% is highly significant for all exchange rates reported except the EUR/GBP. Performing a one-sided binomial test on the faction of sell returns yields a highly significant difference for all the exchange rates in the sample. In Table IIIb the results of the binomial test are in line with previous observations. The one-sided binomial test shows that the fraction of sell returns is significantly less than 50% for all h; while the fraction of sell returns is significantly more than 50% for h equal to 3, 4, 5, 6, 7 and 8 (this pattern of results can be found to hold across all the spot exchange rates in the sample).

The last column in Table IIIa and Table IIIb report the calculated statistic for the Kolmogorov-Smirnov test of the equality of the normalised return distributions conditional on buy and sell signals. Based on the asymptotic distribution of the Kolmogorov-Smirnov test statistic the results show that the calculated Kolmogorov-Smirnov statistics are strongly significant across all exchange rates and for all vales of parameter h. Although the criticisms of the Kolmogorov-Smirnov test expressed in Section 5.1 still hold, there is strong evidence to suggest that the return distributions conditional on buy and sell signals are not the same

The results of this section imply that the signals generated by the RPP trading rule may possess some informational content and there may be a degree of predictability of hourly foreign exchange returns. However before any conclusions are made, the RPP is brought under greater scrutiny using the bootstrap methodology.

5.2.2 Random Walk Model

On average, the bootstrap results under the assumption of random walk null model for the exchange rate process corroborate the results of the preceding subsection.

Again we present only a portion of the results in the body of the paper.[53] Table IVa displays the results of the RPP (4) rule for the eleven exchange rates, while Table IVb presents the results of the RPP (h) rule for all h for the EUR/USD exchange rate. In the first two columns, "μ(Buy)" and "μ(Sell)", we present the mean buy and sell returns, while in the third column, "Buy-Sell", we show the difference between these two means. Column four and five, "σ(Buy)" and "σ(Sell)", are the standard deviation of buy and sell returns respectively. Finally the last three columns present, "t(Buy)", "t(Sell)" and "t(Buy-Sell)", the t-statistics for the difference in means between: buy returns and the unconditional mean return; sell returns and the unconditional mean return; as well as buy and sell returns. After 500 simulations the fractions of the simulated results which are larger than the results for the original exchange rate series are calculated. One can interpret these fractions as the probability that average simulated statistic is greater than those generated by the actual series. These can be thought of as simulated "p-values", and we report it accordingly in parenthesis under each value.

As was reported earlier, RPP (4) buy returns for all the currencies are positive, while the sell returns are negative. The average, of the eleven currencies, p-values for mean buy and sell returns are 0.0025 and 0.9995 respectively. The interpretation is that only 0.25% of the simulated random walks generate a mean buy return as large (or larger) as that from the original exchange rate series. And similarly, it shows that on average for the eleven currencies 99.95% of random walks generate a mean sell return as large (or larger) as that from the original series. Turning to the Buy-Sell column, the difference between buy and sell returns is positive and significant for all eleven exchange rates i.e. the average p-value of 0.0000 shows that none of the simulated random walks generated a difference between mean buy and sell returns as high as that of the original exchange rate series. For all the exchanged rates in the sample, the t-tests reported in the last three columns wholly uphold the strong significance of the results based on percentile method of inference.

In Table IVb one can observe that, based on the percentile method, in the case of EUR/USD exchange

[53] Full set of results may be found in the Section B2 of the Appendices.

rate the mean buy returns and mean sell returns are significant at the 5% level for h equals to 3, 4, 5, 6 and 7. For mean buy and sell returns the significance is reduced at h equal to 8 (the results are only significant at 10% confidence level) and completely dissipates at higher values of h. In the case of the difference between mean buy and sell returns, results remain significant at the 10% for all h up to and including h equal to 10, but also become insignificant at higher values of h. As was mentioned earlier the t-test provides more reliable testing and in this case the t-tests offer marginally different diagnosis as the t-tests show mean buy returns, mean sell returns and their respective difference to be significant for all h up to and including h equal to 10.[54] A similar pattern holds across the eleven spot exchange rates as significance on average decreases with higher value of h. However the results for CAD/USD, ZAR/USD, EUR/CHF, and EUR/GBP appear to be completely insensitive to parameter choice as the t-tests show significance for all values of h at 5% confidence level in the case of CAD/USD and significance at the 1% confidence level for the other three spot rates. Given that the RPP is a contrarian rule, it may indicate that the four spot rates have such a strong degree of mean reversion, that it could be captured even with sub-optimally parameterised trading rule. However Neely and Weller (2003, p. 227) suggest that certain currencies are traded most actively during business hours of the local exchange and after hours trading is often highly illiquid and transaction costs are significantly higher. Therefore the "overly" significant results for the CAD/USD, ZAR/USD, EUR/CHF, and EUR/GBP may simply be an artefact of off-peak hours quote data and do not necessarily signify viable profit opportunities, but we will examine the matter further in the next section.

In the columns "σ(Buy)" and "σ(Sell)" the p-values can be interpreted as the percentage of simulated series that generated standard deviations of buy or sell returns as large (or greater) than the original exchange rate series. In Table IVa for seven exchange rates there does not appear to be a significant difference between the standard deviations of simulated exchange rate series and the original series. For example for EUR/USD there is no evidence of difference between the original buy and sell return standard deviations and their simulated counterparts. Essentially by construction we know that under the null random walk model the simulated series both buy and sell returns standard deviations are on average equal to the unconditional standard deviation of the original series. Therefore on average buy and sell return standard deviations are insignificantly different from the unconditional standard deviation of the

[54] In contrasting cases we take the t-test results as being more accurate, but essentially both methods lead us to the same conclusion as in the full set of results the *percentile* and t-test methods offer on average equivalent diagnostics.

series. As can be seen in Table IVb, this result is on average insensitive to the choice of h. Conversely in the case of GBP/USD, JPY/USD, AUD/USD and EUR/JPY the standard deviations of buy returns are significantly higher than standard deviations of the simulated buy returns, while the standard deviations of the sell returns are significantly lower. For example in case of AUD/USD the p-value is equal to 1.0000, the interpretation of which is that the standard deviations of sell returns for all 500 simulated series are greater than the sell return standard deviation of the original spot exchange rate (alternatively we could say that the standard deviation of sell returns is significantly smaller than the unconditional standard deviation). These significant results are also on average insensitive to the value of parameter h. However we should regard any inference about difference in variance with a degree of scepticism because the random walk null model does not account for the either the GARCH or the intraday seasonality that is clearly present in the volatility of the exchange rates.

As consistency check, Table IVc reports the average statistics for the 500 random walk bootstraps of EUR/USD spot exchange rate. The first and second columns, "N(Buy" and "N(Sell)", are the average number of buy and sell signals over 500 bootstraps. There is small sell bias as there are more sell than buy periods, however the sell bias is not as distinct as in the original exchange rate series. Column two to ten correspond to columns one to eight in Tables IVa and Table IVb. And the last three columns of Table IVc report the average simulated absolute value of the t-statistics, which simply offers a quick gauge of the size of the statistics. The average simulated mean buy and sell returns as well as their respective standard deviations are equivalent across all value of h. Finally the absolute value of average simulated t-statistics across all values of h and all exchange rates never exceeds unity. Thus the average performance of the RPP trading algorithm on the simulated series is in line with expectations of a technical rules performance on a series, whose returns follow a random walk.

The random-walk bootstrap results are undeniably suggestive that the RPP trading algorithm possesses at least some predictive ability. In fact, more precisely, the results suggest that forecasting exchange rates with the use of the RPP algorithm would fare better than a naive, random-walk approach. However, the random walk model fails to capture a number of prominent characteristics of the data, such as the serial correlation of returns. Therefore, before making any further comments about RPP's effectiveness, one should examine its performance against a more realistic model of the underlying exchange rate process.

5.2.3 GARCH (1,1)-MA (1) Model

On average, the bootstrap results under the assumption of GARCH (1,1)-MA (1) model with intraday seasonality contrast the random walk bootstrap results.

Table Va displays the GARCH(1,1)-MA(1) model results of RPP (4) rule for the eleven exchange rates, while Table Vb presents the results of the RPP (h) rule for all h for the EUR/USD exchange rate.[55] The columns are labelled identically to those in the previous subsection. From Table Va it is immediately evident that except for the case of EUR/USD exchange rate, all the results are insignificantly for all the exchange rates. For example the two highest t-statistics testing the difference between mean buy and sell returns, t(Buy-Sell), occur in the case of ZAR/USD and EUR/CHF and are equal to 16.08899 and 17.37878 respectively. However the bootstrapped p-values for the two statistics under the GARCH (1,1)-MA (1) null model are 0.9920 and 0.9020 respectively. The p-values imply that on average over 90% of the simulated t(Buy-Sell) are greater than the t-statistics calculated on the original series. One could also interpret the number as saying that the probability that the average simulated t(Buy-Sell) is larger than the t statistic of the original series is over 90 percent. Also the significant results for the EUR/USD spot exchange rate are only significant at 10% level. The p-value for the t(Buy-Sell) of EUR/USD is equal to 0.0560, which implies that 5.6% of the simulated series generate a t(Buy-Sell) statistic as large (or larger) as that from the original exchange rate series. Thus although the EUR/USD result is still significant, it substantially less significant than under the null random walk model.

The results presented in Table Vb show that based on the t(Buy-Sell) statistic there is a significant difference between mean buy and sell returns in the EUR/USD exchange rate at the 10% confidence level only for h values of 3, 4 and 5. The pattern is similar to the random walk bootstrap results in the fact that significance is reduced with higher values of h, however in this case significance dissipates much sooner. So at h equal to 6 and higher, the buy and sell returns of the RPP(h) signal are indistinguishable from each other under the assumption that the exchange rate returns are defined by a GARCH(1,1)-MA(1) process with seasonal volatility. The results for all other exchange rates are not at all supportive of RPP's predictive ability. As we specify earlier, the two hypotheses to be tested are (1) whether the mean buy/sell returns are different from the unconditional mean return and (2) whether mean buy return is different from the mean sell return. Under GARCH (1,1)-MA (1) the t(Buy), t(Sell) and t(Buy-Sell) is not significant for all values of h in ten of the eleven exchange rates (the only significant result is found in

[55] Full set of results may be found in Section B3 of the Appendices.

EUR/USD exchange rate). Thus we could say that the GARCH(1,1)-MA(1) model can sufficiently account for both the spread between conditional and unconditional returns as well as the spread between buy and sell returns. Essentially we cannot on average reject the null hypothesis of no incremental informational content of the RPP trading rule. Also as was expected once the volatility process was correctly specified by this null model, any differences between the standard deviations of buy and sell returns disappeared.

Table Vc, presents the average statistics of the RPP (4) trading rule based on the 500 GARCH (1,1)-MA(1) simulated series for all eleven exchange rates.[56] The labels of the columns are identical to those of the comparable table in the previous subsection. Examining the first two columns we could say at least from casual inspection (as no tests have been performed) that under the GARCH (1,1)-MA (1) null model the differences between number of buy and sell periods were more obvious than under the random walk null model, and thus more in line with the original series. The three illustrative examples are SEK/USD, ZAR/USD and EUR/JPY. In the originals series SEK/USD has a buy period bias, ZAR/USD has an almost symmetrical balance between the numbers of buy and sell periods and EUR/JPY has a noticeable sell period bias. The average statistics of the simulated appear to replicate all these features fairly well. The focus of course is on the conditional returns, and Table Vc clearly demonstrates that the initially surprising results of mean buy returns being positive, while all the sell returns are negative could be replicated under the assumption of a GARCH(1,1)-MA(1) null model. Finally the information in the table also casts light on the inadequacies of traditional t-test methodology. For example in the original series the average across the exchange rates absolute values of the t(Buy-Sell) is around 8.18, which would definitely result in the rejection of the null if asymptotic critical values were used. However examining the average t-statistics of the simulated series (which we can regard it as rough proxies for the bootstrapped critical values) we can notice that across all the exchange rates the average absolute value of t(Buy-Sell) statistic is around 9.33.

The results of this subsection show that, under the fitted GARCH(1,1)-MA(1) with seasonal volatilities null model, RPP loses most of its significant forecasting prowess, except in the case of the EUR/USD (though the predictive power is very sensitive to the choice of parameter h). It is important to note that RPP's predictive ability is, on average, insignificant relative to the fitted null model. Nevertheless, RPP

[56]In the previous subsection we presented a table of average statistics for the 500 simulated bootstraps of EUR/USD spot exchange rate, but in this sectioned we deemed it to be more informative to show the average statistics for RPP(4) rule across the eleven exchange rates instead.

would still fare better than, for instance, a forecast of a random walk model. Table Vc offers a glimpse of why most of the statistics became insignificant, which, in essence, is due to the fact that the fitted null model expertly replicates the peculiarities of the exchange rate data that allows the RPP (h) rule to have forecasting ability.

5.3 Concluding Remarks

The results of this section paint a contrasting picture of the RPP rule's predictive ability. The results of the Kolmogorov-Smirnov test offer strong evidence that the distributions of returns, conditional on RPP's buy and sell signals, are different. This implies that the signals generated by the RPP rule may be informative. Next, the bootstrap results under the null random walk model offer further support of significant difference (1) between conditional and unconditional returns and (2) between buy and sell returns. These results imply that, under the assumption that hourly exchange rate changes follow a random walk, the probability of obtaining the statistics (for example the high, positive difference between mean buy and sell returns) which were calculated on the original series are minuscule. Additionally, under the random walk null model, the predictive ability of the RPP rule was found to be robust across all of the exchange rates and relatively insensitive to the choice of h (although on average significance decreases with higher values of h, which offers support to the hypothesis that prices may be sluggish, but only at short-term horizons). However, the results of the bootstrap random walk model essentially say more about the inadequacy of the random walk model in describing the hourly exchange rate process, than about the effectiveness of the RPP trading rule.

Indeed, the bootstrap results under the GARCH (1,1)-MA(1) null model confirm this concern, as most of the statistics are found to be insignificant. This analysis shows that the probability the RPP rule yields similar results on a series approximated by a GARCH (1,1)-MA(1) model as on the actual exchange rates is very high. In other words, the RPP's performance on actual exchange rate series is not out of the ordinary under the assumption that exchange rate changes are represented a GARCH (1,1)-MA(1) process. As we point out earlier, a crucial advantage of the bootstrap approach is that it allows one to evaluate the ability of a particular null model in accounting for the predictive ability of a trading rule. The bootstrap results show that, except for the case of EUR/USD, the RPP trading rule does not capture any incremental information above what is accounted for by the GARCH (1,1)-MA(1) null model. Thus, the RPP rule may be picking up on the same regularities in the data that are explicitly controlled by the null model which is most likely the significant negative autocorrelation in the exchange rate returns (but we leave a more detailed discussion for the subsequent sections). Importantly, one should bear in mind that the fact that the RPP rule, on average, does not offer predictive power above the null model, does not make it entirely useless. Indeed, Neftci (1991, p.550) argues that a technical trading rule may still be valuable even if it is inefficient compared to an econometric models because technical rules have the ability to generate trading signals (such as buy or sell) at random moments in time, whilst econometric models do not. Furthermore even under the GARCH (1,1)-MA(1) null model, the RPP rule possesses some predictive ability in the EUR/USD market for h equal to 3, 4 and 5. In other words, the signals generated by the RPP (3), RPP (4) and RPP (5) trading rules still contain incremental information. But incremental information does not necessary imply that the RPP rule may be used to generate profitable trading strategies. In fact, especially with strategies utilizing high levels of transactions, predictive ability does not have to have to result in a profitable trading strategy. Thus, in the next section we thoroughly examine the RPP rule from the perspective of profitability.

6 Profitability

When dealing with few transactions (as was the case in the earlier studies which make use of daily data) predictive ability is, in essence, synonymous with profitability- especially in the accounting sense of the term. However, in the case of high frequency trading, transaction costs develop into a critical variable that needs to be suitably accounted for prior to making any inference about the profitability of a trading strategy. Furthermore, academics are primarily interested in the ability of a trading rule or strategy to yield economic profits and such analysis requires a systematic examination of the risks. In this section, we distance ourselves from the possible causes of the RPP rule's predictive ability and temporarily set aside the results of the previous section which showed that, on average, the RPP rule fails to deliver a predictive edge above the GARCH(1,1)-MA(1) model. Thus, we focus solely on testing whether the RPP trading algorithm can deliver significant risk-adjusted profits in the face of transaction costs.[57]

6.1 Methodology

This subsection presents the tools we use in analysing the profitability of the RPP rule. The focus of this part of the analysis is the viability of the RPP rule in practice; therefore emphasis is placed on realism whenever possible.

For this exercise the RPP trading rule is viewed as a complete, automated trading system that operates in real time.[58] In other words all positions are opened and closed exclusively based on the signals provided by the RPP rule and the rule makes each decision at time t based only on the prices up to and including time t. There are no "stop loss" or "take profit" levels because RPP rule provides both the "trade entry" and the "trade exit" signals. Trading in the foreign exchange market occurs around the clock during business days and open positions are easily relayed across time zones, thus we assume trading takes place 24 hours a day during the business week. However given the high-frequency nature of technical rule trading, a speculative position is unlikely to be left open over the weekend as that unnecessarily increases

[57] In light of the bootstrap results we ought to only focus on the RPP(3),RPP(4) and RPP(5) rules in the EUR/USD market as these rules were found to have a predictive edge beyond that of a GARCH(1,1)-MA(1) model. However despite the results of the previous section for consistency we test the profitability of the RPP rule on the entire sample of exchange rates for all values of h.

[58] The mechanics of the RPP trading rule are presented in Section 3.4

the risks. Thus we assume that no positions are left open over the weekend. Any open positions are closed at the last available price on Friday afternoon (which is on average occurs at 17:59) and a new position is opened at the first available price on Sunday afternoon (which on average occurs at 16:00). The analysis is performed under the assumption that it is possible to trade without altering the path taken by subsequent prices, which is likely to not be an issue given the size and liquidity of the FOREX market. We also assume that realised trade price is equal to the pre-trade decision price (i.e. we assume zero or negligible implementation shortfall, which in the FOREX market is also reasonable).[59]

We define the holding period return (transaction return) as follows:

$$r(t, t+H) = r_j = \frac{p_{t+H} - p_t}{p_t} \tag{19}$$

where H is length of time measured in hours the position remains open.[60] Gourieroux and Jasiak (2001, p. 12) suggest that the returns defined by Equation are used by banks and other market players. Lee and Marthur (1996, p. 952) and Martin (2001, p. 61) who evaluate the profitability of technical trading rules in the currency markets also utilise the above definition of returns.[61] Also we omit the interest rate differential in the calculation of returns because firstly in the case of intraday returns the interest rate is almost zero and secondly because even in the analysis of daily data Sweeney (1986), LeBaron (1999) as well Olson (2004) report that the omission of interest rate differentials has only a negligible impact on profitability of currency trading strategies.[62]

Dacorogna *et al* (2001, p. 303) introduce a number of performance statistics for the evaluation of trading models, which we adopt in this study.

The total return, R_T, is a measure of the overall success of a trading strategy over a period T, and is defined as follows

$$R_T = \sum_{j=1}^{n} r_j \tag{20}$$

[59] Of course the analysis of the entire paper is made on the assumption that the midquote prices are actually fair proxies for transaction prices, but prior research suggests that it is indeed the case (Danielsson and Payne, 2002).

[60] All returns correspond to unlevered positions.

[61] In the previous sections defined returns as the difference in the natural logs of exchange rates in order to provide continuity with the works whose methodology was utilised.

[62] Eddelbuttel (1997 cited in Gavridis, 1998, p.11) reports that the yield differential has only marginal explanatory power at high frequency, thus offering further justification for the exclusion of interest rate in our calculation of returns.

where n is the total number of transactions during period T, j is the j^{th} transaction and r_j is the return from the j^{th} transaction. The total return expresses the amount of profit/loss made by a trader always investing up to his or her initial capital or credit limit in the home currency.

Another measure of success it the *cumulative return*, C_T, wherein the trader always reinvests all his or her current capital including gains or losses. It is defined as follows:

$$C_T = \prod_{j=1}^{n}(1 + r_j) - 1 \tag{21}$$

Finally two valuable metrics that help measure the predictive power of the strategy are the *directional accuracy* (or *percentage of winning trades*) and *profit over loss ratio* which are defined as follows:

$$A_T = \frac{N_T(r_j|r_j > 0)}{N_T} \tag{22}$$

$$\frac{P_T}{L_T} = \frac{N_T(r_j|r_j > 0)}{N_T(r_j|r_j < 0)} \tag{23}$$

where N_T is a function that gives the number of elements of a particular set of variables under certain conditions. In this case the function gives the numbers of profitable and unprofitable trades during a period T.

Transaction returns do not easily lend themselves to comparison with returns on other investments because each transaction return r_j is calculated over variable horizons. In other words the actual holding period, be it four hours or six hours, is a random variable, which makes it difficult to find a suitable comparison. For example it would be inaccurate to compare hourly stock market returns to the RPP rule's transaction returns that may have on average been calculated over 4 hours. It also limits our analysis as we know a priori that transaction returns are not identically distributed (simply because they are calculated over different intervals). For these reasons we create a series of weekly RPP returns.[63]

We define weekly returns of the RPP trading strategy as a cumulative return CT calculated over a trading week. In other words we assume that an investor invests the same amount of capital at the beginning of each week, but he or she reinvests the profits or losses during each given week. As a form of justification for this approach one could think of the RPP rule as a hedge fund the performance of which

[63] Weekly returns are examined in the context of technical trading rule profitability by Kho (1996).

is only evaluated on a weekly basis.[64] Therefore, although each weekly return is a product of a random number of transaction returns an investor who in only able to evaluate the performance on a weekly basis only cares about the final, weekly, returns.

Once we have a series of weekly returns we can adequately evaluate the risks of the strategy in respect to other investment alternatives. The Sharpe ratio is one of the most cited statistics in financial analysis and it offers an intuitive way of calculating a risk-adjusted return of an investment, thus aiding in making comparisons among investments.[65] We thus estimate the Sharpe ratios for the RPP rule, which Lo (2002, p. 37) defines as follows:

$$\widehat{SR} = \frac{\widehat{\mu} - R_f}{\widehat{\sigma}} \tag{24}$$

where $\widehat{\mu}$ is the historical mean return of the investment and $\widehat{\sigma}$ the standard deviation of the historical returns, while R_f is a risk free rate.[66]

But evaluation of investment performance using only the first two moments of the distribution of returns is only justified either if returns are jointly normally distributed or if investors' choices can be characterised by quadratic utility money functions (Ingersoll, 1987, p. 95-97). Such an assumption would be too limiting, we thus follow Brunnermeier *et al* (2008) and further evaluate the RPP rule's performance using the sample skewness (a negatively skewed distribution implies greater risk of extreme negative outcomes i.e. negative tail risk and is consequently an unwelcome characteristic).

The main contribution of this section is the introduction of transaction costs and we account for costs by subtracting it from each transaction return.[67] Lyons (2001, p.43) explains that transaction costs vary depending on the categories of market participants. The spreads per transaction of $10 million or higher between two large banks during active trading hours is between one and two basis points (one basis point equals one-hundredth of 1 percent). The effective spreads in the brokered interdealer trading is around 2-3 basis points. While in the customer dealer trading, a high volume customer can expect to pay anything between 3 and 7 basis points in spreads. But in all the cases spreads can significantly rise during off-

[64] For example the hedge funds may only allow redemptions on a weekly basis, thus from the point of view of an investor only the weekly return series matter as he or she has no control over each transaction that the hedge fund makes.

[65] Martin (2001) uses the Sharpe ratio in her analysis of the profitability of technical trading rules in the spot foreign exchange markets of developing countries.

[66] As a proxy for the risk free rate we use the US Treasury Bill rate sourced from the IMF International Financial Statistics.

[67] This paper ignores implicit costs, which may include costs such as the opportunity cost of failing to execute the order in a timely manner (thus the profitability estimators may contain a slight upward bias).

peak hours when liquidity and trading activity are reduced (Neely and Weller, p. 229). For the initial profitability analysis with transaction costs, we follow LeBaron (1999) and Olson (2004) in assuming a minimum possible roundturn cost of 1 basis point. However fixed transaction costs are not guaranteed and often vary depending on the liquidity of a particular currency and time of day, thus similar to Neely and Weller (2003) we calculate break-even costs (transaction costs that reduce the cumulative returns to zero) to give an indication of the resilience of the RPP rule's profitability.

6.2 Results

6.2.1 Zero Transaction Costs

We first consider the case with zero transaction costs as it again highlights the pure predictive power of the RPP rule and makes for a useful benchmark. The results clearly reiterate the predictive power of the RPP trading rule as for example the average proportion of winning trades of the RPP (4) rule across the eleven exchange rates is 67 percent and if zero transaction costs were possible an investor following this strategy would be able to enjoy an average annual compound return of around 39 percent. Moreover analysis of the RPP rule's performance across different sub-periods demonstrates that the rule's performance is consistent across time and based on a casual examination appears to have a very low correlation with global macroeconomic performance. Finally analysis of weekly returns shows that in many cases the RPP rule yields a superior risk adjusted performance to a number of investments alternatives.

Holding Period Returns Table VIa and Table VIb present the profitability statistics based on holding period returns. Table VIa Panel A presents the profitability results of the RPP(4) rule for all currencies, while Table VIb reports the results for RPP(h) for only the EUR/USD exchange rate.[68] Table VIa Panel B present the profitability performance results of the RPP(4) rule in the EUR/USD market for different non-overlapping subperiods. The interpretation of the results is more intuitive than of the results of Section 5, thus we focus only on the highlights

Columns two and three, "N(Long)" and "N(Short)" report the respective numbers of long and short positions, while column four, "Average Holding Period (hours)" shows the average number of hours a position remains open. On average the RPP (4) rule takes a similar number of short and long positions and, in line with the results of Section 5, in certain markets there are slight sell or buy biases that

[68] Complete set of results is available in Section C1 of the Appendices.

correspond to the long term depreciation/appreciation of the exchange rates during the sample period. An average position remains open for approximately 3 hours. In Table VIb one can notice that in line with expectations higher values of h result in significantly less transactions. For example in the EUR/USD market the RPP (3) rule takes 11862 long positions, while the RPP(24) rule only takes 3107 long positions. A similar picture is painted by the average holding period as the time a position remains open gradually increases from 2.57 hours for RPP(3) to 9.76 hours for RPP(24). On average higher values of h result in lower returns as RPP rules with higher h parameters are "slower" and do not take advantage of as many opportunities, however later we show that in the presence of transaction costs the relationship becomes less obvious.

Columns four to eight report the mean, minimum, maximum, standard deviation and skewness of the holding period returns.[69] The mean is positive across all the exchange rates and the minimum is always greater than the maximum, thus the largest losses are greater than the largest wins. Indeed the distribution of holding period returns for all exchange rates is negatively skewed. Also on average there appears to be a positive relationship between mean return and standard deviation. For example the mean holding period return and standard deviation for the RPP (4) in the EUR/USD market is 0.000061 and 0.00206 respectively while the respective mean return and standard deviation in the AUD/USD market are 0.000173 and 0.00305. In Table VIb one can notice the general pattern that higher values of h result in lower mean holding period return and in the case of EUR/USD the RPP(20) and the RPP(24) rule yields negative mean holding period returns. But that is not the case for all the exchange rates. For most exchange rates the RPP(20) and the RPP(24) rules do yield the lowest mean holding period returns, but for many exchange rates the highest average holding period returns are produced at h values equal to 6 and higher (we present the best performing rules based on different metrics in Table X and provide a discussion later in this section). Additionally across the exchange rates higher holding period returns appear to be associated with higher skewness, hence the RPP rule is unlikely to be capturing any pure arbitrage opportunities. Finally a regular pattern that is consistent across all the exchange rates is that negative skewness on average increases in absolute terms with higher values of h. This result is in line with the intuition behind the mechanics of the rule: the higher the value of h the less sensitive is the rule

[69]he holding periods are not uniform across the different returns, therefore in a very strict sense the standard deviations and skewness statistics are incorrectly defined. However given that the differences in holding period across returns is fairly small and we are not using the statistics for further tests, these statistics will suffice.

to new information which could lead to protracted periods of losses before the signal is generated to close the losing position.

Columns nine and ten, "% of win" and "P_T/L_T" show the percentage of winning trades and the profit and loss ratio respectively. The results highlight the RPP rule's predictive edge. Across the eleven exchange rates on average 67 percent of the RPP (4) rule's trades result in a positive profit (the statistic can be interpreted as directional accuracy). A different way of looking at this is with an aid of the profit and loss ratio which shows that on average the RPP (4) rule had 2.25 times more profitable positions than unprofitable positions. These results hold for all eleven exchange rates and are robust to the choice of parameter h. However it is important to note that such a high win ratio does not guarantee a profitable trading strategy as the strategy could still lose money if the average loss is greater than the average profit. It often appears to be the case as for example is evident in Table VIb where the RPP (24) rule wins 73 percent of its trades but still yield a negative mean return.

The last three columns present the total returns and the cumulative returns for the entire sample period as well as the average compound annual return (annual return hereafter) during that period. The average across the eleven exchange rates of the annual returns is 39 percent per annum. The smallest annual return is achieved in the JPY/USD market which equals 9. 75 percent per annum, while the highest return of 180% per annum is realised in the ZAR/USD market (the ZAR/USD results are clear outliers and are discussed in detail further on in this section). In Table VIb the average annual compound return across all values of h is equal to 6.2 percent per annum. Thus although there is a degree of variability of annual returns with respect to h, for all currencies annual returns are positive for values of h up to 20. For example in the case of AUD/USD the RPP(4) rule yields an annual return of 41.43 percent while the RPP(12) rule yields an annual compound return of 18.45 percent, which is still a good return on investment. To put the results into perspective during the same time period investors in the S&P 500 Index received an unimpressive negative compound annual return of 1.66 percent, while investors in the JSE All Share Index would have received an annual return of 13.72 percent. Of course comparison of investment choices need to be made whilst accounting for both risks and returns, and we do that in the examination of the series of weekly returns.

Finally in Table VIa Panel B we present the profitability results of the RPP(4) rule in the EUR/USD market during four subperiods, which aids in the evaluation of the robustness of results to the choice of time period. We look for time consistency of the results.[70] The most important observation is that the RPP(4) rule yields positive mean holding period returns and percentage of winning trades remains around 65 percent for all subperiods. This result provides support to the notion that the RPP rule's predictive success is not simply a peculiarity of the chosen sample. As we explain in Section 4 the four subperiods are selected as to be representative of different periods of global risk. The performance of the RPP(h) is remarkably stable over the subperiods as for example it yields 11.52 per annum during the 2007-2009 recession (in the same period the S&P 500 lost around 40 percent of its value). Interestingly the RPP rule's best performance is recorded in the post-recession period between June 2009 and July 2010 as it yields a return of 37.71 percent per annum. Although no tests are performed the standard deviations of the recessionary periods of 01/2001-01/2003 and 06/2007-06/2009 are larger than the standard deviation of holding period returns during the low risk period of 01/2003-06/2007. Additionally the negative skewness of returns during the 01/2003-06/2007 period appears to be relative smaller, in absolute terms, than the skewness of returns during more volatile periods. Thus the RPP(h) rule is not entirely immune for global market performance. Nevertheless even a casual examination would illustrate that the rule's performance is almost uncorrelated with the global stock market returns (as proxied by the S&P 500) and thus, if zero transaction costs were possible, could be a welcome addition to an investor's portfolio.

Weekly Returns Analysis of the weekly return series shows that in a world with zero transaction costs the RPP trading strategy may be superior to a number of alternative investment strategies.

Table VII present the profitability statistics of the RPP (4) rule based on weekly series of returns for all the exchange rates. We present the estimated Sharpe ratios of the strategy in column seven of Table VII Panel A. As a comparison we replicate the Sharpe ratios of a carry trade strategy reported by Hassan and Smith (2010, p. 12) in column eight.[71] In column nine, "Weekly Mean Buy and Hold" we show the mean

[70] Based on the results of this and the previous sections we have a degree of confidence that the performance of the RPP(4) rule in the EUR/USD market is a fair proxy for the performance of the RPP(h) rule in all the analysed markets, thus to save on computational costs and time sub-period analysis is only performed on the RPP(4) rule in the EUR/USD market.

[71] Hassan and Smith (2010) evaluate the performance of a carry trade strategy using a number of currencies. Essentially the strategy involves borrowing Japanese Yen and investing in a risk free asset in another country (target country). For each currency, the carry trade Sharpe ratio we include in Table VII correspond on average to the carry trade strategy involving Japanese yen and that currency. For example the Sharpe ratio reported in the ZAR/USD row is the ratio achieved by a carry trade strategy involving the Japanese Yen and the South African Rand. In the cases where Hassan and Smith (2010) do not report on a specific currency (such as Swedish Krona), we simply use the carry trade Sharpe ratio of the yen-USD strategy.

weekly return on a long position in a given spot exchange rate, which provides an indication of average weekly changes of each exchange rate.

The mean weekly return is positive for all the exchange rates and is substantially higher than the average weekly fluctuations of the exchange rate series. The results are comparable to those of Maillet and Michel (2000) who show that, under the assumption of zero transaction costs, technical trading rules yield superior returns in the daily spot foreign exchange market relatively to the buy and hold on the basis of both the mean-variance and second stochastic dominance criteria. On the other hand a comparison with a more realistic alternative, the carry trade strategy, shows that the RPP rule strategy only yields superior performance based on the Sharpe Ratios in six out of eleven exchange rate markets (but it is important to note that the carry trade Sharpe Ratios are estimated based on the period of 04/1997 to 07/2007 and thus do not represent a perfect comparison). Examination of the RPP rule's performance yields similar results to the previous subsection, as the RPP(4) rule remains profitable in all economic climates but its risk adjusted performance is the highest during the period of low global volatility and is the lowest during the highly volatile periods between 2007 and 2009. Thus although the RPP rue's performance is resilient to global volatility, it is not entirely immune.

Examining the skewness of returns our results contradict the findings of Maillet and Michel (2000) who find that the returns conditional on moving average technical trading rules are less negatively skewed than the unconditional returns. This result offers insight into the difference between the types of trading rules. The moving average trading rule is a momentum or a trend following rule that aims to always follow the market trend, while the RPP rule is a contrarian rule that operates under the assumption of mean reversion in prices and trades accordingly. Thus during periods of protracted upward or downward trends the RPP rule can accumulate very large losses as it repeatedly bets on mean reversion.

In sum it appears that especially in the case of less liquid currencies the RPP rule provides a superior risk adjusted performance to the carry trade strategy, however we need to considerer transaction costs before drawing any conclusions.

6.2.2 Impact of Transaction Costs[72]

The next step in profitability analysis is the introduction of transaction costs. Introduction of minimal observed transaction costs of 1 basis points per round-turn trade renders the RPP rule based strategy unprofitable in five out of the eleven markets. Furthermore break-even costs analysis suggests that even in the markets where the RPP rule strategy is profitable, profitability may be highly sensitive to the level of transaction costs and is unlikely to be replicable in practice.

Table VIIIa reports the same statistics (apart from for an additional column reporting break-even costs) as Table VIa, except the results are calculated under the assumption of a 1 basis point cost per roundtrip trade. The introduction of transaction costs renders the RPP (4) trading rule strategy unprofitable in the EUR/USD, GBP/USD, JPY/USD, CHF/USD and EUR/JPY markets. The trading strategy leads to an average loss of 7.4 percent per annum in the five markets, where the rule is unprofitable.[73] Therefore the average transaction returns are unable to cover the average transaction cost charged per each trade, resulting in a sustained destruction of wealth. The RPP(4) rule yields an average profits of 29.83% per annum in the six markets in which it remains profitable in the presence of transaction costs, however omitting ZAR/USD, the average comes down to 9.75% per annum. If we assume that an investor holds an equally weighted portfolio of the RPP rule strategy across the eleven markets, the average annual return is 12.9 percent per annum, and is only 1.1 percent per annum if one excludes ZAR/USD, which is a clear outlier.

The introduction of transaction costs notably reduces the relative risk-adjusted performance of the strategy. Table IX present the profitability statistics based on the weekly return series in the presence of 1 basis point roundtrip transaction costs. The columns are labeled identically as in Table VII and again for ease of comparison the Sharpe Ratios of a carry trade strategy (with transaction costs) reported in Hassan and Smith (2010) are presented in the last column. In all the markets within which the RPP strategy is profitable, the weekly Sharpe ratios are still superior to the negative weekly ratio of the S&P 500 and a Sharpe ratio of 0.056 of the Johannesburg Stock Exchange All Share Index.[74] However when compared to

[72] Given that the introduction of transaction costs simply brings down the average transaction returns by the amount of the cost, there is no value added in performing the evaluation on every specification of the RPP rule for every exchange rate like we do in other sections. Thus we analyse and report only a representative subset.

[73] Less formally, one could say that the RPP trading strategy is bleeding money.

[74] We use the Johannesburg Stock Exchange All Share Index data from DataStream and the South African government Treasury bill rate, sourced from the IMF International Financial Statistics, to calculate the Sharpe ratio.

the carry trade strategy, the Sharpe ratios produced by the RPP strategy are lower than those of the carry trade strategy in every market. Of course one should again note that the performance of the carry trade strategy has been calculated during a slightly different time period, we thus consult an alternative source as a precaution. Burnside *et al* (2008, p. 31) report average annual Sharpe ratios of an equally-weighted carry trade strategy (adjusted by transaction costs) during the period 1976-2008 to be equal to 0.867. We can assume that this figure represents a long term average carry trade strategy Sharpe ratio and we can convert it to a weekly figure simply by dividing by the square root of 52, which yields a weekly Sharpe ratio of 0.1202. Comparing the Sharpe ratios, we find that in four out of the six markets where RPP is profitable the Sharpe ratios are higher than 0.1202[75], however in the case of AUD/USD and EUR/CHF the differences are very slight.[76] Furthermore the average skewness of the weekly RPP returns in the markets where the strategy is profitable is -0.2602, which is greater in absolute terms (i.e. less favorable) than the average weekly skewness of the carry trade strategy returns (which equals -0.2103) reported by Hassan and Smith (2010, p. 13).Thus on average based on both the Sharpe ratio and the skewness statistic the RPP rule trading strategy is unlikely to be superior to a carry trade investment strategy. Nevertheless, if one can guarantee 1 basis point transaction costs the strategy may still be viable for inclusion in a well diversified portfolio because based on the profitability evaluation across subperiods, it seems unlikely that the profits of the RPP rule strategy represent compensation for bearing systematic risk (we however do not investigate this matter any further).

The last column of Table VIII reports the break-even transaction costs for each of the examined spot foreign exchange rates. Break-even transaction costs seek to establish the level of costs that would bring the cumulative return for the strategy to zero. Essentially the break-even transaction cost is equal to the mean return per trade at zero transaction costs, because if the average return per trade fails to produce a profit above the transaction cost charged per trade the strategy would not yield any profits.[77] Firstly the average break-even transaction cost in the markets where the RPP rule is unprofitable (namely: EUR/USD, JPY/USD, GBP/USD, CHF/USD and EUR/JPY) is equal to 0.000063, which is substantially below the

[75] Lo (2002) warns that such a simple adjustment is only warranted under the assumptions that returns are independently identically distributed, however for our purposes the adjustment ought to suffice.

[76] However no significance tests are performed, thus our comparisons remain casual.

[77] The break-even transaction costs reported in Table VII were found using an iterative procedure and due to compounding (given that we seek to make the cumulative return zero) are slightly smaller than the mean transaction return under the assumption of zero transaction costs.

minimal interdealer spread. Setting aside the ZAR/USD market, the average break-even transaction cost across five markets where RPP rule is profitable (AUD/USD, CAD/USD, SEK/USD, EUR/GBP and EUR/CHF) is equal to 0.000144 which although slightly higher than 1 basis point spread is still within range of normal direct interdealer spreads that are reported to be between 1 and 2 basis points.

Given that the performance of the RPP rule in the ZAR/USD market remains vividly profitable even in the presence of transaction costs; we thus subject the results to further evaluation. Table VIIb reports the profitability results of the RPP(4) trading rule in the ZAR/USD market for different levels of roundturn transaction costs (namely: zero, one, two, three and four basis points per trade). The results show that although profitability decreases with higher transaction costs, the strategy remains profitable (yielding 22.69 percent per annum) in the presence of transaction costs as high as 4 basis points per trade and the break-even transaction costs is found to be 0.000497 per roundtrip trade. However the strategy is unlikely to succeed as the trader would probably face transaction costs above the break-even cost.

Burnside *et al* (2007, p. 334) report that for developed countries, the median bid-ask spread in the spot market was between 0.039 and 0.051 percent during the period October 1997 to November 2006 (which is similar to the sample period used in this paper). While Hassan and Smith (2010, p. 12) during a similar period calculate the median bid-ask spread for the spot ZAR/USD market to be around 0.006581 (interestingly the highest mean return per trade, which could be interpreted as a break-even cost, is achieved by the RPP(8) rule in the ZAR/USD and is equal to 0.000681). It is also important to note that except for some major currencies against the USD, currencies tend to be traded more specifically in their own geographical markets. Thus our assumption of around the clock trading during business week in ZAR/USD and other less liquid currencies is likely to be unrealistic. In other words a trader attempting to trade ZAR/USD or AUD/USD (or another relatively illiquid currency) during the times when the relevant local markets are closed is likely to either find no liquidity or to experience exceptionally high transaction costs. Interestingly the RPP trading rule is unprofitable in the presence of minimal transaction costs when applied to major exchange rate pairs i.e. the ones that could realistically be assumed to be traded around the clock (EUR/USD, JPY/USD, GBP/USD and JPY/USD). In sum the RPP trading rule is unlikely to yield profits in the face of realistic transaction costs.

Finally for the purpose of providing further insight into the mechanics of the RPP trading rule and technical trading rules in general, we present in Table X the best performing specifications of the RPP rules for each currency. The best specification of the rule varies according to the criteria used. If the criteria is to maximise the cumulative return, under the assumption of zero transaction costs the rules with low a low value of h perform the best. Out of the eleven currencies RPP(3) rule is the best performing rule in six markets, the RPP(4) is best in a single market and the RPP(5) rule is the best rule in the other four remaining markets. Given that nearly all the RPP rules have a directional accuracy of above 60 percent, the rules with a low h parameter offer a superior performance due to the larger level of transactions. By trading very frequently small profits compound to yield a high cumulative return. A contrasting example is presented when we select the best rules according to the highest mean return per trade. In that case the RPP(5) rule is optimal only in three markets, while in the other markets the rules with h value equal to 6 and higher are the best performing. The number of transactions is lower and the percentage of winning trades is higher for the RPP rule with higher values of the h parameter. Essentially the rules are more selective about the trades, which results in lower levels of transactions, greater proportion of winning trades, but lower cumulative return. The advantage, of course, is that the returns per trade are higher which makes the rules more resilient to transaction costs. Thus although the predictive power of the RPP trading rule is generally robust to parameter choice, different users may benefit from optimising the parameter choice to be in line with their objectives.

6.3 Concluding Remarks

In this section, we evaluate the profitability of the RPP trading algorithm and take into account both the risks and the transaction costs. The empirical results further corroborate the findings of the predictability analysis in showing that the RPP rule possesses predictive power. Under the assumption of zero transaction costs, the RPP rule is profitable in all of the examined exchange rate markets and, based on the Sharpe Ratio criterion, yields superior returns to a carry trade strategy in six cases. However, with the introduction of a minimal possible transaction cost of 1 basis point, the RPP strategy makes losses in five markets, which happen to be the most liquid markets. The break-even cost analysis shows that within the markets in which the RPP trading rule strategy is profitable, a cost of approximately 2 basis points per trade would lead to zero profits. Realistic, empirically estimated transaction costs in the spot market range from 3.9 basis points to 5.1 basis points, and in the case of the South African Rand, the median costs are reported to be around 6.5 basis points. In the face of these transaction costs, there exists no specification of the rule that would be able to make a profit. In fact, it would most likely make consistent losses as returns per trade (although on average positive) would be unable to cover transaction costs.

The results of this section shed light on the possible source of reported profitability in many previous studies. Researchers do not necessarily need to commit data snooping biases to find profitable trading rules; one can simply underestimate the true transaction costs which, until recently, have been difficult to measure.

7 Discussion

The RPP rule is found to have strong predictive power, but fails to produce profits upon the introduction of realistic transaction costs. In this section we relate these results to prior research and offer some tentative explanations for our findings.

The result that the RPP rule is unprofitable in the face of transaction costs is in line with previous research and with the notion of market efficiency. In the studies using daily exchange rate data earlier works (Sweeney, 1986; Levich and Thomas, 1993) find evidence of trading rule profitability in the foreign exchange market, but most subsequent studies agree that trading rule profitability has been declining over time and has essentially disappeared since the 1990s (Lee and Marthur, 1996; Martin, 2001; LeBaron, 2002; Olson, 2008). There also does not appear to be much evidence in support of profitability in the case of technical rule trading in the intraday foreign exchange market (Curcio *et al*, 1997; Neely and Weller, 2003).

Further confirmation is found in the two papers conducting detailed studies of the intraday foreign exchange trading by dealer banks. Lyons (1998) shows that intermediation accounts for more than 90 percent of the dealer's profits and that speculative positions are on average unprofitable. A more recent and detailed study by Mende and Menkhoff (2006) corroborate the results of Lyons (1998) concluding that the main source of revenue for the bank is customer dealings, while that a bank's speculative positions are not profitable and are unlikely to be profitable given the transaction costs. Indeed similar to our results many studies dealing with different markets attribute the inability to translate predictive power of technical trading rules into profits to transaction costs (Bessembinder and Chan, 2002; Ready, 2002; Bajgrowicz and Scaillet, 2010). Neely and Weller (2003, p. 235) note that a striking feature of their results is that break-even transaction costs generally converge to a level close to that faced by a large institutional trader, namely, 2 to 3 basis points per one-way trade. Our results similarly suggest that although the RPP rule may still generate profits in less liquid markets when transaction costs are assumed to be minimal, the break-even costs are often remarkably close to the true empirically observed transaction costs. The absence of profitability is thus not very surprising, and we further argue that the strong predictive ability of the RPP rule could be reconciled with both theory and prior empirical research.

One of the defining features of high frequency data is the clear evidence of negative first-order autocorrelation. The phenomenon of negative serial correlation could possibly be explained by the hypothesis that market participants with diverging opinions revise their views upon the arrival of new information or it could be spuriously induced due to a microstructure artefact such as for example non-synchroneity of the quoted rates or fluctuations across the bid/ask spread (bid-ask bounce or, in the case of midquote data, midpoint bounce)[78] (Gavridis, 1998 p. 10, Baillie and Bollerslev, 1991, p. 582). But, as was discussed in Section 3, by using hourly as opposed to higher frequency data, we afford our results a relative degree of protection from microstructural artefacts.

Thus the negative autocorrelation may likely be a true feature of the data as Ito and Roley (1986, cited in Goodhart 1988, pp. 442) as well as Goodhart *et al* (1993, p. 12) find evidence that large changes in the exchange rates in a number of markets tended systematically to be partially reversed in the next hour. Weller *et al* (2007) offer further support to the notion as they develop an asset pricing model, in which investors are subject to confirmation bias, that is able to replicate, among other things, the negative autocorrelations of asset prices over very short horizons. Notwithstanding the explanation for this empirical regularity, the most important factor is that the significant negative autocorrelation found in the hourly exchange rate series could be the driver behind the predictive power of the RPP trading rule. Indeed Taylor (1994, cited in Taylor, 2005 p. 184) applies a technical trading rule to a simulated ARMA (1,1) process. He demonstrates that a technical trading rule can exploit even very low levels of autocorrelation and yield significant trading profits.

Coincidently in our study there appears to be correlation between the profitability of the RPP rule (under the assumption of zero transaction costs) and the magnitude of the autocorrelation of the exchange rate series. The foreign exchange rates that yielded the highest profits, namely ZAR/USD, AUD/USD, EUR/GBP and EUR/CHF, also happen to have the highest degree of negative autocorrelation among the eleven exchange rates. Figure 11 shows the plots of the coefficients of autocorrelations of the four foreign exchange rates that yielded the greatest and the smallest profits respectively. It is evident that the less liquid exchange rates (also the exchange rates the trading of which produces the most profits under the assumption of zero transaction cost) have the most pronounced negative autocorrelation. Neely and Weller (2003, p. 235) come to the conclusion that the evidence of predictive power they find in their results is most likely attributed to negative serial correlation. However the bootstrap allows us to go further and rigorously test whether the RPP rule is able to capture any incremental information above what is explained by a GARCH(1,1)-MA(1) model with seasonal volatility. And our results show that except for

[78] Bid-ask bounce or midpoint bounce is induced by dealers with order imbalances (Taylor, 2005, p. 312).

the case of RPP(3), RPP(4) and RPP(5) rules in the EUR/USD market, the RPP rule fails to provide incremental information above the null model.[79] In that we have considerable confidence in concluding that the RPP rule predictive ability is exploiting all or some of the features of the data that is essentially being controlled for by the GARCH(1,1)-MA(1) model. Although the volatility process, in particular the intraday seasonal component, may be a feature captured by the RPP rule and a factor in its predictive ability, the rule is most likely exploiting the serial autocorrelation (accounted for by the moving average process of the null model). In fact Bianchi *et al* (2005) come to a similar conclusion utilising the bootstrap method to test the performance of momentum strategy in daily foreign exchange market as they find that the source of excess returns is a function of the autocorrelation.

In sum it appears that the negative autocorrelation is a true feature of the data and the RPP rule appears to be simply exploiting this linear dependency. If that is the case, the rule is arguably doing so in an inefficient manner because as explained by Neftci (1991, p. 549) Wiener-Kolmogorov theory should yield the best in the mean square error (MSE) sense forecasts of linear stochastic processes. However that does not mean that the RPP rule is redundant because the shortcoming of Wiener-Kolmogorov approach is that it cannot be easily synthesized into a trading signal (Neftci, 1991, p. 550). Essentially although the bootstrap results show that the RPP rule fails, on average, to add incremental information above the GARCH(1,1)-MA(1) model, the RPP rule is able to provide clearly defined trading signals while the null model is not. Furthermore the use of the RPP rule in practice could be rationalised by the information cost type of argument as for example is presented in Skouras (2001, p. 284) who argues that discrete rules (such as technical trading rules) are easier to learn than optimal decision rules (which may be continuous). This argument is especially fitting given that the foundations of the RPP trading rule lie in efficient algorithm development. So even if the RPP rule is merely exploiting the negative autocorrelation in the series, it

[79] The bootstrap approach is dependent on the null model, so in the case of the three rules that are still found to add incremental information above the GARCH(1,1)-MA(1) it is possible that the rules may be utilising some features of the data for which the null model does not account. Harris and Yilmaz (2009, p. 1580) point out that the existence of significant autocorrelation might be a sufficient condition for the effectiveness of technical trading rules, but is not a necessary condition because technical trading rules may exploit both linear and non-linear dependence in returns. This is especially applicable to our study as Aparicio Acosta (1998) finds significant evidence of nonlinearity in the means of several hourly exchange rates. Hence even though we have introduced a degree of nonlinearity through explicitly modelling the intraday seasonality of volatility, the incremental predictive power may be attributed to some sort of a non-linear feature of the data. However given that the RPP rule has significant predictive ability in only three cases, we do not pursue the issue further.

may still be an optimal heuristic for this task and be of incremental value to dealers or traders trading on private information[80].

Finally the analysis of the RPP trading rule offers insight into the mechanics behind technical trading rules and allows one to draw some generalisations. Trading rules can be classified as either trend following (momentum) or contrarian (mean-reverting) and Schulmeister (2006) shows empirically that although there exists a plethora of trading rules, on average, trading rules of a similar category produce signals on the same side of the market. Therefore an analysis of a single contrarian rule like the RPP rule could provide general results that apply to most contrarian rules (also the RPP rule's theoretical heritage and the fact that it is shown to be analytically superior to a number of other technical rules adds further credibility to this approach).[81] Based on our results we can thus argue that the predictive power of any contrarian rule that is utilised in the intraday foreign exchange market is likely to lie in its exploitation of negative serial autocorrelation and is unlikely to add any incremental value to a GARCH(1,1)-MA(1) model forecast. It is also probable that the predictive edge is not sufficient to be profitably exploitable in the presence of transaction costs. In addition, as it was evident from the risks examination of the RPP rule, any contrarian strategy (even the one that is able to generate average trade returns above costs) is likely to be exposed to significant negative tail risk as it would be making losses during periods of sustained unidirectional price movements.[82] The foreign exchange market experiences both trending and mean reverting periods, and within each period different classes of rules are optimal. Therefore the final profitability of each trading rule is dependent on whether they are applied during the "correct" period, which is of course dependent on the human trader.

[80] Our intuition is guided by the Brown and Jennings' (1989) model, which shows that technical analysis used in conjunction with private information may add value in disentangling the prices from the noise induced by supply uncertainty.

[81] Nevertheless a good extension of this research would be an application of the bootstrap methodology to a larger set of trading rules in the intraday foreign exchange market.

[82] It is also important to bear in mind that capital constraints are a factor, thus a trader experiencing a prolonged period of losses may relinquish the trading rule even if it may be profitable in the long run (Schulmeister, 2009, p. 199).

8 Conclusion

Using a large sample of hourly exchange rates, this paper investigates the predictive ability and profitability of the RPP trading rule which possesses a traditionally sought after quality of being grounded in theory. We find significant support to reject the premise that the signals generated by RPP algorithms are merely random noise with zero information about the future. Despite its simplicity, the RPP rule possesses a substantial degree of predictive power that is robust across different exchange rates and is also, on average, insensitive to the parameter choice. However, the bootstrap analysis shows that the RPP trading rule does *not* capture any incremental information above what is accounted for by the GARCH (1,1)-MA (1) null model. In light of this, we argue that the RPP's predictive power stems simply from the negative autocorrelation inherent in the intraday foreign exchange data, a finding that it is in line with prior research.

Analysing the profitability of the RPP rule, we discover that, although under the assumption of zero transaction costs, the rule on average yields superior risk-adjusted profits and appears almost immune to systematic risk; profits turn into systematic losses with the introduction of realistic transaction costs. Hence, market efficiency (in the sense of unavailability of consistent abnormal profit opportunities) appears to reign supreme in the intraday spot currency market. Nevertheless, the RPP rule could serve as a useful heuristic for currency traders or dealers' forecasts, especially if one views it from Simon's (1955) "satisficing" criterion. Thus, a natural extension and avenue for future research is the examination of the rule's relative predictive power against other technical trading rules in order to investigate whether the degree of optimality relative to other rules (as suggested by theory) holds empirically.

Ultimately, although it appears that the RPP rule cannot generate profits, a degree of uncertainty (or hope) about the profitability of the RPP rule (and technical trading rules in general) always remains, in the words of Surajaras and Sweeney (1992, cited in Hakkio, 1993, p. 2047), "The only fully satisfactory conclusion is, you can't know until you try it in real time with real money on real currencies."

A Figures

Figure1 EUR/USD exchange rate and RPP(4)

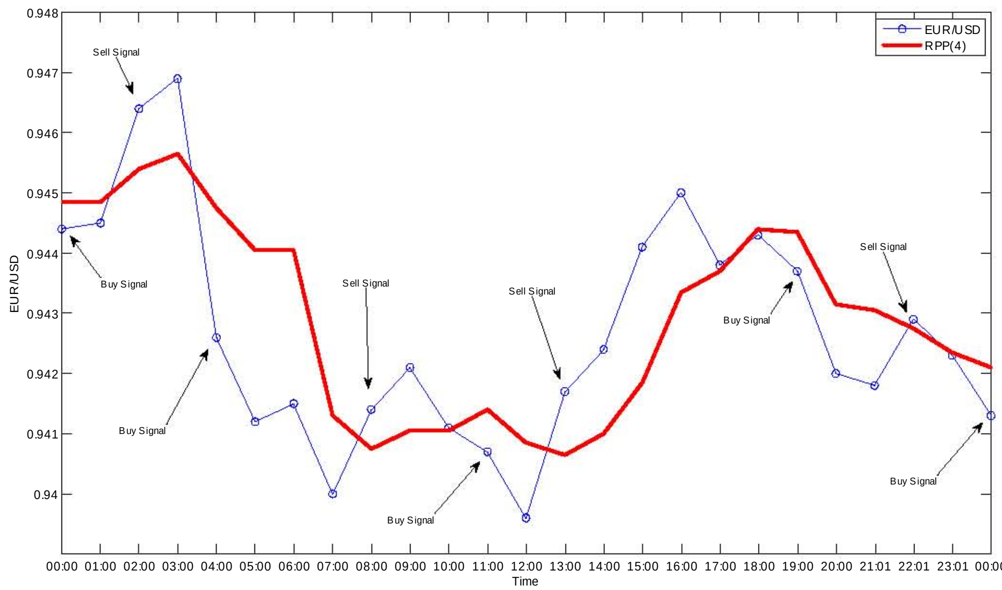


Figure 2 EUR/USD Exchange Rate and RPP(10)

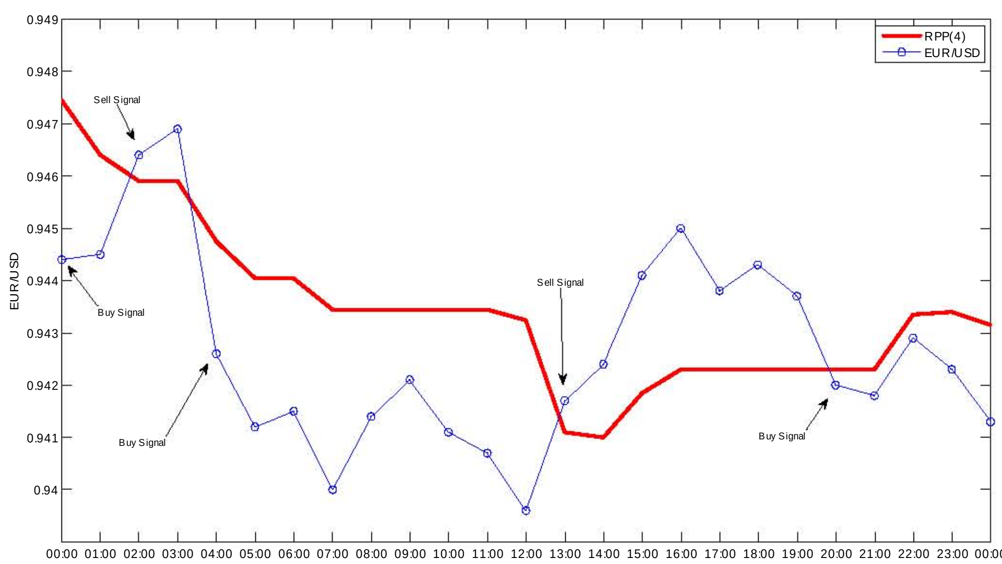


Figure 3 Long term trends in exchange rates (January 2001 - July 2010)

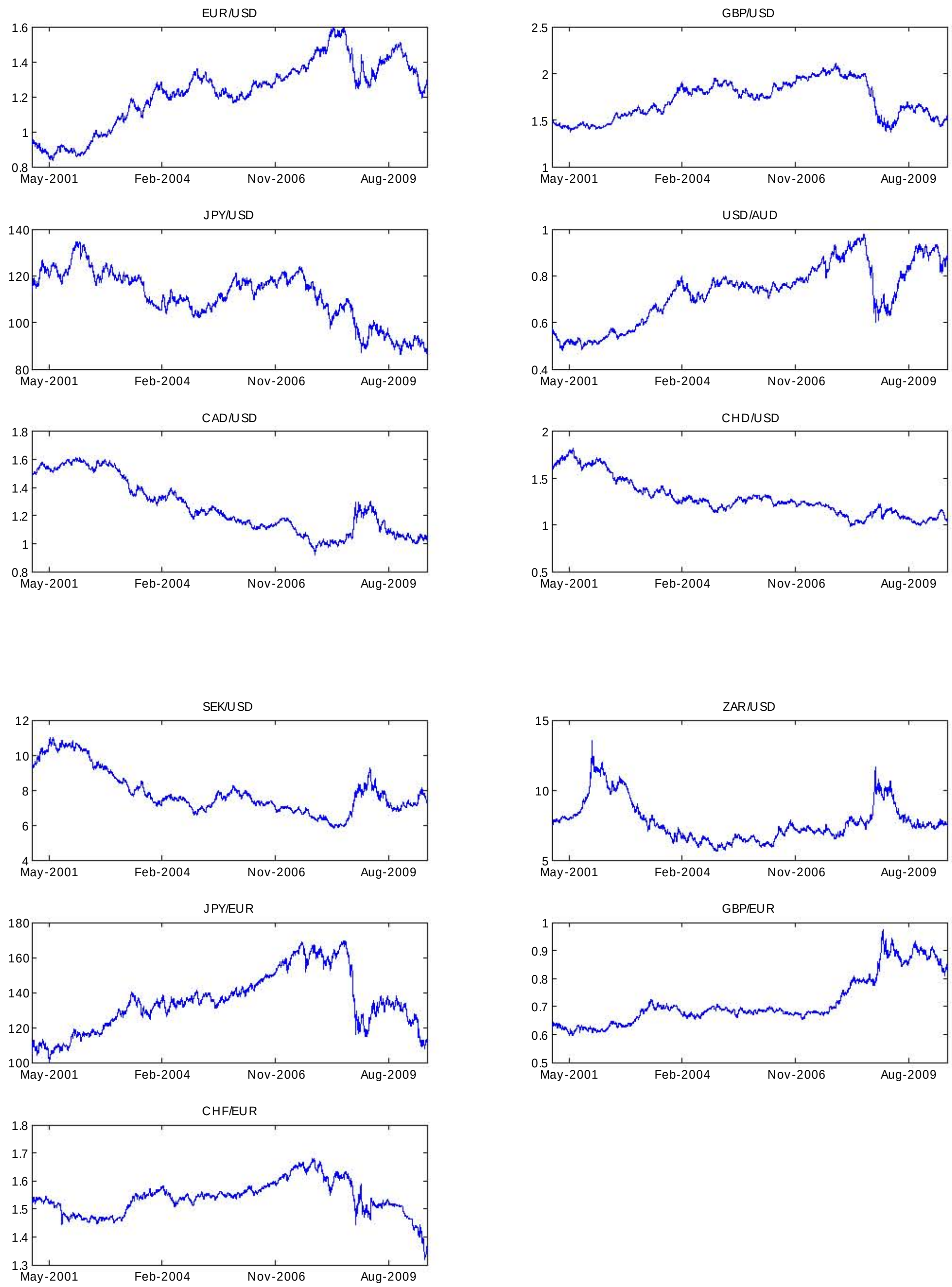
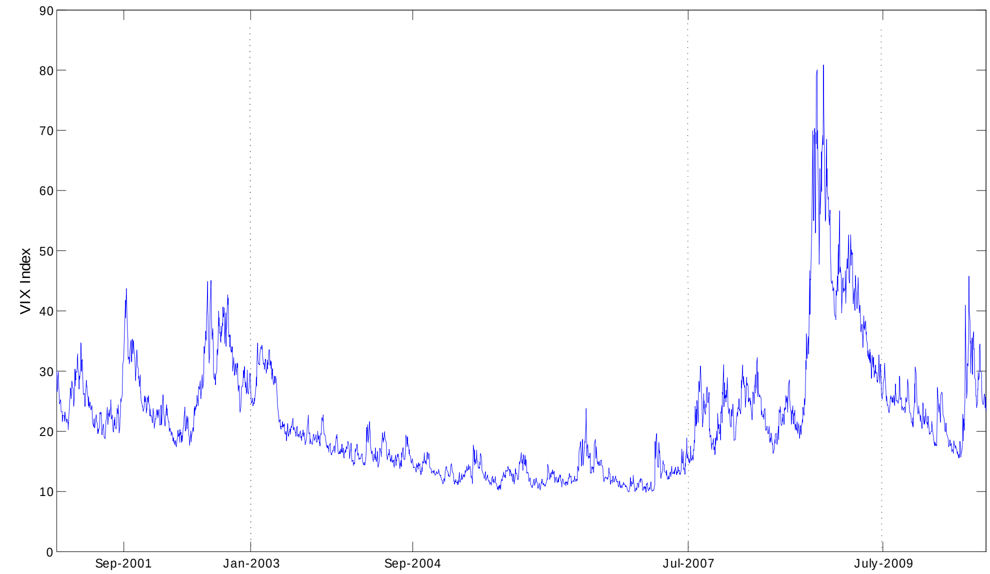


Figure 4 Daily CBOE Volatility Index - VIX (January 2001 - July 2010)



Source: Chicago Board Options Exchange (CBOE)

Figure 5 Daily S&P 500 Composite Index (January 2001 - July 2010)

Source: DataStream

Figure 6 Fifteen Simulated EUR/USD Exchange Rate Series

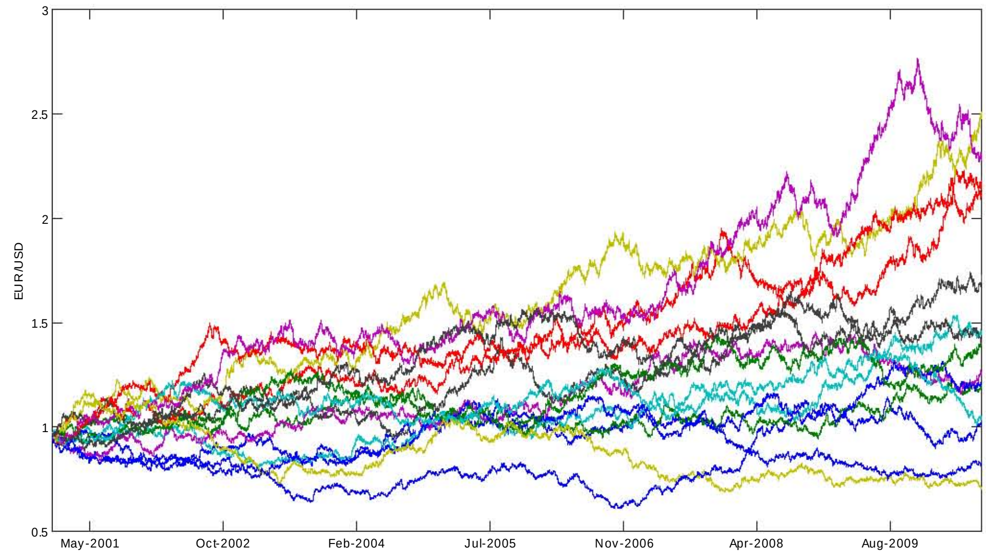


Figure 7 Estimated Seasonal Variance EUR/USD Exchange Rate

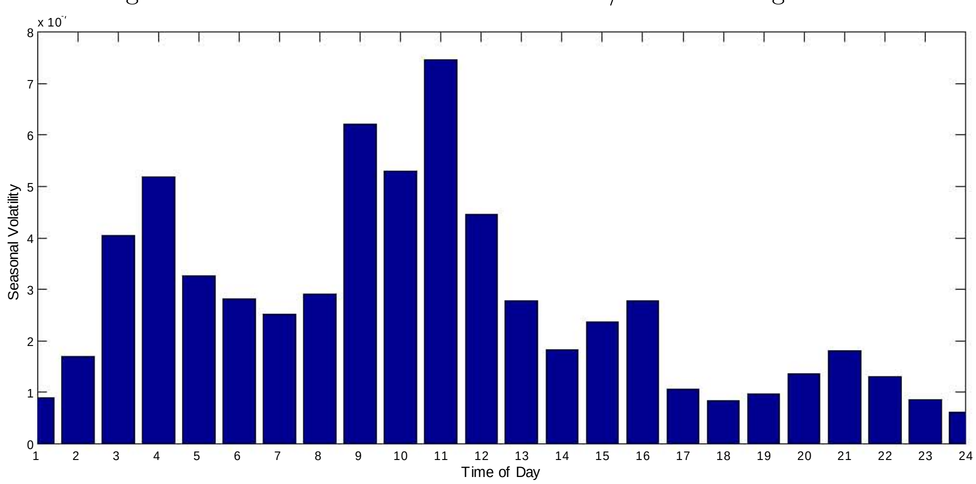


Figure 8 Actual EUR/USD Exchange Rate vs a Single Simulated EUR/USD series

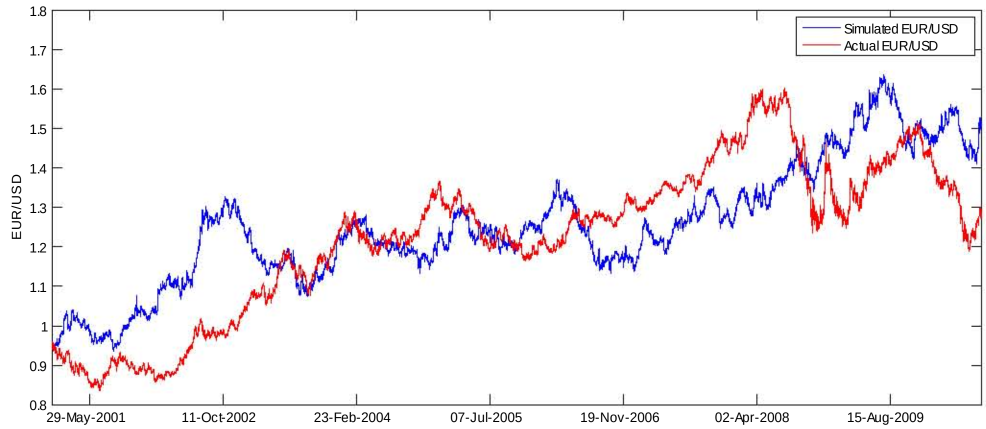


Figure 9 A Comparison of Actual and Simulated EUR/USD Returns on a Single Day

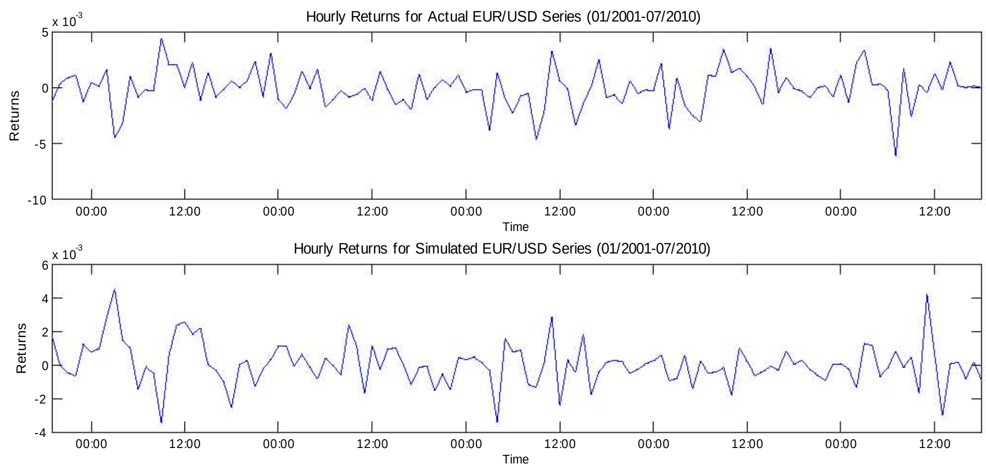


Figure 10 A Comparison of Actual and Simulated EUR/USD Returns (full sample period)

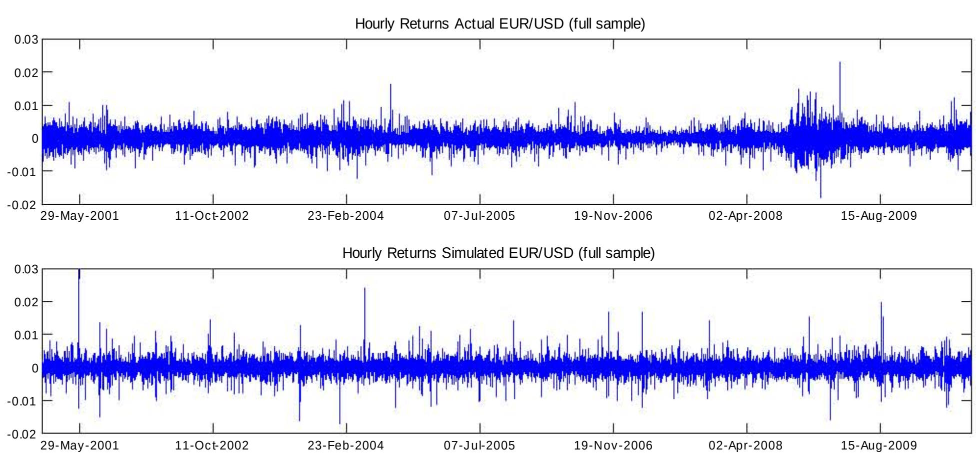
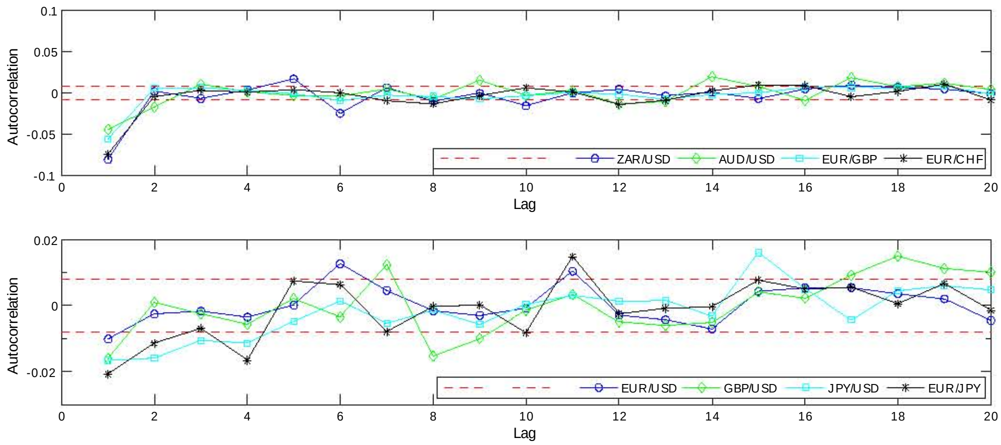


Figure 11 A Comparison of Autocorrelation Across the Exchange Rates



Note: The top panel shows the autocorrelation coefficients of the four exchange rates which, when applied to the RPP, resulted in the greatest profits. The bottom panel shows autocorrelation coefficients of the four exchange rates which, when applied to the RPP, resulted in the lowest profits. The horizontal lines indicate the asymptotic 95% confidence interval for zero autocorrelation.

B Tables

Table I

Descriptive Statistics (Full Sample)

	N	Mean	Std. Dev.	Skew	Kurt	Min	Max	ρ(1)	ρ(2)	ρ(3)	ρ(4)	*Q* (6)	*Q* (12)	*Q* (24)	LM(12)
EUR/USD	61166	0.000576	0.13247	0.08949	13.524	-0.01795	0.02309	-0.01011	-0.00252	-0.00169	-0.00350	17.31	26.42	45.49	198.00
GBP/USD	61090	0.000126	0.12966	-0.23255	16.128	-0.02094	0.01797	-0.01612	0.00092	-0.00251	-0.00563	19.26	51.04	98.27	382.84
JPY/USD	61123	-0.000373	0.13986	-0.54580	20.986	-0.02987	0.01792	-0.01662	-0.01591	-0.01059	-0.01140	48.69	53.30	90.27	262.64
AUD/USD	61097	0.000911	0.18767	-0.15702	27.945	-0.03879	0.03743	-0.04440	-0.01726	0.01025	0.00132	146.87	178.67	272.88	781.50
CAD/USD	61045	-0.000514	0.13431	-0.19239	14.736	-0.02117	0.01445	-0.03161	-0.01568	-0.00059	-0.01737	97.15	110.58	150.87	427.44
CHF/USD	61028	-0.000582	0.14045	0.09939	15.582	-0.01861	0.02647	-0.00860	0.00123	-0.00056	0.00078	12.30	15.55	35.69	91.19
SEK/USD	60907	-0.000248	0.16948	-0.00868	12.811	-0.03044	0.02211	-0.03213	-0.00174	-0.00062	-0.00093	78.28	86.29	98.76	330.58
ZAR/USD	58761	0.000366	0.27761	0.08857	24.028	-0.05855	0.04775	-0.08061	0.00207	-0.00681	0.00377	439.15	463.02	488.04	507.36
JPY/EUR	61083	0.000153	0.16591	-0.33794	25.598	-0.03570	0.02663	-0.02074	-0.01139	-0.00694	-0.01663	59.89	81.71	139.49	578.79
GBP/EUR	61131	0.000507	0.10816	0.25093	13.713	-0.01489	0.01476	-0.05622	0.00539	0.00649	0.00303	203.59	209.75	243.90	387.51
CHF/EUR	61144	-0.000166	0.07033	0.32940	42.926	-0.01891	0.02144	-0.07435	-0.00467	0.00309	0.00071	340.83	373.26	407.35	180.54

Note: The table presents statistics for log exchange rate changes constructed from a full data set. The sample period is from January 7th, 2001 through to July 23rd, 2010. Mean and standard deviation are multiplied by 100. The skewness and kurtosis statistics would be distributed as standard normal variables if the underlying series were normal and the standard errors of skewness and kurtosis would equal to $\sqrt{(6/T)}$ and $\sqrt{(24/T)}$ respectively. "Min" and "Max" records the smallest and largest log exchange rate changes over the sample period. ρ(i) records the autocorrelation coefficient at lag *i*. Q(q) is the Ljung-Box statistic at lag *n*, and is distributed as a chi-squared with *q* degrees of freedom. The LM (12) statistic is the ARCH LM test up to the twelfth lag and under the null of no ARCH effects asymptotically it has a $\chi^2(q)$ distribution, where *q* is the number of lags. The $Q^2(12)$ statistic is the Ljung-Box test on the squared residuals of the conditional mean regression up to the twelfth order. Under the null hypothesis of no serial correlation, the test is also distributed as a $\chi^2(q)$ where *q* is the number of lags.

Table II

Quasi-maximum likelihood estimates of GARCH (1,1)-MA (1) Model

	EUR/USD	GBP/USD	JPY/USD	AUD/USD	CAD/USD	CHF/USD	SEK/USD	ZAR/USD	EUR/JPY	EUR/GBP	EUR/CHF
$\mu_0(i)$	0.02787	0.02643	0.01014	0.04004	-0.05957	-0.01285	-0.02348	-0.01915	0.04133	0.01532	0.02586
std. error	0.00865	0.00865	0.00956	0.00796	0.00876	0.00877	0.00760	0.00909	0.00793	0.00785	0.00884
	(0.0013)	(0.0022)	(0.2887)	(0.0000)	(0.0000)	(0.1430)	(0.0020)	(0.0352)	(0.0000)	(0.0508)	(0.0034)
$\theta_1(i)$	-0.02189	-0.04193	-0.02535	-0.05526	-0.08406	-0.02916	-0.05988	-0.18165	-0.03965	-0.11530	-0.15303
std. error	0.00489	0.00480	0.00509	0.00458	0.00542	0.00480	0.00479	0.00536	0.00480	0.00471	0.00523
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\phi(i)$	0.05163	-0.07750	-0.02845	-0.04318	0.07426	0.03762	0.04256	0.07493	-0.05436	-0.01989	-0.04390
std. error	0.01008	0.01117	0.01051	0.01126	0.01302	0.01069	0.01253	0.13008	0.00991	0.02221	0.03229
	(0.0000)	(0.0000)	(0.0068)	(0.0001)	(0.0000)	(0.0004)	(0.0007)	(0.5646)	(0.0000)	(0.3705)	(0.1740)
$\omega_0(i)$	0.22214	0.01599	0.57342	0.02055	2.54098	0.20232	0.00437	0.11565	0.02486	0.00557	0.06013
std. error	0.01994	0.00312	0.05299	0.00290	0.03449	0.01922	0.00135	0.01282	0.00328	0.00178	0.01205
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0012)	(0.0000)	(0.0000)	(0.0017)	(0.0000)
$\alpha_1(i)$	0.07425	0.01957	0.12257	0.02609	0.24657	0.05755	0.00891	0.06091	0.03990	0.01467	0.04739
std. error	0.00403	0.00141	0.00761	0.00178	0.00827	0.00353	0.00066	0.00326	0.00213	0.00115	0.00585
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\beta_1(i)$	0.89093	0.97784	0.79526	0.97148	0.45587	0.90857	0.99047	0.92777	0.95741	0.98460	0.94645
std. error	0.00582	0.00151	0.01410	0.00193	0.00000	0.00573	0.00069	0.00343	0.00203	0.00120	0.00552
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\psi(i)$	0.72901	0.11732	0.31129	-0.38675	-4.67165	0.78264	-0.13733	2.73840	-0.01009	0.01024	0.23833
std. error	0.29385	0.21897	0.44169	0.14046	0.06313	0.35537	0.13261	0.65819	0.15376	0.15488	0.40022
	(0.0131)	(0.5921)	(0.4809)	(0.0059)	(0.0000)	(0.0276)	(0.3004)	(0.0000)	(0.9477)	(0.9473)	(0.5515)

Note: The table reports the estimated coefficients together with asymptotic robust standard errors for the GARCH (1,1)-MA (1) model of deseasonalised returns. The p-values are in parenthesis.

Table III a

RPP(4) trading rule performance test results for eleven spot foreign exchange rates

Currency Pair	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0		Sell>0		Kolmogorov-Smirnov Stat	
EUR/USD	29614	31549	0.000030	-0.000017	0.5164	(0.000)	0.4503	(0.000)	0.06809	(0.000)
GBP/USD	29590	31497	0.000024	-0.000021	0.5213	(0.000)	0.4594	(0.000)	0.06340	(0.000)
JPY/USD	29756	31364	0.000015	-0.000022	0.5136	(0.000)	0.4519	(0.000)	0.06385	(0.000)
AUD/USD	28961	32133	0.000070	-0.000046	0.5124	(0.000)	0.4525	(0.000)	0.06413	(0.000)
CAD/USD	30123	30919	0.000042	-0.000051	0.5092	(0.001)	0.4391	(0.000)	0.07234	(0.000)
CHF/USD	30256	30769	0.000021	-0.000032	0.5102	(0.000)	0.4425	(0.000)	0.06901	(0.000)
SEK/USD	30863	30041	0.000044	-0.000051	0.5228	(0.000)	0.4601	(0.000)	0.06513	(0.000)
ZAR/USD	29256	29502	0.000188	-0.000179	0.5325	(0.000)	0.4347	(0.000)	0.10282	(0.000)
EUR/JPY	29153	31927	0.000030	-0.000024	0.5262	(0.000)	0.4674	(0.000)	0.06421	(0.000)
EUR/GBP	29690	31438	0.000063	-0.000050	0.4996	(0.553)	0.4094	(0.000)	0.09050	(0.000)
EUR/CHF	29641	31500	0.000049	-0.000050	0.5199	(0.000)	0.4165	(0.000)	0.10566	(0.000)

Table III b

RPP (h) trading rule performance test results for the spot EUR/USD exchange rate

h	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0		Sell>0		Kolmogorov-Smirnov Stat	
3	29737	31427	0.000034	-0.000021	0.5158	(0.000)	0.4506	(0.000)	0.06651	(0.000)
4	29614	31549	0.000030	-0.000017	0.5164	(0.000)	0.4503	(0.000)	0.06809	(0.000)
5	29570	31592	0.000028	-0.000015	0.5153	(0.000)	0.4514	(0.000)	0.06606	(0.000)
6	29644	31517	0.000025	-0.000013	0.5136	(0.000)	0.4529	(0.000)	0.06402	(0.000)
7	29722	31438	0.000022	-0.000010	0.5115	(0.000)	0.4547	(0.000)	0.06049	(0.000)
8	29744	31415	0.000016	-0.000004	0.5087	(0.001)	0.4574	(0.000)	0.05622	(0.000)
10	29809	31348	0.000013	-0.000001	0.5042	(0.072)	0.4615	(0.000)	0.04688	(0.000)
12	29818	31337	0.000011	0.000001	0.5024	(0.207)	0.4633	(0.000)	0.04235	(0.000)
20	29644	31503	-0.000003	0.000014	0.4956	(0.935)	0.4699	(0.000)	0.03093	(0.000)
24	29423	31720	-0.000001	0.000013	0.4961	(0.910)	0.4696	(0.000)	0.03126	(0.000)

Note: "μ(Buy)" and "μ(Sell)" are mean returns conditional on Buy and Sell signals respectively. "N(Buy)" and "N(Sell)" are the number of buy and sell signals reported during the sample. "Buy>0" and "Sell>0" are the fraction of buy and sell returns greater than zero. The numbers in parenthesis are the p-values from a one-sided binomial test under the null that fractions of buy and sell returns greater than zero are equal to 0.5.The last column presents the statistic for Kolmogorov-Smirnov test of the equality of the return distributions conditional on buy and sell signals. The numbers in parenthesis are the p-values based on the asymptotic distribution of the Kolmogorov-Smirnov test statistic.

Table IV a

RPP (4) trading rule random walk model bootstrap test results for eleven spot foreign exchange rates

Currency Pair	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
EUR/USD	0.000030	-0.000017	0.000047	0.00132	0.00133	2.60499	-2.49051	4.41325
	(0.0040)	(0.9980)	(0.0000)	(0.6600)	(0.4020)	(0.0000)	(1.0000)	(0.0000)
GBP/USD	0.000024	-0.000021	0.000045	0.001319	0.001275	2.49931	-2.45556	4.28875
	(0.0020)	(1.0000)	(0.0000)	(0.0340)	(0.9080)	(0.0000)	(1.0000)	(0.0000)
JPY/USD	0.000015	-0.000022	3.70E-05	0.001433	0.001365	1.89273	-1.88517	3.26914
	(0.0160)	(0.9960)	(0.0000)	(0.0320)	(0.9800)	(0.0000)	(1.0000)	(0.0000)
AUD/USD	0.000070	-0.000046	0.000116	0.00197	0.001787	4.41691	-4.39640	7.60886
	(0.0000)	(1.0000)	(0.0000)	(0.0040)	(1.0000)	(0.0000)	(1.0000)	(0.0000)
CAD/USD	0.000042	-0.000051	0.000093	0.001333	0.001351	5.00877	-4.87914	8.56497
	(0.0000)	(1.0000)	(0.0000)	(0.6340)	(0.1860)	(0.0000)	(1.0000)	(0.0000)
CHF/USD	0.000021	-0.000032	0.000052	0.001404	0.001405	2.67828	-2.65096	4.61544
	(0.0000)	(1.0000)	(0.0000)	(0.5200)	(0.5560)	(0.0000)	(1.0000)	(0.0000)
SEK/USD	0.000044	-0.000051	0.000095	0.001675	0.001714	3.96904	-3.99018	6.89249
	(0.0000)	(1.0000)	(0.0000)	(0.9000)	(0.1380)	(0.0000)	(1.0000)	(0.0000)
ZAR/USD	0.000188	-0.000179	0.000368	0.002739	0.002800	9.37623	-9.18931	16.08899
	(0.0000)	(1.0000)	(0.0000)	(0.7840)	(0.2160)	(0.0000)	(1.0000)	(0.0000)
EUR/JPY	0.000030	-0.000024	0.000054	0.001722	0.001599	2.33351	-2.29990	4.00488
	(0.0060)	(1.0000)	(0.0000)	(0.0480)	(0.9940)	(0.0000)	(1.0000)	(0.0000)
EUR/GBP	0.000063	-0.000050	0.000113	0.001086	0.001074	7.54810	-7.32930	12.88817
	(0.0000)	(1.0000)	(0.0000)	(0.3840)	(0.8220)	(0.0000)	(1.0000)	(0.0000)
EUR/CHF	0.000049	-0.000050	0.000099	0.000713	0.000691	10.12356	-9.93741	17.37878
	(0.0000)	(1.0000)	(0.0000)	(0.2540)	(0.8360)	(0.0000)	(1.0000)	(0.0000)

Note: "μ(Buy)" and "μ(Sell)" are mean returns conditional on Buy and Sell signals respectively. "Buy-Sell" is the difference between mean returns conditional on Buy and Sell signals. "σ(Buy)" and "σ(Sell)" are the standard deviation of buy and sell returns respectively. The "t(Buy)", "t(Sell)" and "t(Buy-Sell)" are t-statistics calculating difference in mean between buy returns and unconditional returns; sell returns and unconditional returns; and buy and sell returns. After 500 simulations the fractions of the simulated results which are larger than the results for the original exchange rate series are calculated and reported as "p-values" (in parenthesis).

Table IV b

RPP (h) trading rule random walk model bootstrap test results for the EUR/USD spot exchange rate

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000034	-0.000021	0.000054	0.00132	0.00133	2.99430	-2.87667	5.08497
	(0.0000)	(1.0000)	(0.0000)	(0.7020)	(0.3780)	(0.0000)	(1.0000)	(0.0000)
4	0.000030	-0.000017	0.000047	0.00132	0.00133	2.60499	-2.49051	4.41325
	(0.0040)	(0.9980)	(0.0000)	(0.6600)	(0.4020)	(0.0000)	(1.0000)	(0.0000)
5	0.000028	-0.000015	0.000043	0.00133	0.00132	2.37462	-2.28166	4.03226
	(0.0040)	(0.9960)	(0.0000)	(0.3900)	(0.6880)	(0.0000)	(1.0000)	(0.0000)
6	0.000025	-0.000013	0.000038	0.00133	0.00132	2.07087	-2.00279	3.52742
	(0.0060)	(0.9940)	(0.0000)	(0.3880)	(0.6920)	(0.0000)	(1.0000)	(0.0000)
7	0.000022	-0.000010	0.000032	0.00134	0.00131	1.73230	-1.68761	2.96105
	(0.0140)	(0.9900)	(0.0020)	(0.1680)	(0.9020)	(0.0020)	(0.9980)	(0.0020)
8	0.000016	-0.000004	0.000021	0.00134	0.00131	1.12135	-1.09163	1.91609
	(0.0860)	(0.9140)	(0.0280)	(0.1480)	(0.9100)	(0.0280)	(0.9700)	(0.0280)
10	0.000013	-0.000001	0.000015	0.00134	0.00131	0.80489	-0.79070	1.38132
	(0.1900)	(0.8300)	(0.0720)	(0.1520)	(0.9000)	(0.0760)	(0.9240)	(0.0760)
12	0.000011	0.000001	0.000010	0.00134	0.00131	0.53151	-0.51755	0.90830
	(0.2760)	(0.7200)	(0.1700)	(0.1680)	(0.8920)	(0.1760)	(0.8260)	(0.1760)
20	-0.000003	0.000014	-0.000017	0.00134	0.00131	-0.93293	0.93562	-1.61716
	(0.8880)	(0.1560)	(0.9500)	(0.1420)	(0.8840)	(0.9520)	(0.0440)	(0.9540)
24	-0.000001	0.000013	-0.000014	0.00135	0.00131	-0.76056	0.76274	-1.31795
	(0.8300)	(0.1760)	(0.9120)	(0.0460)	(0.8920)	(0.9180)	(0.0780)	(0.9200)

Note: See Table IV a for details

Table IV c

Average statistics of the RPP (h) trading rule performance over 500 bootstrapped, simulated series of random walk model for EUR/USD exchange rate

h	N(Buy)	N(Sell)	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)	|t(Buy)|	|t(Sell)|	|t(Buy-Sell)|
3	30842	30288	0.000006	0.000006	0.000000	0.00108	0.00108	-0.01116	0.01138	-0.01971	0.46194	0.46752	0.80494
4	30557	30572	0.000006	0.000006	0.000000	0.00108	0.00108	-0.00071	0.00108	-0.00173	0.46893	0.46830	0.81165
5	30493	30635	0.000006	0.000006	0.000000	0.00108	0.00108	-0.01712	0.01742	-0.03008	0.44819	0.44627	0.77448
6	30459	30668	0.000006	0.000006	0.000000	0.00108	0.00108	-0.02522	0.02557	-0.04422	0.46060	0.45861	0.79589
7	30429	30697	0.000006	0.000006	0.000000	0.00108	0.00108	-0.02094	0.02122	-0.03677	0.45985	0.45658	0.79352
8	30400	30725	0.000006	0.000006	0.000000	0.00108	0.00108	-0.02752	0.02820	-0.04852	0.46115	0.45806	0.79576
10	30354	30769	0.000006	0.000006	0.000000	0.00108	0.00108	-0.01288	0.01357	-0.02315	0.44745	0.44436	0.77218
12	30314	30807	0.000006	0.000006	0.000000	0.00108	0.00108	-0.00968	0.01055	-0.01773	0.44668	0.44275	0.77002
20	30183	30930	0.000006	0.000006	0.000000	0.00108	0.00108	-0.02132	0.02218	-0.03789	0.46004	0.45306	0.79055
24	30129	30980	0.000006	0.000006	0.000000	0.00108	0.00108	-0.00544	0.00606	-0.01025	0.46478	0.45694	0.79793

Note: "N(Buy" and "N(Sell)" are the average number of buy and sell signals over 500 bootstraps. "μ(Buy)", "μ(Sell)" and "Buy-Sell" are the average means of buy and sell returns as well as average difference in buy and sell means over 500 replications. "σ(Buy)" and "σ(Sell)" are the mean standard deviation of buy and sell returns over 500 replications, respectively. The "t(Buy)", "t(Sell)" and "t(Buy-Sell)" are the mean t-value of buy, sell and the difference of buy and sell returns over 500 replications.

Table V a

RPP (4) trading rule GARCH (1,1)–MA(1) model bootstrap test results for eleven spot foreign exchange rates

Currency Pair	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
EUR/USD	0.000030	-0.000017	0.000047	0.00132	0.00133	2.60499	-2.49051	4.41325
	(0.2640)	(0.9320)	(0.0720)	(0.6220)	(0.4520)	(0.0500)	(0.9380)	(0.0560)
GBP/USD	0.000024	-0.000021	0.000045	0.00132	0.00127	2.49931	-2.45556	4.28875
	(0.9080)	(0.5420)	(0.7820)	(0.1620)	(0.2960)	(0.8340)	(0.1680)	(0.8340)
JPY/USD	0.000015	-0.000022	3.70E-05	0.00143	0.00136	1.89273	-1.88517	3.26914
	(0.5040)	(0.4860)	(0.5200)	(0.3680)	(0.8140)	(0.5000)	(0.5080)	(0.4980)
AUD/USD	0.000070	-0.000046	0.000116	0.00197	0.00179	4.41691	-4.39640	7.60886
	(0.2540)	(0.6840)	(0.2500)	(0.1420)	(0.3860)	(0.4100)	(0.6520)	(0.3820)
CAD/USD	0.000042	-0.000051	0.000093	0.00133	0.00135	5.00877	-4.87914	8.56497
	(0.9420)	(0.0800)	(0.9760)	(0.8140)	(0.6380)	(0.9660)	(0.0200)	(0.9720)
CHF/USD	0.000021	-0.000032	0.000052	0.00140	0.00140	2.67828	-2.65096	4.61544
	(0.2940)	(0.7360)	(0.1880)	(0.6220)	(0.6060)	(0.1700)	(0.8140)	(0.1780)
SEK/USD	0.000044	-0.000051	0.000095	0.00167	0.00171	3.96904	-3.99018	6.89249
	(0.3400)	(0.1240)	(0.6840)	(0.2020)	(0.1620)	(0.8400)	(0.1280)	(0.8660)
ZAR/USD	0.000188	-0.000179	0.000368	0.00274	0.00280	9.37623	-9.18931	16.08899
	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9920)	(0.0080)	(0.9920)
EUR/JPY	0.000030	-0.000024	0.000054	0.00172	0.00160	2.33351	-2.29990	4.00488
	(0.9120)	(0.4880)	(0.8460)	(0.3780)	(0.5880)	(0.8120)	(0.2080)	(0.8020)
EUR/GBP	0.000063	-0.000050	0.000113	0.00109	0.00107	7.54810	-7.32930	12.88817
	(0.9840)	(0.0540)	(0.9920)	(0.4780)	(0.5020)	(0.9840)	(0.0120)	(0.9860)
EUR/CHF	0.000049	-0.000050	0.000099	0.00071	0.00069	10.12356	-9.93741	17.37878
	(0.9780)	(0.0720)	(0.9900)	(0.4900)	(0.6000)	(0.8960)	(0.0960)	(0.9020)

Note: See Table IV a for details

Table V b

RPP (h) trading rule GARCH (1,1)–MA(1) model bootstrap test results for EUR/USD exchange rate

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000034	-0.000021	0.000054	0.00132	0.00133	2.99430	-2.87667	5.08497
	(0.1720)	(0.9700)	(0.0320)	(0.6080)	(0.4420)	(0.0200)	(0.9720)	(0.0240)
4	0.000030	-0.000017	0.000047	0.00132	0.00133	2.60499	-2.49051	4.41325
	(0.2640)	(0.9320)	(0.0720)	(0.6220)	(0.4520)	(0.0500)	(0.9380)	(0.0560)
5	0.000028	-0.000015	0.000043	0.00133	0.00132	2.37462	-2.28166	4.03226
	(0.2980)	(0.9260)	(0.0820)	(0.5140)	(0.5380)	(0.0740)	(0.9140)	(0.0800)
6	0.000025	-0.000013	0.000038	0.00133	0.00132	2.07087	-2.00279	3.52742
	(0.4000)	(0.9020)	(0.1420)	(0.5180)	(0.5460)	(0.1280)	(0.8580)	(0.1320)
7	0.000022	-0.000010	0.000032	0.00134	0.00131	1.73230	-1.68761	2.96105
	(0.5120)	(0.8540)	(0.2500)	(0.4180)	(0.6580)	(0.2480)	(0.7360)	(0.2620)
8	0.000016	-0.000004	0.000021	0.00134	0.00131	1.12135	-1.09163	1.91609
	(0.7720)	(0.6220)	(0.6080)	(0.4160)	(0.6600)	(0.6120)	(0.3840)	(0.6100)
10	0.000013	-0.000001	0.000015	0.00134	0.00131	0.80489	-0.79070	1.38132
	(0.8280)	(0.4960)	(0.7440)	(0.4180)	(0.6440)	(0.7400)	(0.2620)	(0.7400)
12	0.000011	0.000001	0.000010	0.00134	0.00131	0.53151	-0.51755	0.90830
	(0.8660)	(0.4340)	(0.7940)	(0.4280)	(0.6460)	(0.8000)	(0.1960)	(0.8000)
20	-0.000003	0.000014	-0.000017	0.00134	0.00131	-0.93293	0.93562	-1.61716
	(0.9920)	(0.0440)	(0.9980)	(0.4080)	(0.6480)	(0.9980)	(0.0020)	(0.9980)
24	-0.000001	0.000013	-0.000014	0.00135	0.00131	-0.76056	0.76274	-1.31795
	(0.9880)	(0.0780)	(0.9960)	(0.3440)	(0.6400)	(0.9960)	(0.0040)	(0.9960)

Note: See Table IV a for details

Table V c

Average statistics of the RPP (4) trading rule performance over 500 bootstrapped, simulated series of GARCH (1,1)–MA(1 model for eleven spot foreign exchange rates

Currency Pair	N(Buy)	N(Sell)	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)	|t(Buy)|	|t(Sell)|	|t(Buy-Sell)|
EUR/USD	30171	30993	0.000025	-0.000006	0.000031	0.00134	0.00133	1.6495	-1.6202	2.8300	1.6499	1.6205	2.8306
GBP/USD	30034	31054	0.000034	-0.000020	0.000054	0.00125	0.00125	3.1296	-3.0607	5.3580	3.1296	3.0607	5.3580
JPY/USD	30256	30865	0.000015	-0.000022	0.000038	0.00143	0.00140	1.9020	-1.8769	3.2621	1.9020	1.8769	3.2621
AUD/USD	29877	31218	0.000064	-0.000041	0.000106	0.00181	0.00178	4.2653	-4.1422	7.2684	4.2653	4.1422	7.2684
CAD/USD	30734	30309	0.000054	-0.000063	0.000117	0.00136	0.00136	6.1219	-6.1792	10.6675	6.1219	6.1792	10.6675
CHF/USD	30698	30328	0.000017	-0.000026	0.000043	0.00141	0.00141	2.1715	-2.1890	3.7764	2.1715	2.1890	3.7764
SEK/USD	30923	29982	0.000040	-0.000062	0.000103	0.00159	0.00159	4.5626	-4.6575	7.9910	4.5626	4.6575	7.9910
ZAR/USD	29416	29343	0.000309	-0.000302	0.000612	0.00347	0.00349	12.3305	-12.3515	21.4173	12.3305	12.3515	21.4173
EUR/JPY	29721	31360	0.000043	-0.000025	0.000068	0.00175	0.00172	2.8604	-2.7603	4.8557	2.8604	2.7603	4.8557
EUR/GBP	30487	30642	0.000079	-0.000063	0.000141	0.00111	0.00111	9.1311	-9.1002	15.7967	9.1311	-9.1002	15.7967
EUR/CHF	30330	30812	0.000059	-0.000056	0.000114	0.00074	0.00073	11.2681	-11.1504	19.4104	11.2681	11.1504	19.4104

Note: See Table IVc for details

Table VI a

Profitability statistics, based on returns per trade, of the RPP(4) trading rule in the eleven spot foreign exchange markets, under the assumption of zero transaction costs

Period	Currency Pair	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
Panel A: Full Sample														
01/2001-07/2010	EUR/USD	9842	9914	3.10	0.000065	-0.030479	0.015403	0.00225	-2.52440	0.66	2.11	1.27927	2.41731	0.13717
	GBP/USD	9833	9875	3.10	0.000063	-0.029698	0.017966	0.00221	-2.49655	0.66	2.09	1.23192	2.26599	0.13179
	JPY/USD	9854	9851	3.10	0.000048	-0.052756	0.025356	0.00233	-3.04029	0.66	2.07	0.94299	1.43374	0.09750
	AUD/USD	9825	9866	3.10	0.000173	-0.077383	0.027110	0.00305	-3.75035	0.66	2.11	3.40677	26.4929	0.41431
	CAD/USD	9999	9969	3.06	0.000134	-0.041575	0.019048	0.00223	-3.03259	0.67	2.24	2.67407	12.79116	0.31585
	CHF/USD	9913	9882	3.08	0.000077	-0.038410	0.022062	0.00244	-2.77728	0.67	2.15	1.51571	3.29115	0.16458
	SEK/USD	9905	9839	3.08	0.000135	-0.039703	0.022115	0.00286	-2.75099	0.68	2.14	2.67435	12.3672	0.31156
	ZAR/USD	10019	10043	2.93	0.000507	-0.150959	0.041790	0.00443	-4.27558	0.71	2.58	10.17981	21547.99	1.83980
	EUR/JPY	9797	9839	3.11	0.000076	-0.075201	0.029090	0.00281	-3.70022	0.66	2.09	1.48688	3.09086	0.15877
	EUR/GBP	10349	10353	2.95	0.000155	-0.028302	0.014894	0.00177	-3.16113	0.68	2.49	3.20701	22.9058	0.39378
	EUR/CHF	10532	10572	2.90	0.000135	-0.039859	0.008214	0.00112	-5.68039	0.70	2.67	2.85406	16.1254	0.34599
	Average	9988	10000	3.05	0.000142	-0.054939	0.022095	0.00250	-3.38089	0.67	2.25	2.85935	1968.29	0.39192
Panel B: Subperiods														
01/2001-01/2003	EUR/USD	2050	2068	3.10	0.000070	-0.018712	0.009947	0.00221	-2.34157	0.66	2.13	0.28936	0.32218	0.14986
01/2003-06/2007	EUR/USD	4617	4635	3.06	0.000067	-0.018205	0.012255	0.00194	-2.29107	0.67	2.20	0.61900	0.82494	0.14302
06/2007-06/2009	EUR/USD	1997	2027	3.16	0.000058	-0.030479	0.015403	0.00285	-2.62709	0.65	1.97	0.23463	0.24382	0.11526
06/2009-07/2010	EUR/USD	3174	3210	3.14	0.000058	-0.030479	0.015403	0.00267	-2.56997	0.65	1.98	0.36848	0.41283	0.37712

Note: "N(Long)" and "N(Short)" report the total number of long and short positions respectively. "Average Holding Period (hours)" shows the average numbers of hours a position remains open. "Mean", "Min", "Max", "Std. Dev" and „Skewness" report the mean, minimum and maximum returns per trade as well as the standard deviation and skewness of these returns. "% of win" and "PT/LT" show the percentage of winning trades and the profit and loss ratio respectively. The total return expresses the amount of profit/loss made by a trader always investing up to his or her initial capital or credit limit during the sample period, while cumulative return is a measure of overall profitability assuming the trader always reinvests all his or her current capital including gains or losses. Average Annual Return is approximated simply as Cumulative Return for the sample period raised to the power of (1/9.56) to yield a rough estimate of annual compound return.

Table VI b

Profitability statistics, based on returns per trade, of the RPP(4) trading rule in the EUR/USD market under the assumption of zero transaction costs

h	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
3	11862	11919	2.57	0.000061	-0.032032	0.014410	0.00206	-2.39024	0.65	1.99	1.46150	3.09949	0.15903
4	9842	9914	3.10	0.000065	-0.030479	0.015403	0.00225	-2.52440	0.66	2.11	1.27927	2.41731	0.13717
5	8517	8605	3.57	0.000067	-0.034591	0.018301	0.00245	-2.70838	0.68	2.25	1.14844	1.99496	0.12158
6	7590	7675	4.01	0.000069	-0.032565	0.018301	0.00259	-2.65941	0.69	2.39	1.04907	1.71175	0.10999
7	6873	6965	4.42	0.000062	-0.031753	0.018301	0.00271	-2.57291	0.70	2.49	0.86184	1.24931	0.08849
8	6319	6398	4.81	0.000041	-0.030219	0.018301	0.00283	-2.56909	0.71	2.54	0.52311	0.60282	0.05059
10	5570	5637	5.46	0.000032	-0.032060	0.018301	0.00302	-2.64507	0.71	2.65	0.36023	0.36183	0.03283
12	4949	5017	6.13	0.000025	-0.031830	0.018301	0.00320	-2.62291	0.72	2.70	0.24754	0.21665	0.02072
20	3537	3594	8.57	-0.000069	-0.050315	0.018301	0.00380	-3.30666	0.72	2.65	-0.49231	-0.41968	-0.05533
24	3107	3158	9.76	-0.000062	-0.077332	0.018301	0.00410	-3.94445	0.73	2.77	-0.39007	-0.35814	-0.04532
Average	6817	6888	5.24	0.000029	-0.038318	0.017622	0.00290	-2.79435	0.70	2.45	0.60486	1.08763	0.06197

Note: See Table VIa for details

Table VII

Profitability statistics, based on weekly returns, of the RPP(4) trading rule in the EUR/USD market under the assumption of zero transaction costs

Period	Currency Pair	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio	Carry Trade Sharpe Ratio	Weekly Mean Buy and Hold
Panel A: Full Sample										
01/2001-07/2010	EUR/USD	40	-0.0714	0.0652	0.0026	0.0133	-0.1394	0.1603	0.2281	0.0007
	GBP/USD	40	-0.0538	0.0433	0.0025	0.0129	-0.2868	0.1572	0.2270	0.0002
	JPY/USD	40	-0.0878	0.0529	0.0019	0.0135	-0.6466	0.1070	0.2270	-0.0005
	AUD/USD	40	-0.1238	0.1045	0.0068	0.0178	-0.2796	0.3606	0.2612	0.0011
	CAD/USD	40	-0.0633	0.0587	0.0054	0.0142	-0.0502	0.3499	0.2270	-0.0006
	CHF/USD	40	-0.1191	0.0775	0.0031	0.0156	-0.5056	0.1676	0.2270	-0.0007
	SEK/USD	40	-0.0629	0.0890	0.0054	0.0184	-0.0051	0.2689	0.2270	-0.0003
	ZAR/USD	40	-0.1939	0.1332	0.0208	0.0320	-0.2472	0.6358	0.5321	0.0003
	EUR/JPY	39	-0.0963	0.1105	0.0030	0.0177	-0.0248	0.1446	0.2292	0.0002
	EUR/GBP	42	-0.0381	0.0394	0.0065	0.0120	-0.3822	0.5035	0.2292	0.0006
	EUR/CHF	42	-0.0475	0.0426	0.0058	0.0086	-0.5757	0.6185	0.2292	-0.0002
	Average	40	-0.0871	0.0742	0.0058	0.0160	-0.2858	0.3158	0.2585	0.0001
Panel B: Subperiods										
01/2001-01/2003	EUR/USD	39	-0.0340	0.0276	0.0027	0.0123	-0.0474	0.1832		
01/2003-06/2007		40	-0.0331	0.0418	0.0027	0.0109	0.2971	0.1959		
06/2007-06/2009		39	-0.0714	0.0652	0.0023	0.0176	-0.0166	0.1087		
06/2009-07/2010		39	-0.0714	0.0652	0.0022	0.0166	-0.2935	0.1340		

Note: The statistics are based on a constructed series of weekly returns. "Mean", "Min", "Max", "Std. Dev" and „Skewness" report the mean, minimum and maximum returns per trade as well as the standard deviation and skewness of these weekly returns under the assumption of zero transaction costs. The Sharpe ratio is calculated as the excess weekly mean return divided by the standard deviation. "Carry Trade Sharpe Ratio" replicates the zero transaction cost Sharpe ratios reported by Hassan and Smith (2010, p.13). The „Weekly Mean Buy and Hold" shows the mean weekly return on a long position in a given spot exchange rate.

Table VIII a

Profitability statistics, based on returns per trade, of the RPP(4) trading rule in the eleven spot foreign exchange markets in the presence of 1 basis point per roundturn trade transaction cost.

Period	Currency Pair	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return	Break-even transaction cost
01/2001-07/2010	EUR/USD	-0.000035	-0.030579	0.015303	0.00225	-2.52440	0.64	1.77	-0.69633	-0.52609	-0.07514	0.000062
	GBP/USD	-0.000037	-0.029798	0.017866	0.00221	-2.49655	0.64	1.81	-0.73888	-0.54489	-0.07905	0.000060
	JPY/USD	-0.000052	-0.052856	0.025256	0.00233	-3.04029	0.63	1.74	-1.02751	-0.66077	-0.10692	0.000045
	AUD/USD	0.000073	-0.077483	0.027010	0.00305	-3.75035	0.66	1.95	1.43767	2.83839	0.15107	0.000168
	CAD/USD	0.000034	-0.041675	0.018948	0.00223	-3.03259	0.65	1.82	0.67727	0.87271	0.06783	0.000132
	CHF/USD	-0.000023	-0.038510	0.021962	0.00244	-2.77728	0.64	1.79	-0.46379	-0.40720	-0.05323	0.000074
	SEK/USD	0.000035	-0.039803	0.022015	0.00286	-2.75099	0.66	1.91	0.69995	0.85624	0.06684	0.000131
	ZAR/USD	0.000407	-0.151059	0.041690	0.00443	-4.27558	0.70	2.31	8.17361	2899.86	1.30244	0.000497
	EUR/JPY	-0.000024	-0.075301	0.028990	0.00281	-3.70022	0.65	1.82	-0.47672	-0.42582	-0.05638	0.000072
	EUR/GBP	0.000055	-0.028402	0.014794	0.00177	-3.16113	0.68	2.11	1.13681	2.01660	0.12243	0.000153
	EUR/CHF	0.000035	-0.039959	0.008114	0.00112	-5.68039	0.65	1.84	0.74366	1.07579	0.07939	0.000135
	Average	0.00004	-0.05504	0.02200	0.00250	-3.38089	0.65	1.90	0.86052	264.09	0.12903	0.00014

Note: Break-even transaction costs are defined as roundturn transaction costs that reduce cumulative return to zero. The rest of the columns are the same as in Table VIa.

Table VIII b

Profitability statistics of the RPP(4) trading rule in the ZAR/USD market for different levels of transaction costs

Period	Currency Pair	Transaction Cost	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
01/2001-07/2010	ZAR/USD	0 b.p.	0.000507	-0.150959	0.041790	0.00443	-4.27558	0.71	2.58	10.17981	21547.99	1.83980
		1 b.p.	0.000407	-0.151059	0.041690	0.00443	-4.27558	0.70	2.31	8.17361	2899.86	1.30244
		2 b.p.	0.000307	-0.151159	0.041590	0.00443	-4.27558	0.68	2.13	6.16741	389.43	0.86673
		3 b.p.	0.000207	-0.151259	0.041490	0.00443	-4.27558	0.66	1.95	4.16121	51.537	0.51344
		4 b.p.	0.000107	-0.151359	0.041390	0.00443	-4.27558	0.64	1.77	2.15501	6.0681	0.22698

Note: Transaction costs are reported as basis points per roundturn trade. The rest of the columns are the same as in Table VI a.

Table IX

Profitability statistics, based on weekly returns, of the RPP(4) trading rule in the eleven spot foreign exchange markets in the presence of 1 basis point per roundturn trade transaction cost,

Period	Currency Pair	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio	Carry Trade Sharpe Ratio
01/2001-07/2010	EUR/USD	40	-0.0745	0.0603	-0.0014	0.0130	-0.1372	-0.1422	0.2281
	GBP/USD	40	-0.0569	0.0387	-0.0015	0.0126	-0.3042	-0.1536	0.2270
	JPY/USD	40	-0.0906	0.0487	-0.0021	0.0132	-0.6777	-0.1902	0.2270
	AUD/USD	40	-0.1264	0.0993	0.0029	0.0174	-0.2860	0.1394	0.2612
	CAD/USD	40	-0.0663	0.0536	0.0014	0.0138	-0.0446	0.0670	0.2270
	CHF/USD	40	-0.1213	0.0723	-0.0009	0.0153	-0.5209	-0.0891	0.2270
	SEK/USD	40	-0.0655	0.0842	0.0014	0.0180	0.0008	0.0541	0.2270
	ZAR/USD	40	-0.1963	0.1280	0.0167	0.0315	-0.2600	0.5149	0.5321
	EUR/JPY	39	-0.0995	0.1061	-0.0010	0.0174	-0.0236	-0.0802	0.2292
	EUR/GBP	42	-0.0410	0.0347	0.0023	0.0116	-0.3838	0.1606	0.2292
	EUR/CHF	42	-0.0508	0.0378	0.0015	0.0083	-0.5878	0.1298	0.2292
	Average	40	-0.0899	0.0694	0.0017	0.0156	-0.2932	0.0373	0.2585

Note: The statistics are calculated under the assumption of a 0.01% transaction cost per roundturn trade. "The Carry Trade Sharpe Ratio" replicates the Sharpe ratios, with inclusion of transaction costs, reported in Hassan and Smith (2010, p. 12). See Table VII for further details.

Table X

Comparison of the best performing specification of the RPP(h) rule in the eleven foreign exchange markets

	Best performing rules based on the cumulative return						Best performing rules based on the mean return per trade					
Currency Pair	Rule	Number of transactions	% of win	Mean return/break-even cost	Cumulative Return	Average Annual Profit	Rule	Number of transactions	% of win	Mean return/break-even cost	Cumulative Return	Average Annual Profit
EUR/USD	*RPP(3)*	23781	0.65	0.000061	3.09949	0.15903	*RPP(6)*	*15265*	0.69	0.000069	1.71175	0.10999
GBP/USD	*RPP(5)*	17177	0.68	0.000087	3.26016	0.16370	*RPP(5)*	*17177*	0.68	0.000087	3.26016	0.16370
JPY/USD	*RPP(5)*	17127	0.67	0.000073	2.30243	0.13311	*RPP(8)*	*12831*	0.70	0.000085	1.81656	0.11440
AUD/USD	*RPP(3)*	23723	0.65	0.000162	41.01760	0.47848	*RPP(5)*	*17147*	0.67	0.000206	30.12427	0.43279
CAD/USD	*RPP(5)*	17642	0.69	0.000169	17.82968	0.35941	*RPP(6)*	*15770*	0.70	0.000179	15.10957	0.33741
CHF/USD	*RPP(3)*	23802	0.65	0.000066	3.54772	0.17167	*RPP(7)*	*13999*	0.71	0.000089	2.28926	0.13263
SEK/USD	*RPP(3)*	23947	0.67	0.000128	18.60116	0.36514	*RPP(6)*	*15432*	0.70	0.000147	7.85816	0.25630
ZAR/USD	*RPP(4)*	20062	0.71	0.000507	21547.99	1.83980	*RPP(8)*	*13826*	0.76	0.000681	10132.21	1.62429
EUR/JPY	*RPP(3)*	23694	0.65	0.000063	3.16769	0.16103	*RPP(5)*	*16993*	0.68	0.000079	1.34362	2.54812
EUR/GBP	*RPP(3)*	24657	0.67	0.000153	41.54109	0.48039	*RPP(10)*	*12355*	0.73	0.000178	7.78366	0.25519
EUR/CHF	*RPP(3)*	25056	0.68	0.000125	21.87318	0.38736	*RPP(20)*	*8854*	0.79	0.000196	4.60738	0.19763
Average		21879	0.67	0.000145	1973.11	0.42719		14514	0.71	0.000182	928.01	0.56113

Note: All the reported statistics are based on the assumption of zero transaction costs. The left panel presents profitability statistics for the rules which yield the highest cumulative returns. The right panel presents profitability statistics for the rules which yield the highest mean returns per trade. The interpretation of the column labels is the same as in Table VI a

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Appendices

A. Data Appendix

1. Descriptive Statistics (Hourly)

Note: See Table I for details

	N	Mean	Std. Dev.	Skew	Kurt	Min	Max	ρ(1)	ρ(2)	ρ(3)	ρ(4)	*Q* (6)	*Q* (12)	*Q* (24)	LM(12)
EUR/USD	60669	0.000573	0.13188	0.07649	13.289	-0.01795	0.02309	-0.00874	-0.00250	-0.00276	-0.00238	14.28	25.64	47.19	202.98
GBP/USD	60593	0.000253	0.12941	-0.24064	16.153	-0.02094	0.01797	-0.01577	0.00173	-0.00235	-0.00578	18.90	45.23	103.85	377.32
JPY/USD	60626	-0.000190	0.13884	-0.51277	19.998	-0.02987	0.01792	-0.01246	-0.01386	-0.00962	-0.00816	31.24	37.73	72.31	280.24
AUD/USD	60600	0.000763	0.18653	-0.32656	25.890	-0.03879	0.03645	-0.04316	-0.01763	0.00722	0.00212	137.29	161.34	221.16	844.85
CAD/USD	60548	-0.000471	0.13429	-0.17569	14.627	-0.02117	0.01445	-0.02977	-0.01550	-0.00279	-0.01523	85.99	95.03	135.90	408.12
CHF/USD	60531	-0.000448	0.14015	0.11217	15.525	-0.01861	0.02647	-0.00769	0.00234	0.00046	0.00109	10.25	11.50	38.07	91.74
SEK/USD	60410	-0.000091	0.16885	0.01966	12.722	-0.03044	0.02211	-0.02919	-0.00185	-0.00142	-0.00098	62.78	67.24	84.80	336.35
ZAR/USD	58265	0.000240	0.27695	0.13516	23.743	-0.05855	0.04775	-0.07740	0.00349	-0.00527	0.00473	398.10	422.45	459.45	528.67
JPY/EUR	60586	0.000356	0.16486	-0.34939	25.425	-0.03570	0.02663	-0.02005	-0.01055	-0.00658	-0.01613	54.50	71.30	107.29	582.20
GBP/EUR	60634	0.000450	0.10778	0.24437	13.802	-0.01489	0.01476	-0.05296	0.00591	0.00738	0.00483	180.67	185.28	233.39	387.51
CHF/EUR	60647	-0.000049	0.06994	0.33601	43.782	-0.01891	0.02144	-0.06866	-0.00301	0.00538	-0.00042	288.90	309.68	351.78	179.14

2. Descriptive Statistics (Weekend)

Note: See Table I for details

	N	Mean	Std. Dev.	Skew	Kurt	Min	Max
EUR/USD	497	0.000931	0.19221	0.58915	16.150	-0.01059	0.01471
GBP/USD	497	-0.015303	0.15658	0.42660	13.457	-0.00864	0.01119
JPY/USD	497	-0.022759	0.23219	-1.11455	27.584	-0.02242	0.01671
AUD/USD	497	0.018873	0.29572	4.96334	56.574	-0.00813	0.03743
CAD/USD	497	-0.005791	0.13699	-2.11032	26.744	-0.01382	0.00624
CHF/USD	497	-0.016977	0.17249	-0.64420	16.731	-0.01186	0.01195
SEK/USD	497	-0.019371	0.23342	-1.19777	12.537	-0.01663	0.01059
ZAR/USD	497	0.015178	0.34644	-2.76681	35.211	-0.03857	0.01549
JPY/EUR	497	-0.024505	0.26361	0.23459	19.695	-0.01693	0.02021
GBP/EUR	497	0.007479	0.14745	0.47442	7.626	-0.00630	0.00892
CHF/EUR	497	-0.014477	0.10724	0.29096	10.613	-0.00458	0.00727

B. Predictability Appendix

1. Goodness of Fit Results

Note: See Table III for details

GBP/USD

Period	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0	Sell>0	Kolmogorov-Smirnov Stat	
3	29598	31490	0.000025	-0.000021	0.5182	0.4622	0.05687	(0.000)
4	29590	31497	0.000024	-0.000021	0.5213	0.4594	0.06340	(0.000)
5	29509	31577	0.000029	-0.000024	0.5229	0.4580	0.06642	(0.000)
6	29502	31583	0.000025	-0.000021	0.5222	0.4587	0.06519	(0.000)
7	29599	31485	0.000023	-0.000019	0.5215	0.4591	0.06461	(0.000)
8	29660	31423	0.000019	-0.000015	0.5196	0.4608	0.06071	(0.000)
10	29695	31386	0.000015	-0.000012	0.5165	0.4636	0.05555	(0.000)
12	29647	31432	0.000011	-0.000008	0.5145	0.4655	0.05254	(0.000)
20	29585	31486	-0.000003	0.000006	0.5032	0.4763	0.03152	(0.000)
24	29531	31536	-0.000004	0.000006	0.5031	0.4765	0.03056	(0.000)

JPY/USD

Period	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0	Sell>0	Kolmogorov-Smirnov Stat	
3	29832	31289	0.000020	-0.000027	0.5146	0.4507	0.06570	(0.000)
4	29756	31364	0.000015	-0.000022	0.5136	0.4519	0.06385	(0.000)
5	29741	31378	0.000021	-0.000027	0.5140	0.4515	0.06603	(0.000)
6	29777	31341	0.000018	-0.000025	0.5124	0.4530	0.06234	(0.000)
7	29766	31351	0.000017	-0.000024	0.5113	0.4541	0.05946	(0.000)
8	29789	31327	0.000018	-0.000024	0.5111	0.4542	0.05987	(0.000)
10	29858	31256	0.000013	-0.000019	0.5088	0.4563	0.05552	(0.000)
12	29882	31230	0.000010	-0.000017	0.5068	0.4581	0.05184	(0.000)
20	29662	31442	-0.000002	-0.000005	0.5004	0.4645	0.04101	(0.000)
24	29710	31390	-0.000001	-0.000006	0.4990	0.4658	0.03948	(0.000)

AUD/USD

Period	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0	Sell>0	Kolmogorov-Smirnov Stat	
3	29293	31802	0.000078	-0.000055	0.5138	0.4506	0.06658	(0.000)
4	28961	32133	0.000070	-0.000046	0.5124	0.4525	0.06413	(0.000)
5	28924	32169	0.000073	-0.000049	0.5119	0.4530	0.06356	(0.000)
6	28826	32266	0.000062	-0.000038	0.5095	0.4553	0.05981	(0.000)
7	28832	32259	0.000054	-0.000031	0.5082	0.4566	0.05629	(0.000)
8	28874	32216	0.000051	-0.000028	0.5072	0.4574	0.05512	(0.000)
10	28843	32245	0.000048	-0.000025	0.5057	0.4587	0.05396	(0.000)
12	28781	32305	0.000039	-0.000017	0.5033	0.4610	0.04982	(0.000)
20	28473	32605	0.000019	0.000001	0.4984	0.4658	0.04306	(0.000)
24	28242	32832	0.000014	0.000005	0.4977	0.4666	0.04255	(0.000)

CAD/USD

Period	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0	Sell>0	Kolmogorov-Smirnov Stat	
3	30191	30852	0.000047	-0.000056	0.5101	0.4381	0.07777	(0.000)
4	30123	30919	0.000042	-0.000051	0.5092	0.4391	0.07234	(0.000)
5	30162	30879	0.000047	-0.000056	0.5092	0.4390	0.07198	(0.000)
6	30219	30821	0.000044	-0.000054	0.5060	0.4420	0.06734	(0.000)
7	30266	30773	0.000038	-0.000048	0.5036	0.4442	0.06195	(0.000)
8	30273	30765	0.000034	-0.000043	0.5024	0.4454	0.05944	(0.000)
10	30442	30594	0.000029	-0.000039	0.4996	0.4479	0.05327	(0.000)
12	30565	30469	0.000027	-0.000038	0.4998	0.4475	0.05389	(0.000)
20	31207	29819	0.000012	-0.000023	0.4936	0.4529	0.04224	(0.000)
24	31450	29572	0.000004	-0.000014	0.4898	0.4566	0.03517	(0.000)

CHF/USD

Period	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0	Sell>0	Kolmogorov-Smirnov Stat	
3	30342	30684	0.000022	-0.000034	0.5092	0.4433	0.06683	(0.000)
4	30256	30769	0.000021	-0.000032	0.5102	0.4425	0.06901	(0.000)
5	30319	30705	0.000018	-0.000029	0.5096	0.4430	0.06766	(0.000)
6	30332	30691	0.000016	-0.000027	0.5091	0.4435	0.06627	(0.000)
7	30362	30660	0.000016	-0.000027	0.5067	0.4458	0.06166	(0.000)
8	30405	30616	0.000011	-0.000023	0.5040	0.4484	0.05649	(0.000)
10	30530	30489	0.000009	-0.000021	0.5011	0.4510	0.05185	(0.000)
12	30581	30436	0.000005	-0.000017	0.4986	0.4534	0.04817	(0.000)
20	30759	30250	-0.000004	-0.000008	0.4929	0.4589	0.03497	(0.000)
24	30888	30117	-0.000005	-0.000007	0.4918	0.4599	0.03314	(0.000)

SEK/USD

Period	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0	Sell>0	Kolmogorov-Smirnov Stat	
3	30813	30092	0.000051	-0.000057	0.5232	0.4598	0.06621	(0.000)
4	30863	30041	0.000044	-0.000051	0.5228	0.4601	0.06513	(0.000)
5	30960	29943	0.000041	-0.000047	0.5202	0.4626	0.06040	(0.000)
6	31023	29879	0.000037	-0.000044	0.5202	0.4624	0.05944	(0.000)
7	31141	29760	0.000032	-0.000038	0.5172	0.4653	0.05576	(0.000)
8	31151	29749	0.000028	-0.000035	0.5152	0.4674	0.05220	(0.000)
10	31230	29668	0.000024	-0.000031	0.5134	0.4692	0.04688	(0.000)
12	31271	29625	0.000018	-0.000024	0.5107	0.4719	0.04127	(0.000)
20	31637	29251	0.000003	-0.000009	0.5040	0.4786	0.03425	(0.000)
24	31748	29136	0.000001	-0.000007	0.5028	0.4798	0.03177	(0.000)

ZAR/USD

Period	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0	Sell>0	Kolmogorov-Smirnov Stat	
3	29371	29388	0.000176	-0.000169	0.5301	0.4367	0.09935	(0.000)
4	29256	29502	0.000188	-0.000179	0.5325	0.4347	0.10282	(0.000)
5	29305	29452	0.000180	-0.000172	0.5328	0.4342	0.10235	(0.000)
6	29286	29470	0.000176	-0.000167	0.5305	0.4366	0.09724	(0.000)
7	29373	29382	0.000179	-0.000172	0.5304	0.4364	0.09712	(0.000)
8	29333	29421	0.000173	-0.000165	0.5286	0.4383	0.09178	(0.000)
10	29524	29228	0.000156	-0.000150	0.5233	0.4430	0.08264	(0.000)
12	29692	29058	0.000140	-0.000136	0.5196	0.4464	0.07887	(0.000)
20	30365	28377	0.000085	-0.000084	0.5086	0.4563	0.05990	(0.000)
24	30470	28268	0.000068	-0.000066	0.5064	0.4585	0.05288	(0.000)

EUR/JPY

Period	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0	Sell>0	Kolmogorov-Smirnov Stat	
3	29278	31803	0.000030	-0.000025	0.5261	0.4673	0.06276	(0.000)
4	29153	31927	0.000030	-0.000024	0.5262	0.4674	0.06421	(0.000)
5	29097	31982	0.000028	-0.000023	0.5251	0.4686	0.06020	(0.000)
6	29016	32062	0.000023	-0.000018	0.5240	0.4697	0.05937	(0.000)
7	28944	32133	0.000019	-0.000014	0.5206	0.4729	0.05428	(0.000)
8	28885	32191	0.000020	-0.000015	0.5197	0.4738	0.05224	(0.000)
10	28629	32445	0.000017	-0.000012	0.5169	0.4766	0.05044	(0.000)
12	28474	32598	0.000013	-0.000008	0.5150	0.4785	0.04630	(0.000)
20	27907	33157	0.000001	0.000003	0.5087	0.4845	0.04048	(0.000)
24	27520	33540	-0.000003	0.000006	0.5073	0.4858	0.04060	(0.000)

EUR/GBP

Period	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0	Sell>0	Kolmogorov-Smirnov Stat	
3	29278	31803	0.000030	-0.000025	0.5261	0.4673	0.06276	(0.000)
4	29153	31927	0.000030	-0.000024	0.5262	0.4674	0.06421	(0.000)
5	29097	31982	0.000028	-0.000023	0.5251	0.4686	0.06020	(0.000)
6	29016	32062	0.000023	-0.000018	0.5240	0.4697	0.05937	(0.000)
7	28944	32133	0.000019	-0.000014	0.5206	0.4729	0.05428	(0.000)
8	28885	32191	0.000020	-0.000015	0.5197	0.4738	0.05224	(0.000)
10	28629	32445	0.000017	-0.000012	0.5169	0.4766	0.05044	(0.000)
12	28474	32598	0.000013	-0.000008	0.5150	0.4785	0.04630	(0.000)
20	27907	33157	0.000001	0.000003	0.5087	0.4845	0.04048	(0.000)
24	27520	33540	-0.000003	0.000006	0.5073	0.4858	0.04060	(0.000)

EUR/CHF

Period	*N(Buy)*	*N(Sell)*	μ(Buy)	μ(Sell)	Buy>0	Sell>0	Kolmogorov-Smirnov Stat	
3	29912	31230	0.000053	-0.000055	0.5228	0.4128	0.11083	(0.000)
4	29641	31500	0.000049	-0.000050	0.5199	0.4165	0.10566	(0.000)
5	29784	31356	0.000046	-0.000047	0.5178	0.4180	0.10154	(0.000)
6	29845	31294	0.000046	-0.000047	0.5166	0.4190	0.10034	(0.000)
7	29865	31273	0.000043	-0.000044	0.5138	0.4216	0.09620	(0.000)
8	29881	31256	0.000042	-0.000043	0.5120	0.4233	0.09273	(0.000)
10	30021	31114	0.000040	-0.000042	0.5083	0.4264	0.08631	(0.000)
12	30056	31077	0.000038	-0.000040	0.5070	0.4276	0.08463	(0.000)
20	30057	31068	0.000029	-0.000031	0.4971	0.4372	0.06852	(0.000)
24	30103	31018	0.000024	-0.000026	0.4947	0.4395	0.06482	(0.000)

2. Random Walk Model Results

Note: See Table IV for details

GBP/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000025	-0.000021	0.000046	0.00131	0.00128	2.58312	-2.51475	4.41379
	(0.0020)	(0.9960)	(0.0000)	(0.1380)	(0.7840)	(0.0000)	(1.0000)	(0.0000)
4	0.000024	-0.000021	0.000045	0.00132	0.00127	2.49931	-2.45556	4.28875
	(0.0020)	(1.0000)	(0.0000)	(0.0340)	(0.9080)	(0.0000)	(1.0000)	(0.0000)
5	0.000029	-0.000024	0.000053	0.00132	0.00127	2.94350	-2.89419	5.05196
	(0.0000)	(1.0000)	(0.0000)	(0.0200)	(0.9520)	(0.0000)	(1.0000)	(0.0000)
6	0.000025	-0.000021	0.000047	0.00133	0.00127	2.57743	-2.54437	4.43162
	(0.0020)	(0.9980)	(0.0000)	(0.0080)	(0.9840)	(0.0000)	(1.0000)	(0.0000)
7	0.000023	-0.000019	0.000042	0.00133	0.00127	2.29693	-2.27439	3.95569
	(0.0040)	(0.9980)	(0.0000)	(0.0120)	(0.9760)	(0.0000)	(1.0000)	(0.0000)
8	0.000019	-0.000015	0.000034	0.00133	0.00127	1.87411	-1.85911	3.23056
	(0.0100)	(0.9880)	(0.0000)	(0.0140)	(0.9740)	(0.0000)	(1.0000)	(0.0000)
10	0.000015	-0.000012	0.000027	0.00133	0.00126	1.49719	-1.49931	2.59231
	(0.0340)	(0.9660)	(0.0000)	(0.0000)	(0.9940)	(0.0020)	(1.0000)	(0.0000)
12	0.000011	-0.000008	0.000019	0.00133	0.00126	1.03470	-1.04928	1.80243
	(0.0900)	(0.9060)	(0.0260)	(0.0000)	(0.9920)	(0.0260)	(0.9740)	(0.0260)
20	-0.000003	0.000006	-0.000009	0.00133	0.00126	-0.48978	0.49708	-0.85355
	(0.7560)	(0.3000)	(0.8280)	(0.0040)	(0.9820)	(0.8240)	(0.1700)	(0.8260)
24	-0.000004	0.000006	-0.000010	0.00133	0.00126	-0.52577	0.53419	-0.91661
	(0.7620)	(0.2800)	(0.8480)	(0.0020)	(0.9900)	(0.8320)	(0.1640)	(0.8380)

JPY/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000020	-0.000027	0.000047	0.00143	0.00137	2.38535	-2.38133	4.12529
	(0.0060)	(0.9980)	(0.0000)	(0.0420)	(0.9720)	(0.0000)	(1.0000)	(0.0000)
4	0.000015	-0.000022	0.000037	0.00143	0.00136	1.89273	-1.88517	3.26914
	(0.0160)	(0.9960)	(0.0000)	(0.0320)	(0.9800)	(0.0000)	(1.0000)	(0.0000)
5	0.000021	-0.000027	0.000048	0.00143	0.00136	2.43497	-2.42891	4.20864
	(0.0040)	(1.0000)	(0.0000)	(0.0260)	(0.9860)	(0.0000)	(1.0000)	(0.0000)
6	0.000018	-0.000025	0.000043	0.00144	0.00136	2.19762	-2.19610	3.80175
	(0.0080)	(0.9960)	(0.0000)	(0.0220)	(0.9920)	(0.0000)	(1.0000)	(0.0000)
7	0.000017	-0.000024	0.000041	0.00144	0.00136	2.08010	-2.08932	3.60669
	(0.0100)	(1.0000)	(0.0000)	(0.0180)	(0.9980)	(0.0000)	(1.0000)	(0.0000)
8	0.000018	-0.000024	0.000042	0.00144	0.00136	2.12344	-2.13471	3.68352
	(0.0080)	(1.0000)	(0.0000)	(0.0120)	(0.9980)	(0.0000)	(1.0000)	(0.0000)
10	0.000013	-0.000019	0.000032	0.00145	0.00135	1.61004	-1.63171	2.80360
	(0.0380)	(0.9780)	(0.0000)	(0.0080)	(1.0000)	(0.0020)	(0.9980)	(0.0020)
12	0.000010	-0.000017	0.000027	0.00145	0.00135	1.36531	-1.38210	2.37623
	(0.0660)	(0.9580)	(0.0080)	(0.0080)	(1.0000)	(0.0080)	(0.9920)	(0.0080)
20	-0.000002	-0.000005	0.000003	0.00146	0.00134	0.15281	-0.14495	0.25767
	(0.4780)	(0.6020)	(0.4200)	(0.0000)	(1.0000)	(0.4180)	(0.5800)	(0.4180)
24	-0.000001	-0.000006	0.000004	0.00147	0.00133	0.23032	-0.21161	0.38265
	(0.4260)	(0.6340)	(0.3760)	(0.0020)	(1.0000)	(0.3720)	(0.6220)	(0.3780)

AUD/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000078	-0.000055	0.000133	0.00196	0.00179	5.04041	-5.06288	8.72922
	(0.0000)	(1.0000)	(0.0000)	(0.0060)	(0.9980)	(0.0000)	(1.0000)	(0.0000)
4	0.000070	-0.000046	0.000116	0.00197	0.00179	4.41691	-4.39640	7.60886
	(0.0000)	(1.0000)	(0.0000)	(0.0040)	(1.0000)	(0.0000)	(1.0000)	(0.0000)
5	0.000073	-0.000049	0.000122	0.00198	0.00178	4.61938	-4.61541	7.96940
	(0.0000)	(1.0000)	(0.0000)	(0.0020)	(1.0000)	(0.0000)	(1.0000)	(0.0000)
6	0.000062	-0.000038	0.000100	0.00198	0.00178	3.79344	-3.78104	6.53433
	(0.0000)	(1.0000)	(0.0000)	(0.0000)	(1.0000)	(0.0000)	(1.0000)	(0.0000)
7	0.000054	-0.000031	0.000085	0.00199	0.00177	3.22005	-3.23197	5.56265
	(0.0000)	(1.0000)	(0.0000)	(0.0000)	(1.0000)	(0.0000)	(1.0000)	(0.0000)
8	0.000051	-0.000028	0.000080	0.00199	0.00177	3.01149	-3.01911	5.20042
	(0.0000)	(1.0000)	(0.0000)	(0.0020)	(1.0000)	(0.0000)	(1.0000)	(0.0000)
10	0.000048	-0.000025	0.000073	0.00201	0.00175	2.75286	-2.79878	4.78015
	(0.0020)	(1.0000)	(0.0000)	(0.0000)	(1.0000)	(0.0000)	(1.0000)	(0.0000)
12	0.000039	-0.000017	0.000056	0.00202	0.00174	2.10532	-2.13431	3.64958
	(0.0060)	(0.9960)	(0.0000)	(0.0000)	(1.0000)	(0.0000)	(1.0000)	(0.0000)
20	0.000019	0.000001	0.000019	0.00202	0.00175	0.71900	-0.69735	1.21997
	(0.2080)	(0.8120)	(0.1120)	(0.0000)	(1.0000)	(0.1120)	(0.8880)	(0.1120)
24	0.000014	0.000005	0.000008	0.00203	0.00173	0.32242	-0.31126	0.54511
	(0.3700)	(0.6760)	(0.3020)	(0.0000)	(1.0000)	(0.2900)	(0.7040)	(0.2960)

CAD/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000047	-0.000056	0.000103	0.00133	0.00135	5.53565	-5.40687	9.47886
	(0.0000)	(1.0000)	(0.0000)	(0.6400)	(0.1720)	(0.0000)	(1.0000)	(0.0000)
4	0.000042	-0.000051	0.000093	0.00133	0.00135	5.00877	-4.87914	8.56497
	(0.0000)	(1.0000)	(0.0000)	(0.6340)	(0.1860)	(0.0000)	(1.0000)	(0.0000)
5	0.000047	-0.000056	0.000104	0.00134	0.00134	5.53503	-5.46379	9.52721
	(0.0000)	(1.0000)	(0.0000)	(0.3200)	(0.4600)	(0.0000)	(1.0000)	(0.0000)
6	0.000044	-0.000054	0.000098	0.00134	0.00134	5.23733	-5.18313	9.02598
	(0.0000)	(1.0000)	(0.0000)	(0.3380)	(0.4560)	(0.0000)	(1.0000)	(0.0000)
7	0.000038	-0.000048	0.000086	0.00134	0.00135	4.62173	-4.54906	7.94332
	(0.0000)	(1.0000)	(0.0000)	(0.5360)	(0.2460)	(0.0000)	(1.0000)	(0.0000)
8	0.000034	-0.000043	0.000077	0.00134	0.00135	4.11572	-4.05526	7.07703
	(0.0000)	(1.0000)	(0.0000)	(0.5320)	(0.2540)	(0.0000)	(1.0000)	(0.0000)
10	0.000029	-0.000039	0.000068	0.00133	0.00136	3.61851	-3.56182	6.21842
	(0.0000)	(1.0000)	(0.0000)	(0.7140)	(0.1220)	(0.0000)	(1.0000)	(0.0000)
12	0.000027	-0.000038	0.000065	0.00133	0.00136	3.47766	-3.43176	5.98337
	(0.0000)	(1.0000)	(0.0000)	(0.7680)	(0.1020)	(0.0000)	(1.0000)	(0.0000)
20	0.000012	-0.000023	0.000034	0.00132	0.00137	1.81517	-1.82274	3.14868
	(0.0180)	(0.9900)	(0.0020)	(0.9080)	(0.0200)	(0.0020)	(0.9980)	(0.0020)
24	0.000004	-0.000014	0.000018	0.00132	0.00137	0.95304	-0.95829	1.65382
	(0.1560)	(0.8940)	(0.0580)	(0.9120)	(0.0120)	(0.0580)	(0.9400)	(0.0580)

CHF/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000022	-0.000034	0.000056	0.00141	0.00140	2.82701	-2.83129	4.90024
	(0.0000)	(1.0000)	(0.0000)	(0.3060)	(0.7560)	(0.0000)	(1.0000)	(0.0000)
4	0.000021	-0.000032	0.000052	0.00140	0.00140	2.67828	-2.65096	4.61544
	(0.0000)	(1.0000)	(0.0000)	(0.5200)	(0.5560)	(0.0000)	(1.0000)	(0.0000)
5	0.000018	-0.000029	0.000047	0.00140	0.00140	2.38122	-2.36203	4.10787
	(0.0060)	(0.9980)	(0.0000)	(0.5200)	(0.5460)	(0.0000)	(1.0000)	(0.0000)
6	0.000016	-0.000027	0.000043	0.00141	0.00140	2.19311	-2.18144	3.78849
	(0.0040)	(0.9980)	(0.0000)	(0.4760)	(0.5620)	(0.0000)	(1.0000)	(0.0000)
7	0.000016	-0.000027	0.000043	0.00140	0.00141	2.17011	-2.14925	3.74071
	(0.0100)	(0.9980)	(0.0000)	(0.6620)	(0.4260)	(0.0000)	(1.0000)	(0.0000)
8	0.000011	-0.000023	0.000034	0.00140	0.00141	1.73747	-1.72531	2.99882
	(0.0300)	(0.9940)	(0.0040)	(0.6420)	(0.4400)	(0.0020)	(0.9940)	(0.0020)
10	0.000009	-0.000021	0.000030	0.00140	0.00141	1.53912	-1.54412	2.67009
	(0.0540)	(0.9880)	(0.0100)	(0.5600)	(0.4640)	(0.0100)	(0.9900)	(0.0100)
12	0.000005	-0.000017	0.000022	0.00140	0.00141	1.12869	-1.14716	1.97089
	(0.1260)	(0.9540)	(0.0320)	(0.5700)	(0.4860)	(0.0260)	(0.9720)	(0.0280)
20	-0.000004	-0.000008	0.000003	0.00141	0.00140	0.16035	-0.18515	0.29923
	(0.4960)	(0.6280)	(0.4100)	(0.5080)	(0.5480)	(0.4000)	(0.6100)	(0.3980)
24	-0.000005	-0.000007	0.000002	0.00141	0.00140	0.10257	-0.12872	0.20033
	(0.5380)	(0.5940)	(0.4560)	(0.4040)	(0.6360)	(0.4560)	(0.5560)	(0.4520)

SEK/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000051	-0.000057	0.000108	0.00167	0.00171	4.55567	-4.56387	7.89763
	(0.0000)	(1.0000)	(0.0000)	(0.9040)	(0.1280)	(0.0000)	(1.0000)	(0.0000)
4	0.000044	-0.000051	0.000095	0.00167	0.00171	3.96904	-3.99018	6.89249
	(0.0000)	(1.0000)	(0.0000)	(0.9000)	(0.1380)	(0.0000)	(1.0000)	(0.0000)
5	0.000041	-0.000047	0.000088	0.00167	0.00172	3.69803	-3.71343	6.41708
	(0.0000)	(1.0000)	(0.0000)	(0.9580)	(0.0720)	(0.0000)	(1.0000)	(0.0000)
6	0.000037	-0.000044	0.000081	0.00167	0.00172	3.37233	-3.39736	5.86120
	(0.0000)	(1.0000)	(0.0000)	(0.9560)	(0.0740)	(0.0000)	(1.0000)	(0.0000)
7	0.000032	-0.000038	0.000070	0.00167	0.00172	2.93096	-2.97714	5.11522
	(0.0000)	(1.0000)	(0.0000)	(0.9180)	(0.1080)	(0.0000)	(1.0000)	(0.0000)
8	0.000028	-0.000035	0.000063	0.00167	0.00172	2.63603	-2.68031	4.60284
	(0.0000)	(1.0000)	(0.0000)	(0.9100)	(0.1220)	(0.0000)	(1.0000)	(0.0000)
10	0.000024	-0.000031	0.000055	0.00167	0.00172	2.26764	-2.31823	3.97017
	(0.0040)	(0.9980)	(0.0000)	(0.9460)	(0.0900)	(0.0000)	(1.0000)	(0.0000)
12	0.000018	-0.000024	0.000042	0.00167	0.00172	1.73969	-1.79018	3.05587
	(0.0280)	(0.9940)	(0.0040)	(0.9600)	(0.0540)	(0.0040)	(0.9960)	(0.0040)
20	0.000003	-0.000009	0.000013	0.00165	0.00174	0.50553	-0.55295	0.91654
	(0.3560)	(0.8100)	(0.1980)	(1.0000)	(0.0000)	(0.2180)	(0.8020)	(0.2080)
24	0.000001	-0.000007	0.000009	0.00165	0.00174	0.33801	-0.39006	0.63092
	(0.4400)	(0.7480)	(0.2700)	(0.9980)	(0.0020)	(0.2840)	(0.7280)	(0.2760)

ZAR/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000176	-0.000169	0.000345	0.00274	0.00280	8.76631	-8.63657	15.07974
	(0.0000)	(1.0000)	(0.0000)	(0.7820)	(0.2060)	(0.0000)	(1.0000)	(0.0000)
4	0.000188	-0.000179	0.000368	0.00274	0.00280	9.37623	-9.18931	16.08899
	(0.0000)	(1.0000)	(0.0000)	(0.7840)	(0.2160)	(0.0000)	(1.0000)	(0.0000)
5	0.000180	-0.000172	0.000353	0.00274	0.00280	8.98527	-8.81979	15.42866
	(0.0000)	(1.0000)	(0.0000)	(0.7880)	(0.2020)	(0.0000)	(1.0000)	(0.0000)
6	0.000176	-0.000167	0.000343	0.00275	0.00280	8.72896	-8.59125	15.00841
	(0.0000)	(1.0000)	(0.0000)	(0.7440)	(0.2380)	(0.0000)	(1.0000)	(0.0000)
7	0.000179	-0.000172	0.000351	0.00273	0.00281	8.94624	-8.79698	15.37425
	(0.0000)	(1.0000)	(0.0000)	(0.8400)	(0.1660)	(0.0000)	(1.0000)	(0.0000)
8	0.000173	-0.000165	0.000338	0.00272	0.00282	8.63124	-8.41399	14.76733
	(0.0000)	(1.0000)	(0.0000)	(0.9260)	(0.0980)	(0.0000)	(1.0000)	(0.0000)
10	0.000156	-0.000150	0.000306	0.00268	0.00286	7.85902	-7.57801	13.36387
	(0.0000)	(1.0000)	(0.0000)	(0.9980)	(0.0140)	(0.0000)	(1.0000)	(0.0000)
12	0.000140	-0.000136	0.000275	0.00268	0.00287	7.05627	-6.84443	12.03012
	(0.0000)	(1.0000)	(0.0000)	(0.9980)	(0.0040)	(0.0000)	(1.0000)	(0.0000)
20	0.000085	-0.000084	0.000169	0.00264	0.00291	4.29999	-4.23277	7.37118
	(0.0000)	(1.0000)	(0.0000)	(0.9980)	(0.0000)	(0.0000)	(1.0000)	(0.0000)
24	0.000068	-0.000066	0.000133	0.00265	0.00291	3.36553	-3.33989	5.79236
	(0.0000)	(1.0000)	(0.0000)	(1.0000)	(0.0000)	(0.0000)	(1.0000)	(0.0000)

EUR/JPY

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000030	-0.000025	0.000054	0.00171	0.00161	2.36215	-2.31390	4.04476
	(0.0060)	(1.0000)	(0.0000)	(0.0480)	(0.9940)	(0.0000)	(1.0000)	(0.0000)
4	0.000030	-0.000024	0.000054	0.00172	0.00160	2.33351	-2.29990	4.00488
	(0.0060)	(1.0000)	(0.0000)	(0.0480)	(0.9940)	(0.0000)	(1.0000)	(0.0000)
5	0.000028	-0.000023	0.000051	0.00173	0.00159	2.20904	-2.18538	3.79654
	(0.0000)	(0.9940)	(0.0000)	(0.0020)	(1.0000)	(0.0000)	(1.0000)	(0.0000)
6	0.000023	-0.000018	0.000041	0.00174	0.00158	1.75128	-1.73552	3.01088
	(0.0180)	(0.9820)	(0.0020)	(0.0020)	(1.0000)	(0.0020)	(0.9980)	(0.0020)
7	0.000019	-0.000014	0.000034	0.00174	0.00158	1.45444	-1.43344	2.49344
	(0.0400)	(0.9560)	(0.0060)	(0.0000)	(1.0000)	(0.0060)	(0.9940)	(0.0060)
8	0.000020	-0.000015	0.000034	0.00174	0.00158	1.48389	-1.46258	2.54378
	(0.0360)	(0.9560)	(0.0040)	(0.0020)	(1.0000)	(0.0040)	(0.9960)	(0.0040)
10	0.000017	-0.000012	0.000028	0.00175	0.00157	1.22599	-1.19877	2.09194
	(0.0660)	(0.9300)	(0.0160)	(0.0000)	(1.0000)	(0.0160)	(0.9840)	(0.0160)
12	0.000013	-0.000008	0.000020	0.00175	0.00157	0.89623	-0.85483	1.51115
	(0.1480)	(0.8680)	(0.0760)	(0.0000)	(1.0000)	(0.0640)	(0.9260)	(0.0720)
20	0.000001	0.000003	-0.000002	0.00178	0.00155	-0.07624	0.12393	-0.16895
	(0.5820)	(0.4780)	(0.5400)	(0.0000)	(1.0000)	(0.5340)	(0.4200)	(0.5520)
24	-0.000003	0.000006	-0.000009	0.00180	0.00153	-0.37752	0.41515	-0.67656
	(0.7180)	(0.3500)	(0.7340)	(0.0000)	(1.0000)	(0.7320)	(0.2420)	(0.7420)

EUR/GBP

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000071	-0.000059	0.000131	0.00108	0.00107	8.68973	-8.55918	14.94595
	(0.0000)	(1.0000)	(0.0000)	(0.4600)	(0.7800)	(0.0000)	(1.0000)	(0.0000)
4	0.000063	-0.000050	0.000113	0.00109	0.00107	7.54810	-7.32930	12.88817
	(0.0000)	(1.0000)	(0.0000)	(0.3840)	(0.8220)	(0.0000)	(1.0000)	(0.0000)
5	0.000059	-0.000046	0.000105	0.00109	0.00108	7.02318	-6.83963	12.00897
	(0.0000)	(1.0000)	(0.0000)	(0.4120)	(0.7800)	(0.0000)	(1.0000)	(0.0000)
6	0.000054	-0.000042	0.000096	0.00109	0.00108	6.41358	-6.26574	10.98323
	(0.0000)	(1.0000)	(0.0000)	(0.4400)	(0.7360)	(0.0000)	(1.0000)	(0.0000)
7	0.000052	-0.000040	0.000092	0.00109	0.00107	6.11375	-6.01479	10.50494
	(0.0000)	(1.0000)	(0.0000)	(0.3320)	(0.8360)	(0.0000)	(1.0000)	(0.0000)
8	0.000049	-0.000037	0.000086	0.00109	0.00107	5.69744	-5.61729	9.79990
	(0.0000)	(1.0000)	(0.0000)	(0.3400)	(0.8080)	(0.0000)	(1.0000)	(0.0000)
10	0.000046	-0.000035	0.000081	0.00109	0.00108	5.36943	-5.27240	9.21736
	(0.0000)	(1.0000)	(0.0000)	(0.4640)	(0.7140)	(0.0000)	(1.0000)	(0.0000)
12	0.000042	-0.000031	0.000073	0.00108	0.00108	4.89552	-4.78394	8.38424
	(0.0000)	(1.0000)	(0.0000)	(0.6000)	(0.5800)	(0.0000)	(1.0000)	(0.0000)
20	0.000022	-0.000012	0.000034	0.00108	0.00109	2.28914	-2.24462	3.92645
	(0.0060)	(0.9960)	(0.0000)	(0.7980)	(0.3220)	(0.0000)	(1.0000)	(0.0000)
24	0.000020	-0.000009	0.000029	0.00108	0.00109	1.93550	-1.90736	3.32797
	(0.0180)	(0.9920)	(0.0000)	(0.7840)	(0.3700)	(0.0000)	(1.0000)	(0.0000)

EUR/CHF

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000053	-0.000055	0.000108	0.00071	0.00069	11.01966	-10.92940	19.02009
	(0.0000)	(1.0000)	(0.0000)	(0.2640)	(0.8340)	(0.0000)	(1.0000)	(0.0000)
4	0.000049	-0.000050	0.000099	0.00071	0.00069	10.12356	-9.93741	17.37878
	(0.0000)	(1.0000)	(0.0000)	(0.2540)	(0.8360)	(0.0000)	(1.0000)	(0.0000)
5	0.000046	-0.000047	0.000094	0.00072	0.00069	9.54700	-9.47027	16.47177
	(0.0000)	(1.0000)	(0.0000)	(0.1960)	(0.8800)	(0.0000)	(1.0000)	(0.0000)
6	0.000046	-0.000047	0.000093	0.00071	0.00069	9.48220	-9.37341	16.33474
	(0.0000)	(1.0000)	(0.0000)	(0.2620)	(0.7940)	(0.0000)	(1.0000)	(0.0000)
7	0.000043	-0.000044	0.000087	0.00072	0.00069	8.87062	-8.82946	15.32967
	(0.0000)	(1.0000)	(0.0000)	(0.1840)	(0.8740)	(0.0000)	(1.0000)	(0.0000)
8	0.000042	-0.000043	0.000085	0.00071	0.00069	8.67344	-8.56525	14.93310
	(0.0000)	(1.0000)	(0.0000)	(0.2680)	(0.7700)	(0.0000)	(1.0000)	(0.0000)
10	0.000040	-0.000042	0.000083	0.00071	0.00069	8.44162	-8.35978	14.55533
	(0.0000)	(1.0000)	(0.0000)	(0.3160)	(0.7320)	(0.0000)	(1.0000)	(0.0000)
12	0.000038	-0.000040	0.000079	0.00072	0.00069	7.98229	-8.02085	13.85901
	(0.0000)	(1.0000)	(0.0000)	(0.1600)	(0.8840)	(0.0000)	(1.0000)	(0.0000)
20	0.000029	-0.000031	0.000060	0.00073	0.00068	6.07711	-6.18529	10.61172
	(0.0000)	(1.0000)	(0.0000)	(0.0600)	(0.9820)	(0.0000)	(1.0000)	(0.0000)
24	0.000024	-0.000026	0.000050	0.00073	0.00068	5.03109	-5.18013	8.83243
	(0.0000)	(1.0000)	(0.0000)	(0.0280)	(0.9920)	(0.0000)	(1.0000)	(0.0000)

3. GARCH(1,1)-MA(1) Model Results

Note: See Table IV for details

GBP/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000025	-0.000021	0.000046	0.00131	0.00128	2.58312	-2.51475	4.41379
	(0.9520)	(0.4080)	(0.9080)	(0.1840)	(0.2640)	(0.9260)	(0.0680)	(0.9280)
4	0.000024	-0.000021	0.000045	0.00132	0.00127	2.49931	-2.45556	4.28875
	(0.9080)	(0.5420)	(0.7820)	(0.1620)	(0.2960)	(0.8340)	(0.1680)	(0.8340)
5	0.000029	-0.000024	0.000053	0.00132	0.00127	2.94350	-2.89419	5.05196
	(0.6400)	(0.8280)	(0.3760)	(0.1480)	(0.3220)	(0.4720)	(0.5420)	(0.4660)
6	0.000025	-0.000021	0.000047	0.00133	0.00127	2.57743	-2.54437	4.43162
	(0.7380)	(0.7720)	(0.4560)	(0.1420)	(0.3400)	(0.5520)	(0.4700)	(0.5440)
7	0.000023	-0.000019	0.000042	0.00133	0.00127	2.29693	-2.27439	3.95569
	(0.7800)	(0.7280)	(0.5460)	(0.1520)	(0.3180)	(0.6140)	(0.4060)	(0.6060)
8	0.000019	-0.000015	0.000034	0.00133	0.00127	1.87411	-1.85911	3.23056
	(0.8900)	(0.6100)	(0.7300)	(0.1540)	(0.3200)	(0.7820)	(0.2320)	(0.7760)
10	0.000015	-0.000012	0.000027	0.00133	0.00126	1.49719	-1.49931	2.59231
	(0.9360)	(0.5360)	(0.8460)	(0.1420)	(0.3480)	(0.8680)	(0.1540)	(0.8580)
12	0.000011	-0.000008	0.000019	0.00133	0.00126	1.03470	-1.04928	1.80243
	(0.9720)	(0.3980)	(0.9400)	(0.1340)	(0.3520)	(0.9500)	(0.0600)	(0.9460)
20	-0.000003	0.000006	-0.000009	0.00133	0.00126	-0.48978	0.49708	-0.85355
	(1.0000)	(0.0300)	(1.0000)	(0.1480)	(0.3340)	(1.0000)	(0.0000)	(1.0000)
24	-0.000004	0.000006	-0.000010	0.00133	0.00126	-0.52577	0.53419	-0.91661
	(1.0000)	(0.0560)	(0.9980)	(0.1440)	(0.3400)	(0.9980)	(0.0020)	(0.9980)

JPY/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000020	-0.000027	0.000047	0.00143	0.00137	2.38535	-2.38133	4.12529
	(0.3680)	(0.6280)	(0.3340)	(0.3480)	(0.8260)	(0.3320)	(0.6900)	(0.3200)
4	0.000015	-0.000022	0.000037	0.00143	0.00136	1.89273	-1.88517	3.26914
	(0.5040)	(0.4860)	(0.5200)	(0.3680)	(0.8140)	(0.5000)	(0.5080)	(0.4980)
5	0.000021	-0.000027	0.000048	0.00143	0.00136	2.43497	-2.42891	4.20864
	(0.2040)	(0.7940)	(0.1120)	(0.3720)	(0.8240)	(0.1020)	(0.9020)	(0.0980)
6	0.000018	-0.000025	0.000043	0.00144	0.00136	2.19762	-2.19610	3.80175
	(0.2560)	(0.7400)	(0.1440)	(0.3880)	(0.8260)	(0.1420)	(0.8660)	(0.1280)
7	0.000017	-0.000024	0.000041	0.00144	0.00136	2.08010	-2.08932	3.60669
	(0.2420)	(0.7520)	(0.1520)	(0.3340)	(0.8700)	(0.1440)	(0.8720)	(0.1360)
8	0.000018	-0.000024	0.000042	0.00144	0.00136	2.12344	-2.13471	3.68352
	(0.1940)	(0.8140)	(0.1040)	(0.3520)	(0.8600)	(0.0980)	(0.9100)	(0.0940)
10	0.000013	-0.000019	0.000032	0.00145	0.00135	1.61004	-1.63171	2.80360
	(0.3340)	(0.6620)	(0.2740)	(0.2980)	(0.9040)	(0.2720)	(0.7580)	(0.2540)
12	0.000010	-0.000017	0.000027	0.00145	0.00135	1.36531	-1.38210	2.37623
	(0.4340)	(0.6020)	(0.3640)	(0.3120)	(0.8720)	(0.3620)	(0.6560)	(0.3480)
20	-0.000002	-0.000005	0.000003	0.00146	0.00134	0.15281	-0.14495	0.25767
	(0.8280)	(0.1820)	(0.9060)	(0.2360)	(0.9140)	(0.9040)	(0.0940)	(0.9040)
24	-0.000001	-0.000006	0.000004	0.00147	0.00133	0.23032	-0.21161	0.38265
	(0.7740)	(0.2380)	(0.8660)	(0.2060)	(0.9400)	(0.8620)	(0.1300)	(0.8640)

AUD/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000078	-0.000055	0.000133	0.00196	0.00179	5.04041	-5.06288	8.72922
	(0.1980)	(0.7660)	(0.1580)	(0.1440)	(0.3780)	(0.3180)	(0.7660)	(0.2820)
4	0.000070	-0.000046	0.000116	0.00197	0.00179	4.41691	-4.39640	7.60886
	(0.2540)	(0.6840)	(0.2500)	(0.1420)	(0.3860)	(0.4100)	(0.6520)	(0.3820)
5	0.000073	-0.000049	0.000122	0.00198	0.00178	4.61938	-4.61541	7.96940
	(0.0940)	(0.8660)	(0.0540)	(0.1400)	(0.4100)	(0.1260)	(0.9140)	(0.1080)
6	0.000062	-0.000038	0.000100	0.00198	0.00178	3.79344	-3.78104	6.53433
	(0.2840)	(0.6920)	(0.2460)	(0.1320)	(0.4160)	(0.3820)	(0.6720)	(0.3520)
7	0.000054	-0.000031	0.000085	0.00199	0.00177	3.22005	-3.23197	5.56265
	(0.4540)	(0.5620)	(0.4300)	(0.1240)	(0.4420)	(0.5760)	(0.4880)	(0.5520)
8	0.000051	-0.000028	0.000080	0.00199	0.00177	3.01149	-3.01911	5.20042
	(0.4660)	(0.5460)	(0.4440)	(0.1340)	(0.4380)	(0.5940)	(0.4720)	(0.5620)
10	0.000048	-0.000025	0.000073	0.00201	0.00175	2.75286	-2.79878	4.78015
	(0.4400)	(0.5560)	(0.4440)	(0.1080)	(0.4900)	(0.5600)	(0.5200)	(0.5120)
12	0.000039	-0.000017	0.000056	0.00202	0.00174	2.10532	-2.13431	3.64958
	(0.6840)	(0.3480)	(0.7280)	(0.1080)	(0.4940)	(0.8160)	(0.2260)	(0.7980)
20	0.000019	0.000001	0.000019	0.00202	0.00175	0.71900	-0.69735	1.21997
	(0.9580)	(0.0700)	(0.9840)	(0.1140)	(0.4760)	(0.9880)	(0.0100)	(0.9900)
24	0.000014	0.000005	0.000008	0.00203	0.00173	0.32242	-0.31126	0.54511
	(0.9680)	(0.0340)	(0.9940)	(0.1040)	(0.5180)	(0.9940)	(0.0060)	(0.9940)

CAD/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000047	-0.000056	0.000103	0.00133	0.00135	5.53565	-5.40687	9.47886
	(0.9560)	(0.0640)	(0.9900)	(0.8100)	(0.6740)	(0.9780)	(0.0180)	(0.9820)
4	0.000042	-0.000051	0.000093	0.00133	0.00135	5.00877	-4.87914	8.56497
	(0.9420)	(0.0800)	(0.9760)	(0.8140)	(0.6380)	(0.9660)	(0.0200)	(0.9720)
5	0.000047	-0.000056	0.000104	0.00134	0.00134	5.53503	-5.46379	9.52721
	(0.6420)	(0.3520)	(0.6560)	(0.6580)	(0.8200)	(0.5920)	(0.3140)	(0.6440)
6	0.000044	-0.000054	0.000098	0.00134	0.00134	5.23733	-5.18313	9.02598
	(0.6240)	(0.4100)	(0.6320)	(0.6520)	(0.8120)	(0.5640)	(0.3480)	(0.6220)
7	0.000038	-0.000048	0.000086	0.00134	0.00135	4.62173	-4.54906	7.94332
	(0.7700)	(0.2440)	(0.8460)	(0.7640)	(0.7080)	(0.7800)	(0.1520)	(0.8160)
8	0.000034	-0.000043	0.000077	0.00134	0.00135	4.11572	-4.05526	7.07703
	(0.8600)	(0.1620)	(0.9100)	(0.7480)	(0.7280)	(0.8820)	(0.0860)	(0.9000)
10	0.000029	-0.000039	0.000068	0.00133	0.00136	3.61851	-3.56182	6.21842
	(0.8880)	(0.1460)	(0.9420)	(0.8460)	(0.6300)	(0.9280)	(0.0580)	(0.9360)
12	0.000027	-0.000038	0.000065	0.00133	0.00136	3.47766	-3.43176	5.98337
	(0.8640)	(0.1600)	(0.9300)	(0.8660)	(0.5680)	(0.9080)	(0.0640)	(0.9340)
20	0.000012	-0.000023	0.000034	0.00132	0.00137	1.81517	-1.82274	3.14868
	(0.9820)	(0.0280)	(1.0000)	(0.9380)	(0.3640)	(1.0000)	(0.0000)	(1.0000)
24	0.000004	-0.000014	0.000018	0.00132	0.00137	0.95304	-0.95829	1.65382
	(0.9980)	(0.0040)	(1.0000)	(0.9560)	(0.3500)	(1.0000)	(0.0000)	(1.0000)

CHF/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000022	-0.000034	0.000056	0.00141	0.00140	2.82701	-2.83129	4.90024
	(0.3280)	(0.7260)	(0.1940)	(0.4940)	(0.7060)	(0.1920)	(0.8020)	(0.1960)
4	0.000021	-0.000032	0.000052	0.00140	0.00140	2.67828	-2.65096	4.61544
	(0.2940)	(0.7360)	(0.1880)	(0.6220)	(0.6060)	(0.1700)	(0.8140)	(0.1780)
5	0.000018	-0.000029	0.000047	0.00140	0.00140	2.38122	-2.36203	4.10787
	(0.3680)	(0.6800)	(0.2680)	(0.6060)	(0.5980)	(0.2520)	(0.7360)	(0.2600)
6	0.000016	-0.000027	0.000043	0.00141	0.00140	2.19311	-2.18144	3.78849
	(0.4100)	(0.6480)	(0.2940)	(0.5820)	(0.6240)	(0.2660)	(0.7100)	(0.2720)
7	0.000016	-0.000027	0.000043	0.00140	0.00141	2.17011	-2.14925	3.74071
	(0.3540)	(0.6940)	(0.2140)	(0.6460)	(0.5240)	(0.2120)	(0.7620)	(0.2220)
8	0.000011	-0.000023	0.000034	0.00140	0.00141	1.73747	-1.72531	2.99882
	(0.5160)	(0.5580)	(0.4680)	(0.6420)	(0.5440)	(0.4520)	(0.5400)	(0.4560)
10	0.000009	-0.000021	0.000030	0.00140	0.00141	1.53912	-1.54412	2.67009
	(0.5560)	(0.5480)	(0.5120)	(0.6020)	(0.5720)	(0.4920)	(0.4960)	(0.5020)
12	0.000005	-0.000017	0.000022	0.00140	0.00141	1.12869	-1.14716	1.97089
	(0.6960)	(0.4180)	(0.7260)	(0.6080)	(0.5620)	(0.7080)	(0.2980)	(0.7080)
20	-0.000004	-0.000008	0.000003	0.00141	0.00140	0.16035	-0.18515	0.29923
	(0.8940)	(0.1400)	(0.9520)	(0.5840)	(0.6020)	(0.9440)	(0.0580)	(0.9440)
24	-0.000005	-0.000007	0.000002	0.00141	0.00140	0.10257	-0.12872	0.20033
	(0.8960)	(0.1720)	(0.9440)	(0.5400)	(0.6560)	(0.9460)	(0.0580)	(0.9420)

SEK/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000051	-0.000057	0.000108	0.00167	0.00171	4.55567	-4.56387	7.89763
	(0.3100)	(0.1520)	(0.5840)	(0.2100)	(0.1680)	(0.7720)	(0.1840)	(0.7960)
4	0.000044	-0.000051	0.000095	0.00167	0.00171	3.96904	-3.99018	6.89249
	(0.3400)	(0.1240)	(0.6840)	(0.2020)	(0.1620)	(0.8400)	(0.1280)	(0.8660)
5	0.000041	-0.000047	0.000088	0.00167	0.00172	3.69803	-3.71343	6.41708
	(0.2980)	(0.1380)	(0.6440)	(0.2200)	(0.1520)	(0.7840)	(0.1800)	(0.8020)
6	0.000037	-0.000044	0.000081	0.00167	0.00172	3.37233	-3.39736	5.86120
	(0.3240)	(0.1100)	(0.6480)	(0.2180)	(0.1540)	(0.8180)	(0.1640)	(0.8280)
7	0.000032	-0.000038	0.000070	0.00167	0.00172	2.93096	-2.97714	5.11522
	(0.4080)	(0.0640)	(0.7860)	(0.2060)	(0.1580)	(0.8760)	(0.1000)	(0.8920)
8	0.000028	-0.000035	0.000063	0.00167	0.00172	2.63603	-2.68031	4.60284
	(0.4720)	(0.0540)	(0.8540)	(0.2100)	(0.1580)	(0.9220)	(0.0720)	(0.9260)
10	0.000024	-0.000031	0.000055	0.00167	0.00172	2.26764	-2.31823	3.97017
	(0.4960)	(0.0420)	(0.8860)	(0.2160)	(0.1600)	(0.9460)	(0.0520)	(0.9480)
12	0.000018	-0.000024	0.000042	0.00167	0.00172	1.73969	-1.79018	3.05587
	(0.6340)	(0.0160)	(0.9640)	(0.2260)	(0.1580)	(0.9720)	(0.0260)	(0.9720)
20	0.000003	-0.000009	0.000013	0.00165	0.00174	0.50553	-0.55295	0.91654
	(0.8980)	(0.0040)	(0.9980)	(0.2600)	(0.1340)	(0.9980)	(0.0020)	(0.9980)
24	0.000001	-0.000007	0.000009	0.00165	0.00174	0.33801	-0.39006	0.63092
	(0.8960)	(0.0060)	(1.0000)	(0.2540)	(0.1340)	(1.0000)	(0.0000)	(1.0000)

ZAR/USD

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000176	-0.000169	0.000345	0.00274	0.00280	8.76631	-8.63657	15.07974
	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.0000)	(1.0000)
4	0.000188	-0.000179	0.000368	0.00274	0.00280	9.37623	-9.18931	16.08899
	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9920)	(0.0080)	(0.9920)
5	0.000180	-0.000172	0.000353	0.00274	0.00280	8.98527	-8.81979	15.42866
	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9900)	(0.0080)	(0.9920)
6	0.000176	-0.000167	0.000343	0.00275	0.00280	8.72896	-8.59125	15.00841
	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9840)	(0.0140)	(0.9840)
7	0.000179	-0.000172	0.000351	0.00273	0.00281	8.94624	-8.79698	15.37425
	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9520)	(0.0320)	(0.9620)
8	0.000173	-0.000165	0.000338	0.00272	0.00282	8.63124	-8.41399	14.76733
	(0.9840)	(0.0200)	(1.0000)	(1.0000)	(1.0000)	(0.9420)	(0.0280)	(0.9580)
10	0.000156	-0.000150	0.000306	0.00268	0.00286	7.85902	-7.57801	13.36387
	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9560)	(0.0300)	(0.9620)
12	0.000140	-0.000136	0.000275	0.00268	0.00287	7.05627	-6.84443	12.03012
	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(0.9740)	(0.0140)	(0.9800)
20	0.000085	-0.000084	0.000169	0.00264	0.00291	4.29999	-4.23277	7.37118
	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.0000)	(1.0000)
24	0.000068	-0.000066	0.000133	0.00265	0.00291	3.36553	-3.33989	5.79236
	(1.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(0.0000)	(1.0000)

EUR/JPY

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000030	-0.000025	0.000054	0.00171	0.00161	2.36215	-2.31390	4.04476
	(0.9560)	(0.3520)	(0.9440)	(0.3960)	(0.5620)	(0.9040)	(0.1040)	(0.9040)
4	0.000030	-0.000024	0.000054	0.00172	0.00160	2.33351	-2.29990	4.00488
	(0.9120)	(0.4880)	(0.8460)	(0.3780)	(0.5880)	(0.8120)	(0.2080)	(0.8020)
5	0.000028	-0.000023	0.000051	0.00173	0.00159	2.20904	-2.18538	3.79654
	(0.8860)	(0.5520)	(0.7860)	(0.3640)	(0.6160)	(0.7520)	(0.2800)	(0.7360)
6	0.000023	-0.000018	0.000041	0.00174	0.00158	1.75128	-1.73552	3.01088
	(0.9220)	(0.4140)	(0.8880)	(0.3600)	(0.6220)	(0.8780)	(0.1400)	(0.8680)
7	0.000019	-0.000014	0.000034	0.00174	0.00158	1.45444	-1.43344	2.49344
	(0.9380)	(0.3520)	(0.9120)	(0.3580)	(0.6300)	(0.9100)	(0.1020)	(0.9060)
8	0.000020	-0.000015	0.000034	0.00174	0.00158	1.48389	-1.46258	2.54378
	(0.9260)	(0.4380)	(0.8840)	(0.3580)	(0.6160)	(0.8560)	(0.1460)	(0.8560)
10	0.000017	-0.000012	0.000028	0.00175	0.00157	1.22599	-1.19877	2.09194
	(0.9340)	(0.3980)	(0.8980)	(0.3500)	(0.6280)	(0.8820)	(0.1240)	(0.8780)
12	0.000013	-0.000008	0.000020	0.00175	0.00157	0.89623	-0.85483	1.51115
	(0.9520)	(0.3240)	(0.9420)	(0.3480)	(0.6240)	(0.9280)	(0.0740)	(0.9300)
20	0.000001	0.000003	-0.000002	0.00178	0.00155	-0.07624	0.12393	-0.16895
	(0.9880)	(0.1580)	(1.0000)	(0.3280)	(0.6660)	(1.0000)	(0.0000)	(1.0000)
24	-0.000003	0.000006	-0.000009	0.00180	0.00153	-0.37752	0.41515	-0.67656
	(0.9980)	(0.1100)	(1.0000)	(0.3020)	(0.7080)	(1.0000)	(0.0000)	(1.0000)

EUR/GBP

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	0.000071	-0.000059	0.000131	0.00108	0.00107	8.68973	-8.55918	14.94595
	(0.9560)	(0.0960)	(0.9500)	(0.4740)	(0.5040)	(0.9600)	(0.0300)	(0.9660)
4	0.000063	-0.000050	0.000113	0.00109	0.00107	7.54810	-7.32930	12.88817
	(0.9840)	(0.0540)	(0.9920)	(0.4780)	(0.5020)	(0.9840)	(0.0120)	(0.9860)
5	0.000059	-0.000046	0.000105	0.00109	0.00108	7.02318	-6.83963	12.00897
	(0.9720)	(0.0720)	(0.9800)	(0.4820)	(0.5000)	(0.9880)	(0.0120)	(0.9880)
6	0.000054	-0.000042	0.000096	0.00109	0.00108	6.41358	-6.26574	10.98323
	(0.9820)	(0.0700)	(0.9840)	(0.4840)	(0.4940)	(0.9840)	(0.0140)	(0.9860)
7	0.000052	-0.000040	0.000092	0.00109	0.00107	6.11375	-6.01479	10.50494
	(0.9680)	(0.1040)	(0.9740)	(0.4680)	(0.5140)	(0.9800)	(0.0200)	(0.9800)
8	0.000049	-0.000037	0.000086	0.00109	0.00107	5.69744	-5.61729	9.79990
	(0.9740)	(0.1180)	(0.9660)	(0.4740)	(0.5040)	(0.9840)	(0.0160)	(0.9840)
10	0.000046	-0.000035	0.000081	0.00109	0.00108	5.36943	-5.27240	9.21736
	(0.9480)	(0.1800)	(0.9280)	(0.4820)	(0.4980)	(0.9620)	(0.0380)	(0.9640)
12	0.000042	-0.000031	0.000073	0.00108	0.00108	4.89552	-4.78394	8.38424
	(0.9520)	(0.1760)	(0.9500)	(0.4980)	(0.4900)	(0.9480)	(0.0480)	(0.9540)
20	0.000022	-0.000012	0.000034	0.00108	0.00109	2.28914	-2.24462	3.92645
	(1.0000)	(0.0080)	(1.0000)	(0.5100)	(0.4720)	(1.0000)	(0.0000)	(1.0000)
24	0.000020	-0.000009	0.000029	0.00108	0.00109	1.93550	-1.90736	3.32797
	(1.0000)	(0.0080)	(1.0000)	(0.5080)	(0.4780)	(1.0000)	(0.0000)	(1.0000)

EUR/CHF

h	μ(Buy)	μ(Sell)	Buy-Sell	σ(Buy)	σ(Sell)	t(Buy)	t(Sell)	t(Buy-Sell)
3	5.35E-05	-5.45E-05	0.000108	0.00071	0.00069	11.01966	-10.92940	19.02009
	(0.9880)	(0.0700)	(0.9920)	(0.4860)	(0.6000)	(0.9000)	(0.1040)	(0.8980)
4	0.000049	-0.000050	0.000099	0.00071	0.00069	10.12356	-9.93741	17.37878
	(0.9780)	(0.0720)	(0.9900)	(0.4900)	(0.6000)	(0.8960)	(0.0960)	(0.9020)
5	0.000046	-0.000047	0.000094	0.00072	0.00069	9.54700	-9.47027	16.47177
	(0.9660)	(0.1500)	(0.9740)	(0.4740)	(0.6320)	(0.8560)	(0.1420)	(0.8540)
6	0.000046	-0.000047	0.000093	0.00071	0.00069	9.48220	-9.37341	16.33474
	(0.8900)	(0.4100)	(0.8100)	(0.4860)	(0.6060)	(0.7040)	(0.3060)	(0.6920)
7	0.000043	-0.000044	0.000087	0.00072	0.00069	8.87062	-8.82946	15.32967
	(0.8720)	(0.4060)	(0.8160)	(0.4820)	(0.6440)	(0.7080)	(0.3180)	(0.6960)
8	0.000042	-0.000043	0.000085	0.00071	0.00069	8.67344	-8.56525	14.93310
	(0.8440)	(0.5080)	(0.6780)	(0.5000)	(0.5860)	(0.5960)	(0.4260)	(0.5840)
10	0.000040	-0.000042	0.000083	0.00071	0.00069	8.44162	-8.35978	14.55533
	(0.6120)	(0.7700)	(0.3540)	(0.5140)	(0.5720)	(0.2840)	(0.7320)	(0.2660)
12	0.000038	-0.000040	0.000079	0.00072	0.00069	7.98229	-8.02085	13.85901
	(0.5320)	(0.8180)	(0.2580)	(0.4620)	(0.6340)	(0.2220)	(0.8460)	(0.1940)
20	0.000029	-0.000031	0.000060	0.00073	0.00068	6.07711	-6.18529	10.61172
	(0.7060)	(0.7420)	(0.4600)	(0.4220)	(0.6920)	(0.4080)	(0.7100)	(0.3360)
24	0.000024	-0.000026	0.000050	0.00073	0.00068	5.03109	-5.18013	8.83243
	(0.8780)	(0.5420)	(0.7600)	(0.3980)	(0.7120)	(0.7020)	(0.4180)	(0.6520)

C. Profitability Appendix

1. Profitability Results with Zero Transaction Costs (Holding Period Returns)

Note: See Table VI for details

GBP/USD

h	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
3	11795	11821	2.59	0.000053	-0.030180	0.017966	0.00202	-2.31502	0.65	1.96	1.25291	2.33472	0.13426
4	9833	9875	3.10	0.000063	-0.029698	0.017966	0.00221	-2.49655	0.66	2.09	1.23192	2.26599	0.13179
5	8560	8617	3.56	0.000087	-0.033995	0.017966	0.00235	-2.50739	0.68	2.30	1.49713	3.26016	0.16370
6	7711	7786	3.94	0.000085	-0.029324	0.017966	0.00247	-2.53744	0.70	2.42	1.31934	2.56791	0.14231
7	7030	7106	4.32	0.000083	-0.039510	0.016411	0.00258	-2.70539	0.70	2.51	1.16972	2.07173	0.12456
8	6458	6533	4.70	0.000073	-0.056202	0.016411	0.00271	-3.05251	0.71	2.56	0.95118	1.46773	0.09910
10	5714	5788	5.31	0.000067	-0.057176	0.016411	0.00285	-3.23130	0.72	2.67	0.77452	1.06972	0.07906
12	5169	5230	5.87	0.000052	-0.049665	0.016411	0.00301	-3.22430	0.72	2.72	0.53666	0.63131	0.05252
20	3610	3645	8.41	-0.000039	-0.062180	0.016411	0.00373	-4.09133	0.73	2.73	-0.28573	-0.28599	-0.03462
24	3202	3228	9.49	-0.000047	-0.062180	0.016411	0.00394	-4.14814	0.73	2.85	-0.30231	-0.29718	-0.03622

JPY/USD

h	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
3	11922	11914	2.56	0.000051	-0.051395	0.025356	0.00212	-2.96614	0.64	1.97	1.20864	2.17353	0.12840
4	9854	9851	3.10	0.000048	-0.052756	0.025356	0.00233	-3.04029	0.66	2.07	0.94299	1.43374	0.09750
5	8571	8556	3.57	0.000073	-0.046507	0.025356	0.00246	-2.73629	0.67	2.18	1.24677	2.30243	0.13311
6	7691	7684	3.97	0.000074	-0.043626	0.025573	0.00258	-2.73107	0.68	2.29	1.14112	1.97297	0.12072
7	6955	6938	4.40	0.000076	-0.035910	0.025573	0.00268	-2.55770	0.69	2.39	1.05825	1.74011	0.11120
8	6418	6413	4.76	0.000085	-0.032864	0.025573	0.00279	-2.60996	0.70	2.48	1.08577	1.81656	0.11440
10	5638	5637	5.42	0.000073	-0.038849	0.025356	0.00298	-2.79295	0.71	2.59	0.82773	1.17588	0.08472
12	5124	5126	5.96	0.000070	-0.039973	0.025356	0.00317	-3.02823	0.72	2.68	0.71700	0.94455	0.07204
20	3584	3594	8.51	0.000005	-0.039359	0.026547	0.00372	-2.99962	0.72	2.71	0.03260	-0.01722	-0.00181
24	3265	3281	9.33	0.000017	-0.044553	0.026547	0.00389	-3.11648	0.74	2.89	0.11410	0.06628	0.00674

AUD/USD

h	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
3	11846	11877	2.58	0.000162	-0.060970	0.027110	0.00280	-2.91880	0.65	2.04	3.83208	41.01760	0.47848
4	9825	9866	3.10	0.000173	-0.077383	0.027110	0.00305	-3.75035	0.66	2.11	3.40677	26.49292	0.41431
5	8544	8603	3.56	0.000206	-0.077383	0.027110	0.00329	-3.58511	0.67	2.24	3.53212	30.12427	0.43279
6	7604	7671	4.00	0.000189	-0.062321	0.027110	0.00349	-3.31450	0.68	2.33	2.88647	15.32168	0.33924
7	6883	6953	4.41	0.000176	-0.065188	0.027110	0.00367	-3.37225	0.70	2.46	2.43456	9.38819	0.27742
8	6383	6439	4.76	0.000181	-0.065188	0.027110	0.00381	-3.30947	0.70	2.56	2.31494	8.21476	0.26150
10	5695	5739	5.34	0.000191	-0.061564	0.027110	0.00400	-3.33763	0.72	2.70	2.18216	7.08094	0.24429
12	5109	5157	5.95	0.000167	-0.060914	0.027110	0.00424	-3.58650	0.72	2.76	1.71270	4.04987	0.18458
20	3736	3786	8.12	0.000086	-0.105722	0.025295	0.00504	-4.71496	0.74	2.97	0.64916	0.73652	0.05943
24	3317	3366	9.14	0.000052	-0.098318	0.025295	0.00525	-4.30330	0.74	2.97	0.34618	0.28750	0.02679

CAD/USD

h	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
3	11993	11952	2.55	0.000121	-0.041575	0.019048	0.00205	-2.96958	0.66	2.15	2.89920	16.26395	0.34713
4	9999	9969	3.06	0.000134	-0.041575	0.019048	0.00223	-3.03259	0.67	2.24	2.67407	12.79116	0.31585
5	8834	8808	3.46	0.000169	-0.038881	0.019048	0.00235	-2.91679	0.69	2.43	2.98479	17.82968	0.35941
6	7895	7875	3.87	0.000179	-0.040056	0.019048	0.00248	-3.06105	0.70	2.56	2.82857	15.10957	0.33741
7	7217	7183	4.24	0.000171	-0.040840	0.019048	0.00259	-3.10029	0.71	2.65	2.46028	10.15009	0.28691
8	6709	6675	4.56	0.000165	-0.041859	0.019048	0.00268	-3.27717	0.72	2.73	2.20655	7.65415	0.25325
10	5923	5891	5.17	0.000166	-0.041859	0.019048	0.00282	-3.06610	0.72	2.76	1.95914	5.76418	0.22136
12	5399	5354	5.68	0.000179	-0.052599	0.019048	0.00297	-3.30045	0.73	2.83	1.92639	5.54456	0.21715
20	3794	3763	8.08	0.000131	-0.060864	0.019679	0.00357	-3.93342	0.73	2.85	0.98713	1.55593	0.10314
24	3256	3223	9.42	0.000071	-0.060864	0.017144	0.00377	-3.90376	0.73	2.89	0.45761	0.50862	0.04395

CHF/USD

h	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
3	11910	11892	2.56	0.000066	-0.029733	0.022062	0.00222	-2.45715	0.65	2.01	1.57375	3.54772	0.17167
4	9913	9882	3.08	0.000077	-0.038410	0.022062	0.00244	-2.77728	0.67	2.15	1.51571	3.29115	0.16458
5	8624	8577	3.55	0.000078	-0.040469	0.025007	0.00260	-2.78491	0.68	2.26	1.34743	2.62853	0.14432
6	7699	7646	3.98	0.000082	-0.040469	0.025007	0.00274	-2.74096	0.69	2.40	1.26218	2.33471	0.13426
7	7033	6966	4.36	0.000089	-0.040469	0.025007	0.00286	-2.70219	0.71	2.54	1.24821	2.28926	0.13263
8	6460	6398	4.75	0.000077	-0.040469	0.025102	0.00299	-2.67285	0.71	2.57	0.99007	1.54040	0.10244
10	5729	5660	5.36	0.000075	-0.040469	0.025007	0.00317	-2.62569	0.72	2.65	0.85375	1.21743	0.08687
12	5187	5113	5.92	0.000063	-0.036619	0.025007	0.00331	-2.57821	0.72	2.72	0.64445	0.79976	0.06340
20	5187	5113	5.92	0.000063	-0.036619	0.025007	0.00331	-2.57821	0.72	2.72	0.64445	0.79976	0.06340
24	3219	3180	9.53	0.000009	-0.092903	0.016301	0.00424	-4.27195	0.74	2.88	0.05516	-0.00299	-0.00031

SEK/USD

h	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
3	11999	11948	2.54	0.000128	-0.045618	0.022115	0.00260	-2.54028	0.67	2.04	3.05692	18.60116	0.36514
4	9905	9839	3.08	0.000135	-0.039703	0.022115	0.00286	-2.75099	0.68	2.14	2.67435	12.36717	0.31156
5	8651	8563	3.54	0.000144	-0.040464	0.022115	0.00307	-2.73328	0.69	2.23	2.47551	9.95193	0.28450
6	7764	7668	3.95	0.000147	-0.040464	0.022115	0.00325	-2.78543	0.70	2.39	2.26337	7.85816	0.25630
7	7023	6920	4.37	0.000140	-0.040464	0.022115	0.00339	-2.79053	0.72	2.54	1.95027	5.48672	0.21602
8	6457	6378	4.74	0.000133	-0.040464	0.022115	0.00350	-2.74022	0.72	2.59	1.71277	4.12158	0.18633
10	5734	5644	5.35	0.000132	-0.040464	0.022115	0.00370	-2.75055	0.72	2.64	1.50311	3.15695	0.16071
12	5167	5090	5.94	0.000114	-0.040957	0.022115	0.00387	-2.79209	0.72	2.65	1.17024	1.98280	0.12111
20	5167	5090	5.94	0.000114	-0.040957	0.022115	0.00387	-2.79209	0.72	2.65	1.17024	1.98280	0.12111
24	3240	3188	9.47	0.000027	-0.062036	0.022115	0.00497	-3.61007	0.74	2.85	0.17594	0.10031	0.01005

ZAR/USD

h	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
3	11822	11855	2.48	0.000405	-0.151639	0.041790	0.00411	-4.17919	0.69	2.36	9.58775	11884.85	1.66845
4	10019	10043	2.93	0.000507	-0.150959	0.041790	0.00443	-4.27558	0.71	2.58	10.17981	21547.99	1.83980
5	8850	8867	3.32	0.000554	-0.164366	0.041790	0.00475	-5.07489	0.73	2.77	9.81070	14835.37	1.73106
6	7993	8002	3.67	0.000594	-0.158662	0.041790	0.00496	-4.67651	0.74	2.93	9.50523	10969.66	1.64617
7	7428	7428	3.95	0.000657	-0.150182	0.041790	0.00511	-4.39362	0.75	3.12	9.75380	14093.03	1.71644
8	6913	6913	4.25	0.000681	-0.150182	0.041790	0.00523	-4.39290	0.76	3.20	9.41900	10132.21	1.62429
10	6215	6193	4.73	0.000678	-0.147505	0.034474	0.00545	-4.42189	0.76	3.23	8.41177	3719.33	1.36315
12	5667	5629	5.20	0.000669	-0.137320	0.047354	0.00570	-4.08133	0.76	3.24	7.55239	1576.10	1.16025
20	3948	3926	7.45	0.000581	-0.120511	0.038935	0.00689	-4.45862	0.76	3.29	4.57321	78.9496	0.58139
24	3478	3453	8.47	0.000508	-0.113801	0.030616	0.00719	-4.45367	0.77	3.39	3.51963	27.0948	0.41752

EUR/JPY

h	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
3	11832	11862	2.58	0.000063	-0.053434	0.029090	0.00254	-3.05215	0.65	1.98	1.50423	3.16769	0.16103
4	9797	9839	3.11	0.000076	-0.075201	0.029090	0.00281	-3.70022	0.66	2.09	1.48688	3.09086	0.15877
5	8473	8520	3.59	0.000079	-0.068212	0.033665	0.00300	-3.29539	0.68	2.20	1.34362	2.54812	0.14165
6	7553	7600	4.03	0.000071	-0.052847	0.033665	0.00315	-3.13903	0.69	2.31	1.06910	1.70001	0.10949
7	6831	6887	4.45	0.000063	-0.059794	0.028589	0.00329	-3.33704	0.69	2.38	0.86669	1.20752	0.08636
8	6331	6390	4.80	0.000075	-0.059794	0.029090	0.00342	-3.16590	0.70	2.45	0.95471	1.41053	0.09640
10	5549	5619	5.47	0.000071	-0.058685	0.033665	0.00365	-3.09998	0.71	2.60	0.79440	1.05313	0.07815
12	5037	5108	6.02	0.000060	-0.076662	0.033665	0.00384	-3.46052	0.72	2.71	0.61238	0.71043	0.05775
20	3690	3743	8.21	-0.000004	-0.088649	0.029257	0.00441	-4.17914	0.73	2.83	-0.02957	-0.09754	-0.01068
24	3260	3322	9.28	-0.000029	-0.095169	0.029090	0.00478	-4.74428	0.74	2.90	-0.19180	-0.23533	-0.02768

EUR/GBP

h	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
3	12323	12334	2.48	0.000153	-0.029164	0.012740	0.00162	-2.93734	0.67	2.39	3.78332	41.54109	0.48039
4	10349	10353	2.95	0.000155	-0.028302	0.014894	0.00177	-3.16113	0.68	2.49	3.20701	22.90576	0.39378
5	9091	9086	3.36	0.000163	-0.027707	0.014894	0.00188	-3.14452	0.69	2.58	2.96054	17.69049	0.35836
6	8157	8150	3.75	0.000165	-0.030822	0.014894	0.00197	-3.20762	0.70	2.70	2.68845	13.24581	0.32032
7	7495	7501	4.08	0.000171	-0.030195	0.014894	0.00204	-3.21055	0.71	2.85	2.56612	11.60986	0.30358
8	6906	6916	4.42	0.000172	-0.031263	0.014894	0.00213	-3.26323	0.72	2.93	2.37900	9.45587	0.27828
10	6170	6185	4.95	0.000178	-0.052229	0.014894	0.00227	-3.97226	0.73	3.10	2.20515	7.78366	0.25519
12	6170	6185	4.95	0.000178	-0.052229	0.014894	0.00227	-3.97226	0.73	3.10	2.20515	7.78366	0.25519
20	4023	4022	7.60	0.000109	-0.047550	0.014894	0.00289	-4.53875	0.75	3.25	0.87664	1.32262	0.09215
24	3562	3566	8.57	0.000103	-0.051368	0.015989	0.00309	-4.54131	0.76	3.39	0.73517	1.01517	0.07605

EUR/CHF

h	N (Long)	N (Short)	Average Holding Period (hours)	Mean	Min	Max	Std. Dev.	Skewness	% of win	P_T/L_T	Total Return	Cumulative Return	Average Annual Return
3	12521	12535	2.44	0.000125	-0.036415	0.008695	0.00103	-4.91432	0.68	2.50	3.14346	21.87318	0.38736
4	10532	10572	2.90	0.000135	-0.039859	0.008214	0.00112	-5.68039	0.70	2.67	2.85406	16.12543	0.34599
5	9221	9246	3.31	0.000145	-0.037823	0.008028	0.00121	-5.76209	0.71	2.82	2.68224	13.41894	0.32199
6	8378	8406	3.64	0.000158	-0.035661	0.008663	0.00125	-4.99448	0.73	3.01	2.65837	13.08457	0.31875
7	7655	7671	3.99	0.000162	-0.035661	0.008861	0.00130	-5.21146	0.74	3.15	2.48508	10.84519	0.29508
8	7165	7163	4.27	0.000170	-0.035661	0.008269	0.00132	-5.14443	0.75	3.27	2.43126	10.22826	0.28785
10	6414	6385	4.78	0.000184	-0.035661	0.007607	0.00139	-5.13762	0.76	3.48	2.35755	9.43325	0.27800
12	5908	5875	5.19	0.000193	-0.035661	0.008695	0.00143	-5.16946	0.77	3.62	2.27002	8.56120	0.26638
20	4424	4430	6.90	0.000196	-0.033432	0.011985	0.00162	-4.86378	0.79	3.93	1.73596	4.60738	0.19763
24	3998	4015	7.63	0.000179	-0.034445	0.011985	0.00172	-4.95467	0.79	4.09	1.43790	3.16142	0.16084

2. Profitability Results with Zero Transaction Costs (Weekly Returns)

Note: See Table VII for details

EUR/USD

h	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio
3	48	-0.054439	0.079835	0.00293	0.01393	0.46041	0.17967
4	40	-0.0714	0.0652	0.0026	0.0133	-0.1394	0.16029
5	34	-0.0830	0.0776	0.0023	0.0134	-0.0348	0.13919
6	31	-0.0644	0.0797	0.0021	0.0132	0.2360	0.12557
7	28	-0.0670	0.0493	0.0017	0.0127	-0.0978	0.10087
8	26	-0.0670	0.0618	0.0010	0.0129	0.0845	0.04652
10	20	-0.0488	0.0442	0.0005	0.0129	0.0755	0.00366
12	14	-0.0949	0.0438	-0.0010	0.0139	-0.4286	-0.10269
20	14	-0.0949	0.0438	-0.0010	0.0139	-0.4286	-0.10269
24	13	-0.1094	0.0784	-0.0008	0.0145	-0.5552	-0.0835

GBP/USD

h	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio
3	47	-0.064124	0.078533	0.00252	0.01376	0.14671	0.18276
4	40	-0.0538	0.0433	0.0025	0.0129	-0.2868	0.19048
5	34	-0.0517	0.0686	0.0030	0.0127	0.0934	0.23626
6	31	-0.0542	0.0441	0.0026	0.0118	-0.1041	0.22176
7	28	-0.0587	0.0440	0.0023	0.0126	-0.0908	0.18597
8	26	-0.0700	0.0439	0.0019	0.0128	-0.3448	0.14856
10	23	-0.0677	0.0528	0.0015	0.0132	-0.1314	0.11735
12	21	-0.0687	0.0408	0.0011	0.0123	-0.2588	0.08605
20	15	-0.0816	0.0638	-0.0006	0.0131	-0.0749	-0.04503
24	13	-0.0779	0.0608	-0.0006	0.0130	-0.1292	-0.0480

JPY/USD

h	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio
3	48	-0.071902	0.049836	0.00243	0.01453	-0.35271	0.13747
4	40	-0.0878	0.0529	0.0019	0.0135	-0.6466	0.10703
5	34	-0.0894	0.0631	0.0025	0.0136	-0.3868	0.15216
6	31	-0.0901	0.0443	0.0023	0.0137	-0.4995	0.13528
7	28	-0.0578	0.0521	0.0021	0.0136	-0.0501	0.12420
8	26	-0.0381	0.0668	0.0022	0.0130	0.3016	0.13396
10	23	-0.0407	0.0791	0.0016	0.0128	0.5176	0.09497
12	21	-0.0432	0.0788	0.0014	0.0136	0.5645	0.07356
20	14	-0.0419	0.0896	0.0001	0.0132	0.7286	-0.02876
24	13	-0.0559	0.0817	0.0002	0.0134	0.4731	-0.0158

AUD/USD

h	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio
3	48	-0.118621	0.156889	0.00773	0.02020	0.98700	0.36165
4	40	-0.1238	0.1045	0.0068	0.0178	-0.2796	0.36060
5	34	-0.0839	0.1056	0.0071	0.0181	0.5173	0.36830
6	31	-0.0833	0.0823	0.0058	0.0178	-0.2337	0.30133
7	28	-0.0726	0.0723	0.0049	0.0176	0.0750	0.25157
8	26	-0.0825	0.1116	0.0046	0.0181	0.2576	0.23225
10	23	-0.0736	0.0871	0.0044	0.0180	0.1330	0.21902
12	21	-0.0659	0.0913	0.0034	0.0178	0.4091	0.16773
20	15	-0.1619	0.0945	0.0013	0.0190	-0.9844	0.04534
24	13	-0.1107	0.0929	0.0007	0.0187	-0.0834	0.0135

CAD/USD

h	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio
3	48	-0.040435	0.093568	0.00315	0.01464	0.63742	0.21524
4	40	-0.1191	0.0775	0.0031	0.0156	-0.5056	0.19507
5	35	-0.1231	0.0833	0.0027	0.0155	-0.5214	0.17455
6	31	-0.0955	0.0665	0.0025	0.0150	-0.2795	0.16879
7	28	-0.0943	0.0738	0.0025	0.0150	-0.0303	0.16719
8	26	-0.0661	0.0637	0.0020	0.0143	0.2636	0.13808
10	23	-0.0380	0.0559	0.0017	0.0138	0.2937	0.12288
12	21	-0.0442	0.0576	0.0013	0.0138	0.2931	0.09248
20	15	-0.0948	0.0564	0.0002	0.0146	-0.3328	0.01105
24	13	-0.0948	0.0576	0.0001	0.0150	-0.1769	0.0071

CHF/USD

h	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio
3	48	-0.040435	0.093568	0.00315	0.01464	0.63742	0.21524
4	40	-0.1191	0.0775	0.0031	0.0156	-0.5056	0.19507
5	35	-0.1231	0.0833	0.0027	0.0155	-0.5214	0.17455
6	31	-0.0955	0.0665	0.0025	0.0150	-0.2795	0.16879
7	28	-0.0943	0.0738	0.0025	0.0150	-0.0303	0.16719
8	26	-0.0661	0.0637	0.0020	0.0143	0.2636	0.13808
10	23	-0.0380	0.0559	0.0017	0.0138	0.2937	0.12288
12	21	-0.0442	0.0576	0.0013	0.0138	0.2931	0.09248
20	15	-0.0948	0.0564	0.0002	0.0146	-0.3328	0.01105
24	13	-0.0948	0.0576	0.0001	0.0150	-0.1769	0.0071

SEK/USD

h	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio
3	48	-0.071331	0.078821	0.00615	0.01792	0.00263	0.34334
4	40	-0.0629	0.0890	0.0054	0.0184	-0.0051	0.29226
5	35	-0.0644	0.0844	0.0050	0.0177	-0.0935	0.28158
6	31	-0.0654	0.0962	0.0045	0.0173	0.0377	0.26240
7	28	-0.0667	0.0808	0.0039	0.0171	-0.0273	0.22793
8	26	-0.0581	0.0660	0.0034	0.0168	-0.1134	0.20432
10	23	-0.0578	0.0683	0.0030	0.0168	-0.2472	0.17919
12	21	-0.0689	0.0566	0.0023	0.0162	-0.2469	0.14398
20	21	-0.0689	0.0566	0.0023	0.0162	-0.2469	0.14398
24	13	-0.0773	0.0810	0.0003	0.0171	-0.1086	0.0198

ZAR/USD

h	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio
3	48	-0.195525	0.193129	0.01957	0.03230	-0.02692	0.60591
4	40	-0.1939	0.1332	0.0208	0.0320	-0.2472	0.64925
5	36	-0.1929	0.1301	0.0200	0.0316	-0.4262	0.63283
6	32	-0.1624	0.1752	0.0194	0.0318	0.0084	0.60898
7	30	-0.1321	0.1903	0.0199	0.0318	0.1852	0.62563
8	28	-0.1117	0.1726	0.0192	0.0309	0.2119	0.62159
10	25	-0.0791	0.1117	0.0171	0.0299	0.1102	0.57296
12	23	-0.0715	0.1429	0.0153	0.0288	0.2555	0.53245
20	16	-0.1020	0.1400	0.0093	0.0288	0.2683	0.32134
24	14	-0.1134	0.1527	0.0072	0.0299	0.4280	0.2402

EUR/JPY

h	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio
3	48	-0.115092	0.113402	0.00304	0.01851	-0.67056	0.16441
4	39	-0.0963	0.1105	0.0030	0.0177	-0.0248	0.16886
5	34	-0.1193	0.0925	0.0027	0.0180	-0.0760	0.15080
6	30	-0.0955	0.0985	0.0021	0.0175	0.1932	0.12296
7	28	-0.1070	0.0969	0.0017	0.0172	0.0874	0.10100
8	26	-0.0879	0.0878	0.0019	0.0167	0.1406	0.11433
10	22	-0.0720	0.1152	0.0016	0.0171	0.4449	0.09296
12	20	-0.0849	0.1262	0.0012	0.0171	0.7178	0.07145
20	15	-0.1130	0.0721	-0.0001	0.0167	-0.3077	-0.00393
24	13	-0.1169	0.0742	-0.0004	0.0172	-0.2056	-0.0228

EUR/GBP

h	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio
3	50	-0.045493	0.072639	0.00764	0.01263	0.16258	0.60499
4	42	-0.0381	0.0394	0.0065	0.0120	-0.3822	0.53939
5	37	-0.0409	0.0481	0.0060	0.0113	-0.3040	0.52576
6	33	-0.0442	0.0389	0.0054	0.0109	-0.3383	0.49419
7	30	-0.0378	0.0369	0.0052	0.0106	-0.3255	0.48767
8	28	-0.0507	0.0448	0.0048	0.0109	-0.3401	0.43813
10	25	-0.0470	0.0556	0.0044	0.0114	-0.1901	0.38815
12	22	-0.0421	0.0549	0.0040	0.0108	-0.2376	0.37385
20	16	-0.0412	0.0343	0.0018	0.0109	-0.2213	0.16110
24	14	-0.0517	0.0456	0.0015	0.0115	-0.1233	0.1279

EUR/CHF

h	Average Trades/Week	Min	Max	Mean	Std. Dev.	Skewness	Sharpe Ratio
3	50	-0.038003	0.056307	0.00634	0.00862	0.14470	0.73604
4	42	-0.0475	0.0426	0.0058	0.0086	-0.5757	0.66840
5	37	-0.0556	0.0310	0.0054	0.0084	-1.0333	0.64522
6	34	-0.0325	0.0296	0.0054	0.0079	-0.4552	0.67850
7	31	-0.0356	0.0269	0.0050	0.0082	-0.7094	0.61384
8	29	-0.0349	0.0265	0.0049	0.0081	-0.7374	0.60353
10	26	-0.0299	0.0366	0.0047	0.0077	-0.3665	0.61932
12	24	-0.0301	0.0286	0.0046	0.0075	-0.3923	0.61177
20	18	-0.0242	0.0248	0.0035	0.0074	-0.1952	0.47093
24	16	-0.0311	0.0281	0.0029	0.0075	-0.2251	0.3837