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On Uncertainty, Market Timing and the Predictability of Tick by Tick Exchange Rates

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Abstract

This paper examines the predictability of exchange rates on a transaction level basis using both past transaction prices and the structure of the order book. In contrast to the existing literature we also recognise that the trader may be subject to (Knightian) uncertainty as opposed to risk regarding the structure by which exchange rates are determined and hence regarding both the model he employs to make predictions and the reliability of any conditioning information. The trader is faced with a two stage decision problem due to this uncertainty; first he needs to resolve a question of market timing as to when to enter the market and then secondly how to trade. We provide a formalisation for this two stage decision problem. Statistical tests indicate the significance of out of sample ability to predict directional changes and the economic value of predictability using one week of tick-by-tick data on the USD-DM exchange rate drawn from Reuters DM2002 electronic trading system. These conclusions rest critically on the frequency of trading which is controlled by an inertia parameter reflecting the degree of uncertainty; trading too frequently significantly reduces profitability taking account of transaction costs.

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Key words: Knightian uncertainty, market timing, predictability, high-frequency data.

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1 Introduction

Considerable research has been devoted over a number of years to examining the predictability of foreign exchange rates following the classic paper by Meese and Rogoff (1983). One reasonable interpretation of this work is that it has been found to be difficult to convincingly overturn their result regarding the inability of standard “macro” based exchange rate models to beat a random walk in out of sample forecasting exercises. Clearly this broad statement could be qualified as research has appeared which claims to provide evidence of predictability in particular exchange rates and over particular sample periods (see for instance Abhyankar, Sarno and Valente (2005)) but the general impression remains that standard fundamentals based models do not consistently dominate a random walk.

At the same time there has been a major development in what has become known as the New Micro Approach to Exchange Rates (see for instance Lyons (2001)) in which attention is focussed more on the characteristics and micro structure of the FX market itself rather than the macro fundamentals that drive the traditional theories of exchange rate determination. In the light of Meese and Rogoff’s results this distinction is critical since any statement regarding predictability is necessarily conditional on the information set employed. A variable may appear to be completely unpredictable if irrelevant data is used as the conditioning information and yet may be highly predictable if the correct conditioning data is used. While both approaches, micro and macro, seek to explain the same exchange rate which is determined on a tick by tick basis in the spot market, they obviously differ critically in the information sets they use to explain exchange rate movements and hence forecast.

In this paper we present what we believe to be the first rigorous tests of predictability of an exchange rate using irregularly spaced tick by tick FX data where the information set involves both the past price history and information on the structure of the order book. Secondly we attempt to formally recognise the uncertainty that a foreign exchange trader faces given that any model he uses to generate forecasts and trading decisions will be incorrect in ways that he cannot capture in a unique probability distribution. We therefore allow our trader’s decisions to reflect Knightian Uncertainty rather than simply risk. In short we find clear evidence of predictability both in terms of directional change and economic value after taking account of transactions costs when the frequency of trades is controlled. The predictors are based on genetic algorithms applied to the tick by tick data and evaluated over a three day out of sample period. White’s reality check is employed to insulate the results from any data snooping bias. The prediction rules are also compared with the results from applying several classic Technical Rules which are shown to indicate substantially less predictability and profitability than the GA trading rules we employ. A further some-

what surprising result is that we find little or no advantage in allowing the predictor to exploit information in the order book. This result is exactly the opposite of what we had expected before carrying out the empirical work but would be consistent with the market price acting as a sufficient statistic and hence that no further information is useful.

Our objective is not to re-examine the question of the predictability of technical rules but to mirror the way in which technical rules appear to be used in practice by currency traders when making their trading decisions. In the first place, there is considerable evidence (see for instance Taylor and Allen (1992), Lui and Mole (1996)) that traders largely use technical rules only for short run decision making, which justifies our use of tick by tick data. Traders also do not follow a single rule but form an impression as to where the market is moving on the basis of a number of technical indicators, dropping those that appear not to have worked well.¹ Secondly we formalise the sequential decision making seen in financial markets where an initial decision must be taken as to when to enter the market – the question of market timing – alongside the decision of how to trade. The market timing decision is intimately related to the degree of uncertainty the trader faces; when he is confident in the direction the market is moving he will act quickly and when he is uncertain he will show inertia and be reluctant to trade.

Our results would seem to justify the investment that has been made by a number of financial institutions to develop and apply automatic trading systems². This does suggest the correct interpretation of the Messe and Rogoff conclusion lies in the fact that the correct conditioning information set had not been used rather than that exchange rates are in fact unpredictable. In addition we show that even when you have the correct information it is critically how and when it is used that determines if profitability will appear since unless the frequency of trading is controlled, profitability disappears. The frequency of trading is controlled by means of an “inertia” parameter reflecting the degree of uncertainty and ensures the system can only trade when the predicted price change is beyond some threshold level (taking transactions costs into account). Human traders clearly do not trade in real time as frequently as our unconstrained trading rules would suggest and so restricting the frequency of trades simply reflects reality.

In the next sections we briefly review the existing literature in this area and then discuss the derivation and application of the Genetic Algorithm trading rules, the testing procedures we have employed before turning to report our results.

¹We have benefited from detailed discussions with the chief currency trader at the Bank of England and the Royal Bank of Scotland regarding their use of technical analysis.

²We know, for instance, of one major bank that has an automatic trading system in place that inspects 1200 currency pairs in real time and we are told delivers profits of the order of 500 million Euro annually.

2 Predictability and Market Timing

Most existing statistical analysis suggests at best weak predictability in the FX market. At the same time, we can clearly observe trends, *ex post*, in exchange rates over particular periods of time which might imply *ex ante* short term predictability if the correct conditioning information can be found and potentially short term arbitrage opportunities. To state the obvious; the issue of market timing is intimately connected to the degree of predictability in a market. Even if there is no predictability over a long period or on average, it may be possible to forecast at some point of time over a short period. It may be more important to identify these moments in time rather than attempting to find a predictor which has good properties on average as is traditionally the case.

In the paper we use a two stage combined predictor in which the first step provides a market timing indicator and the second gives a forecast of the future exchange rate and a related trade. The market timing indicator effectively serves as a filter, extracting irrelevant or uncertain information and noise from the time series data and then the trader uses this filtered information set to take decisions in the market.

The more formal description of the individual's preferences is given in the following section.

2.1 Uncertainty Aversion and Inertia

An investor in real life is invariably faced with different types of uncertainty while making trading decisions in a market. This uncertainty might be due to changing market structure, estimation error or model uncertainty, lack of information, imprecision of information or imperfect trading signals. Risk is defined by the probability of events described by an assumed model structure and a unique probability distribution. We are more concerned with capturing the uncertainty in decision making, beyond risk, which results if there is a lack of knowledge about which model and probability distribution to use. Risk calculus, as employed for instance in VaR or expected utility calculations, is relatively straightforward and provides a confidence interval as the basis for action. However, when we recognise that incorrect decisions can follow from inaccuracy in the assumed model or probability distribution we need to employ additional tools to decide whether to trust a predictor or not. Each transaction is costly because of transaction costs and if future prices do not change as predicted by the model the investor will inevitably lose money. In order to filter weak trading signals we need some rule that suggests you only trade if the predicted value exceeds some threshold that reflects the degree of uncertainty.

Knight's characterisation (Knight 1921) of uncertainty refers to situations when there is no unique probability model supporting traders' decisions. In this case ex-

pected utility fails to be an appropriate model by which to predict or make trading decisions. Technical indicators may in fact reflect the Knightian concept of uncertainty more accurately than expected utility based predictors since they are often viewed as distribution free methods of predicting future prices. However, even technical rules are recognised as being imprecise and may deliver incorrect forecasts which is why technical analysts tend to use several technical indicators simultaneously or interval based rules like Bollinger Bands or stop-loss strategies.

The use of these strategies brings some inertia to the trading process which makes trading less frequent. This notion of trading inertia is entirely consistent with the question of market timing since it implies that the investor does not trade at every feasible point of time but does so by trying to choose the best moment when to enter the market.

There are several ways how the theory of decision-making under uncertainty can be used to model the observed inertia in the market. One of the classic examples is the no-trade condition introduced by Dow and Werlang (1992). Once the trader observes this condition in the market, he becomes “uncertain” about a particular asset and excludes it from his portfolio and doesn’t trade the asset again until the condition disappears. This phenomenon describes some kind of extreme uncertainty aversion in the agent who will have different degrees of uncertainty regarding each asset in the market reflecting the different degree of confidence he has in his information set. It may also be that the investor is uncertain about the market as a whole in that he does not see value in any alternative to his current position. This implies that his position will change only if there is another portfolio which clearly dominates his existing portfolio.

2.1.1 The Market entry/ exit Decision

Theoretical support for preferences with trading inertia has been introduced by Bewley (1986) (see also Bewley (2002), Ghirardato, Maccheroni and Marinacci (2004)) and we now provide a short description of the simplified version of the Bewley’s approach that we will employ.

Uncertainty Averse Preferences. Let S be a set of *states* (of the market) and let \mathcal{B} be the σ -algebra of its Borel sets. An act is a measurable bounded function $f: S \rightarrow \mathbb{R}$ and let $L \subset \mathbb{R}^S$ be the set of all acts on S , i.e., a set of random payoffs available at the moment for decision-making. In our case we consider acts as the return the agent receives from his trades. Effectively, L represent a set of alternative strategies in the market to which the trader is restricted.

There is a binary preference relation \succ_{ua} (stands for ”uncertainty aversion”) defined on L and let it satisfy the following axioms.

A1. Monotonicity If $f(s) > g(s)$ for all $s \in S$ then $f \succ_{ua} g$.

A2. Transitivity If $f \succ_{ua} g$ and $g \succ_{ua} h$ then $f \succ_{ua} h$.

A3. Openness For all $f \in L$, $\{g \in L: g \succ_{ua} f\}$ is open L .

A4. Independence For all $f, g, h \in L$ and for all $\alpha \in (0, 1)$, $g \succ h$ if and only if $\alpha f + (1 - \alpha)g \succ_{ua} \alpha f + (1 - \alpha)h$.

Theorem 2.1. (Bewley, 2002) *If \succ_{ua} satisfies Axioms A1-A4, then there is a closed convex set \mathcal{P} of probability measures on S such that*

(i) *for all f and g and $B \in \mathcal{B}$ we have $f \succ_{ua} g$ if and only if $E_P(f) > E_P(g)$ for all $P \in \mathcal{P}$;*

(ii) *for all $P \in \mathcal{P}$, $P(B) > 0$ for each non-empty $B \in \mathcal{B}$.*

The set of probability measures \mathcal{P} reflects the trader's uncertainty. The key point in the preceding theorem is that the preference relation \succ_{ua} is not complete leading to a set of probability measures \mathcal{P} rather than a unique measure as in the expected utility theory. This means that there may exist two acts which are "incomparable" and the decision-maker can not distinguish which is better nor in fact whether he is indifferent as he does not have sufficient information to evaluate the different options. The notion of incomparability is critically distinct from indifference. The latter means that if the decision-maker is indifferent between f and g he will definitely prefer $f + \varepsilon$ rather than g if $\varepsilon > 0$. In the case of incomparability the investor needs more information beyond f in order to compare two alternatives. This may imply that the decision-maker is not fully rational as discussed in Bewley (2002). If the decision-maker can unambiguously distinguish between two acts then we say that acts f and g are "comparable" and denote this by $f \lesssim_{ua} g$.

There are different solutions as to how to act when there are incomparable portfolios in the market. One is to randomly choose one of them, another is to assume that the investor has a subjective distribution over the set of priors (a probability measure over probability measures) and carries out some form of averaging with respect to his beliefs. This approach leads to Bayesian Model Averaging and its generalization as discussed in Klibanoff, Marinacci and Mukerji (2005). Instead we adopt the inertia approach proposed in Bewley (2002). This implies that the decision-maker will change his portfolio only if a new portfolio strictly dominates it. In order to formalize this we denote by f_t the optimal portfolio for the investor at time t .

Inertia Assumption For each $t_1 < t_2$, $f_{t_1} \neq f_{t_2} \Leftrightarrow f_{t_2} \succ_{ua} f_{t_1}$.

This means that the next choice of the investor will need to strongly dominate the preceding position otherwise they coincide (the previous position will not be changed). He will not update the position in three further cases: if the alternative is worse than the current one, if he is indifferent between the alternative and the current position (i.e., their expected values with respect to all priors coincide) and if the alternative is "incomparable" with the current position. Thus, if the agent does not see any strictly

better alternative to his current portfolio he will not trade until the situation changes. If a new alternative arises which is preferable according to every measure in the prior set, the trader will change his current position. In a real market this inertia is also justified by the presence of transaction costs since an investor would have to pay to switch to an incomparable portfolio which would not be rational.

Although this representation of Bewley's preferences allows us to model trading inertia, it does not provide guidance as to which alternative to choose when faced with several "incomparable" positions each of which is strictly better than the current position. For example, Bewley's preferences do not provide an answer as to what the decision-maker holding the portfolio f should do if there exist g and h such that $g \succ_{ua} f$ and $h \succ_{ua} f$. It may happen that g and h are not comparable. If this is the case, the decision-maker will get a signal that he needs to change his current portfolio, given there are better portfolios than f in the market (both g and h in our case) but he does not know which alternative, g or h to choose.

In order to fill this gap we propose two different preference relations in the space of risky payoffs and construct a composite indicator which the decision-maker uses. The first indicator is based on Bewley's preferences \succ_{ua} as described above which represents the trader's perception of uncertainty and serves as a market timing indicator informing the trader that he should alter his current position. The second indicator, td , (stands for "trading") changes the trading direction and determines the quantity traded. We denote the corresponding preference relation by \succeq_{td} . We do not provide any specific axiomatization for the \succeq_{td} preference relation here as it may be any subjective predictor based on a *complete* preference relation that the trader is willing to use: either based on the expected utility model or a technical indicator or simply the trader's intuition.

The composite preference relation \succeq is then defined as follows:

$$g \succeq f \Leftrightarrow (g \leq_{ua} f) \wedge (g \succeq_{td} f).$$

Effectively decision-making based on the preference relation \succeq is split into two stages: market timing and trading. The uncertainty aversion preference relation \succ_{ua} does not indicate whether one asset is better than another; rather it provides the degree of confidence for the trader that the td indicator has predictive power at the particular point of time. It gives a signal whether it is possible to say that there is an asset structure which unambiguously dominates the current position. If this is the case then the td indicator specifies the clear action of the trader. This trading strategy reflects the "rules-of-thumb" used by technical traders in reality. Indeed, as we have already mentioned, generally technical traders use several indicators in order to be confident they correctly predict the future market direction. Such a composite indicator is more robust since the trading signal is confirmed by both the td and ua rules.

In order to specify the preference relation more precisely we shall make use of a

simple example. Assume that there are two assets in the market – one risky and one risk-free. The agent has only three possibilities: invest his wealth in the risk-free asset, invest everything in risky asset or take a short position in the risky asset which is equal to his current wealth. The current wealth level is denoted by W_0 . The current price of the risky asset is p_0 and its future price is a positive random variable p . The gross return of the risk-free asset is $1+r$. In order to define the set of priors for the model we fix a measure P_0 on the probability space (S, \mathcal{B}) . We assume that all measures in the set \mathcal{P} are absolutely continuous with respect to the measure P_0 . By the Radon-Nikodym theorem for every measure $Q \in \mathcal{P}$ there exists a non-negative random variable η_Q with $E_{P_0}(\eta_Q) = 1$, such that $dQ = \eta_Q dP_0$. Therefore, we can identify the set of priors \mathcal{P} with the set of their Radon-Nikodym derivatives with respect to the probability measure P_0 .

The price expectation under the measure Q can be expressed as $E_Q(p) = \tilde{p} + k_Q$, where $\tilde{p} = E_{P_0}(p)$ and $k_Q = \text{cov}_{P_0}(p, \eta_Q)$. Indeed, $E_Q(p) = E_{P_0}(\eta_Q p) = \text{cov}_{P_0}(p, \eta_Q) + E_{P_0}(p)E_{P_0}(\eta_Q) = k_Q + \tilde{p}$.

Let the set of Radon-Nikodym derivatives of the measures in \mathcal{P} satisfy the condition $C = \{\text{cov}_{P_0}(p, \eta_Q) : Q \in \mathcal{P}\} = [-k_{\min}, k_{\max}]$ with $k_{\min}, k_{\max} > 0$. This assumption characterises the set of priors of the decision-maker.

Let the investor initially only hold the risk-free asset. Then, according to Theorem 2.1, under the above preferences he will decide to switch to the risky asset if $E_Q(\frac{p}{p_0}) > E_Q(1+r) = 1+r$ for all $Q \in \mathcal{P}$, or equivalently $\tilde{p} + k > p_0(1+r)$ for all $k \in [-k_{\min}, k_{\max}]$. Thus, the agent takes a long position if $\tilde{p} > p_0(1+r) + k_{\min}$.

If the agent decides to double his holding in the risk-free asset, he borrows $\frac{W_0}{p_0}$, converts it into cash and invests in the risky asset. At the end of the next period the investor buys $\frac{W_0}{p_0}$ shares of the risky asset and repays his debt. Thus, the final wealth can be calculated by $W_1 = 2W_0(1+r) - \frac{W_0 p}{p_0}$ and the return of the short position is $2(1+r) - \frac{p}{p_0}$.

The investor will prefer the short position to the risk-free asset if $2(1+r) - \frac{E_Q(p)}{p_0} > 1+r$ or equivalently $\tilde{p} < p_0(1+r) - k_{\max}$. Combining these two inequalities we conclude that if $p_0(1+r) - k_{\max} \leq \tilde{p} \leq p_0(1+r) + k_{\min}$ the decision-maker decides to keep his portfolio unchanged according to the inertia assumption.³ In the case $k = k_{\min} = k_{\max}$ (a symmetric band) the latter inequality is simplified to $|\tilde{p} - p_0(1+r)| \leq k$.

The main implication of the example is that there exists a no-trade band around the predicted value of the alternative portfolio which determines the market timing condition. That is, if the value of the proposed portfolio lies within the band then the investor does not rebalance his current portfolio and the converse implies the “trade” signal.

Note that our no-trade band is different from the no-trade condition of Dow and

³We can also obtain the inertia band under more relaxed assumption for the multiple prior set, e.g., $C = \{\text{cov}_{P_0}(p, \eta_Q) : Q \in \mathcal{P}\} \subset \mathbb{R}$ is bounded and $\inf C = -k_{\min}$ and $\sup C = k_{\max}$.

Werlang (1992). Under Dow and Werlang’s condition the investor exits the market and does not re-enter until the condition vanishes. In our case the trader does not exit the market but waits and holds his current portfolio until a better alternative arises.

We consider the simplest case with two assets in the market – long and short positions in the foreign currency. If denote by f the position held at time t which was bought at time t_0 for price p_{t_0} then we say that there exists a position g such that $f \lesssim_{ua} g \Leftrightarrow |p_{t_0} - p_t| > k$ for some pre-defined positive k , where p_t is the current price of the asset g . This can be interpreted as implying there is no asset structure in the market which dominates the one held until the transaction price change is predicted to be large enough. The constant k reflects trader’s subjective attitude to uncertainty in the market. The larger k , the wider the band of inertia which leads to less frequent trading. For the sake of simplicity below we use a symmetric interval for the market timing indicator. Once the price change happens to be big enough the trader uses the td indicator to determine his action in the market. In our case the td rule is provided by a genetic algorithm trading rule which is discussed in the following section.

3 Technical Analysis and Predictability

The debate as to whether using Technical Analysis results in significant profitability has probably been running ever since the Dow Theory came into existence between 1900-1902 when Charles Dow suggested that the direction of prices in “The Industrial Average”, made up of 12 blue chip stocks and “The Rail Average”, made up of 20 railroad companies appeared to be based on a set of rules.

In an early study Fama and Blume (1966), investigated the importance of Technical Rules while analyzing foreign exchange markets and Dooley and Shafer (1976) obtained results in favor of the profitability of similar filter rules. Sweeney (1986) confirmed these positive results and proved their statistical significance. Carol Osler has demonstrated in several papers (Osler (2003), Osler (2000), Chang and Osler (1999), Chang and Osler (1995) and Savin, Weller and Zvingelis (2007))the potential for profitability of more sophisticated technical rules in FX markets such as head and shoulder patterns. Whereas most technical indicators are based simply on historical prices or returns, other information also can be useful in order to form expectations of future prices. Neely and Weller (2001) show that including information on US foreign exchange interventions improves the profitability of their trading rules.

However, the practical relevance of much of this research has equally been called into question. Neely and Weller (2003) for instance emphasise the critical role of transaction costs and inconsistencies between the data used by practitioners and in academic simulations; although most traders transact in real time the majority of the earlier academic studies (Dooley and Shafer (1983), Sweeney (1986), Levich and Thomas (1993),

Neely, Weller and Dittmar (1997)) report the profitability from using technical rules but use daily or weekly data which is clearly unrealistic and misrepresents the information set available to the trader in practice when making a trade using technical analysis. The literature in which high-frequency trading rules are investigated is limited. Curcio, Goodhart, Guillaume and Payne (1997) consider intra-day FX data aggregated to one hour and find little or no evidence of profitability outside of periods when the exchange rate is trending. Neely and Weller (2003) using half hourly *quote* data find considerable out of sample predictability which does not translate into profitability once transaction costs are taken into account which they claim supports the efficiency of the FX market. The research most closely related to our own is that of Michael Dempster (Dempster and Jones (2001)) who applied GP generated rules to FX *transaction* data with one minute aggregation for trading but with indicators evaluated at fifteen minutes. To quote from their conclusions - they find “the return from the 20 strategy portfolio system trading at fifteen minute entry intervals is small and statistically insignificant and is in fact less than the interest differential between pounds and dollars over the same sample period. ... better excess returns would have been available from a static buy and hold strategy.... When only the best strategy is employed it is modestly and statistically significantly profitable (returning 7%)”.

We seek to extend this literature by focussing on transaction level data - in other words irregularly spaced transacted prices as opposed to quotes or temporally aggregated data and by including the structure of the order book in the information set available to the trader or automatic trading system. Secondly as discussed above we introduce uncertainty into the trading process. We also focus on rigorous testing of both directional change and economic value and use White’s reality check to immunise our results from any Data Snooping bias.

3.1 The Genetic Trading Rule

We want to consider evaluating predictability as generally as possible and so it is important not to restrict ourselves to examining the performance of a fixed set of prediction and trading rules. The Genetic algorithm (GA) provides an effective method for searching over a huge space of potential rules, both linear and non-linear, at each period. A GA is essentially a computer based optimization procedure which uses the evolutionary principle – the survival of the fittest – to find an optimum. It provides a systematic search process directed by performance rather than a gradient and in principle can find a global optimum in otherwise intractable problems if the required computing resources are available. In practice computational power is limited and so all GA rules, including those derived below, will not necessarily find the best possible performance but the best *given* the computing and time constraints we have been

forced to impose on the search process. Never the less the rules selected below will have evolved from searching over millions of competing rules and their performance is therefore known to be at least “good” if not achieving the global optimum. This is obviously sufficient for our purposes since if predictability is found with these “good” rules then we know we must at least have understated the potential degree of predictability that might exist. Moreover our results should have much greater applicability than those who have considered a fixed set of technical rules – however large ⁴.

3.2 Genetic Algorithm

Genetic algorithms have been successfully applied in a number of financial applications, most notably for our purposes, Dempster and Jones (2001), Dworman, Kimbrough and Laing (1996), Chen and Yeh (1997b), Chen and Yeh (1997a), Neely et al. (1997), Allen and Karjalainen (1999), Neely and Weller (2001), Chen, Duffy and Yeh (1999), Arifovic (1994), Arifovic (1995), Arifovic (1996), Arifovic (1997).

Starting from an initial set of rules a genetic algorithm evaluates the fitness of various candidate solutions (trading rules) using the given objective function of the optimization problem and provides as an output solutions that have higher fitness values. Two operations of crossover and mutation are applied to create a new generation of decision rules based on the genetic information of the fittest candidate solutions

Crossover operation: for the crossover operation one randomly selects two parents from the population based on their fitness, then take a node within each parent as a crossover point selected randomly and the subtrees at the selected nodes are exchanged to generate two children. One of the offspring then replaces the less fit parent in the population. In our implementation we use a crossover rate of 0.4 for all individuals in the population. This operation combines the features of two parent chromosomes to form two similar offspring by swapping corresponding segments of the parents. in our case these segments are represented by sub-nodes of binary tree. The intuition behind the crossover operator is information exchange between different potential solutions.

Mutation operation: to mutate a rule one selects one of its subtrees at random and replaces it with the new randomly generated tree. This operation guarantees the refreshment of the genetic code within the population. The best 25% of rules are not mutated at all and the remaining are mutated with probability 0.1. The intuition behind the mutation operator is the introduction of some extra variability into the population.

The elements of every trading rule are terminals and operations and the rule pro-

⁴We are also interested in the simplicity of the rules selected by the genetic program and how these may correspond to robust decision rules that may justified formally in the face of uncertainty as opposed to risk in financial markets.

vides a boolean value as the output. If the value of the rule is “true”, it gives the signal to “buy”USD, or equivalently, it indicates the USD-DM exchange rate is increasing. If the rule is “false” – the trader “sells”USD. The rules are represented in the form of randomly created binary trees with terminals and functions in their nodes. We employ the following choices of operations and terminals;

Operations: the function set used to define the technical rules consists of the binary algebraic operations $\{+, -, *, /, \max, \min\}$, binary order relations $\{<, >, \leq, \geq, =\}$, logical operations $\{\text{and}, \text{or}\}$ and unary functions $\{\text{abs}, -\}$ of absolute value and change of sign.

Terminals: the terminal set contains the variables $\{\text{pr}, \text{ret}, \text{lagpr1}, \text{lagpr2}, \text{lagret1}, \text{lagret2}, \text{maxpr5}, \text{maxpr10}, \text{maxpr20}, \text{minpr5}, \text{minpr10}, \text{minpr20}, \text{avgpr5}, \text{avgpr10}, \text{avgpr20}, \text{avgret5}, \text{avgret10}, \text{avgret20}\}$, where the first 6 variables indicate currently observed price and returns of USD in terms of DM and their lag values, maxpr and minpr as well as maxret and minret denote maximum and minimum price over the indicated period of the exchange rate and its return respectively, avgpr and avgret are average value prices and returns over the period. We should make clear that by “period” we mean the irregular instants of time when the transaction is realized.

For the cases when the algorithm searches over order book information we also use the following additional variables: bestbid, bestoffer, bestbidq, bestofferq, quantity, liqbid, liqoff, dpthbid, dpthoffer, time, which represent best bid, best offer, best bid quantity, best offer quantity, transaction quantity, liquidity from the bid side, liquidity from the offer side, market bid depth, market offer depth and duration between transactions in seconds respectively. All their first and second lagged values are also included in the information set.

The terminal set also includes real numbers in the range from 0 to 10 as terminal constants.

The following example illustrates the sort of trading rule that can be generated.

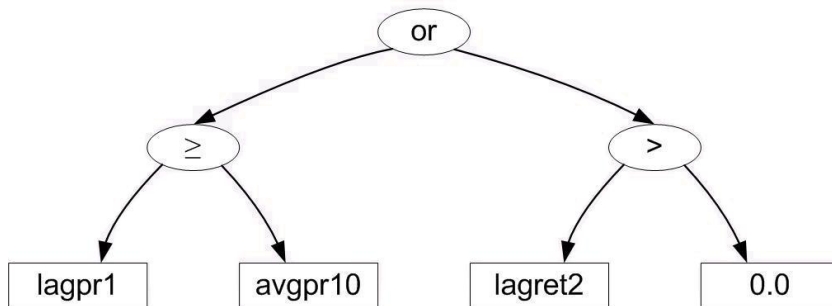


Figure 1: An example of a genetic tree for a trading rule

This example corresponds to the following trading rule:

– switch to USD if the lagged value of the exchange rate is greater than or equal to the average exchange rate over last 10 periods or the second lag of the return is greater than zero;

– otherwise hold DM.

The evolutionary algorithm can be summarized as follows:

1). Create randomly the initial population $P(0)$ and initialize the number of iterations $i = 0$.

2). Set $i := i + 1$.

3). Evaluate fitness of each tree in the population using the fitness function.

4). Generate a new population (i.e. the set of all genetic trees) using the genetic operations (crossover and mutation)

5). Repeat 2)–5) while $i < N$.

In the program we use the population size of 100 individuals and provide 50 iterations of the algorithm (that is, $N = 50$).

The complexity of trading rules are controlled in a probabilistic manner. In fact, the probability for a binary node to appear in the tree is smaller than the probability of a unary one which prevents the tree to become very large.

3.3 Fitness functions

A fitness value also needs to be assigned to each of the generated trees or trading rules in order to solve the optimization problem. We use three different fitness functions. First we consider the percentage of correctly predicted change of directions in the exchange rate by the composite technical rule. Although the trader as described in the previous section, does not make a transaction until the exchange rate changes sufficiently, the information received during the period when the trader remains passive is used to compute the current values. For example, if the exchange rate $e_{t-1} = e_t = e$, the values of variables price and lagpr1 are both set to e . We denote the percentage of correct directional change predictions by DC.

As a second fitness function we consider the economic value of the trading rule measured by the cumulative daily returns. We assume that the investor starts with an initial wealth in DM and considers whether to switch all their wealth into USD or take a short position in dollars. The investor is allowed to trade only if the exchange rate level exceeds the k inertia band created by uncertainty as discussed in the previous section. Let z_t denote the state of the investor's portfolio at time t . That is, $z_t = 1$ if they take a long position and $z_t = -1$ if they are short. We assume z_t does not change while the level of the exchange rate e_t lies within the k -band. The fitness of

each trading rule is then calculated as

$$R_c = \prod_t (1 + z_t r_t) - 1,$$

where $r_t = \frac{e_t - e_{t-1}}{e_{t-1}}$ is the one-period return of the exchange rate e_t . For convenience, we present the results adjusted to the daily basis form, i.e., $R = (1 + R_c)^{\frac{1}{2}}$ and $R = (1 + R_c)^{\frac{1}{3}}$ for in-sample (2 days) and out-of-sample (3 days) returns respectively.

A critical issue is how to take account of transaction costs when calculating the economic value of the trading rules. This provides the third form of the fitness function we consider. Under proportional transaction costs with rate θ the cumulative return can be calculated as

$$R_c^{\text{TC}} = \prod_t \frac{1 + z_t r_t}{(1 + 2\theta)^{h(z_t)}} - 1,$$

where $h(z_t) = \frac{|z_t - z_{t-1}|}{2}$.⁵

4 Data

The data we have used was provided by Reuters and represents all transaction and order book information on USD-DM trades on DM2000-2 electronic dealing system over the week starting 5th October 1998. This electronic market is open 24 hours each day of the week and we have not made any adjustments for overnight periods GMT. The dataset consists of details relating to the 18065 transactions that occurred during the week. It includes the transaction prices, best bid and ask quotes, transaction and best quote quantities, the duration between transactions, depth and liquidity on each side of the limit order book. We use the first two days (Monday and Tuesday) as the in-sample period which is used by the genetic programming in order to find those trading rules with the best performance. The out-of-sample period consists of the last three days and is used to examine the significance of the performance of the selected trading rules.

5 The Formal Testing Framework

Since the ability to predict the market's direction may not lead to excess profits if returns are greater in absolute value at times when mistakes on direction are made than at times when no mistakes on direction are made we need to consider predictability

⁵We have been provided with the transaction costs in terms of spreads used by a major UK based hedge fund.

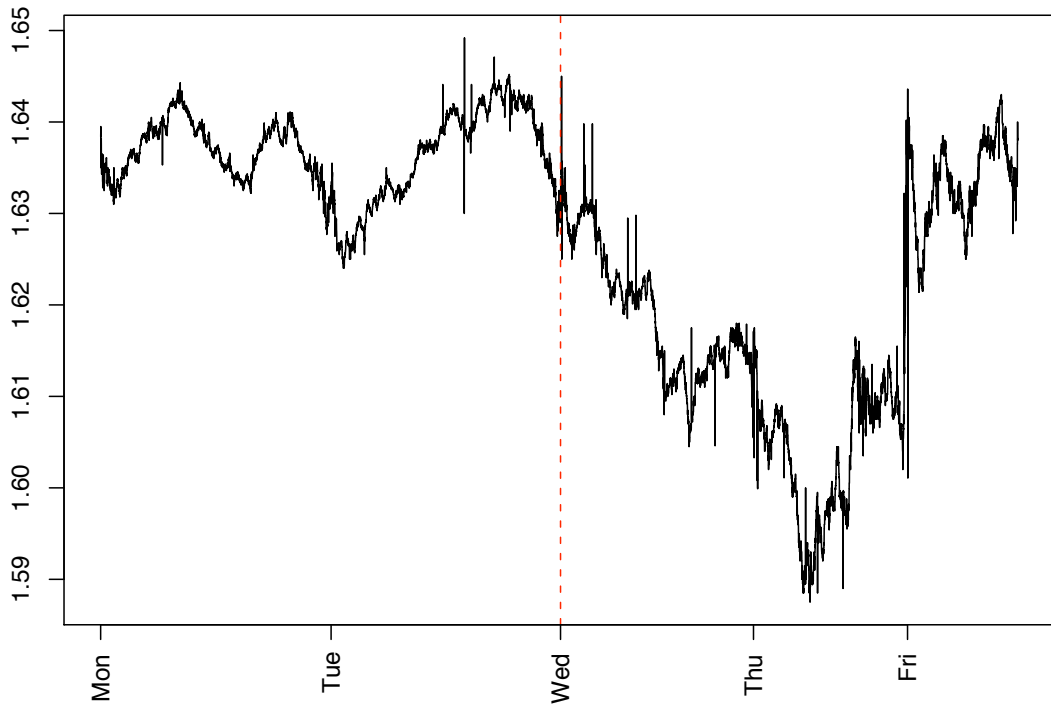


Figure 2: Tick-by-tick USD/DM exchange rate time series from 5.10.1998 to 9.10.1998. The in-sample period Monday – Tuesday, the out-of-sample period Wednesday – Friday.

both in terms of directional accuracy (DA) and economic value or excess predictability (EP) (see Anatolyev and Gerko (2005)). While a DA test like that proposed by Pesaran and Timmermann (see Pesaran and Timmermann (1992), Pesaran and Timmermann (1994)) will be significant in this case an EP statistic will not, hence we need to employ both. We briefly describe the DA and EP tests we have employed in Appendix.

In addition since our data is irregularly spaced and dependent we need to clarify exactly how we have implemented White’s Reality Check for Data Snooping. Data snooping involves the re-use of the same sample data in multiple hypothesis testing and not recognising the impact that prior decisions in the testing sequence have on the significance levels to be used at any stage subsequently down the chain. Our GP approach in fact carries out a simple machine search that involves no explicit inference and we also employ out of sample data to examine predictability but never the less the potential for data snooping still exists with the use of genetic algorithms and so we need to take the issue seriously. The correct statistical approach with sequential inference with multiple model selection is to employ Bonferroni Bounds but this would clearly be infeasible in our case with millions of rules to check and so we have no alternative but to employ simulation methods, in fact subsampling as opposed to the stationary bootstrap, to compute the Reality Check. Based on the procedure proposed by White (2000), the Reality Check enables us to calculate true empirical p -values of the test statistic based on the null of no predictability beyond the benchmark. The formal framework used for the Reality Check is provided in the Appendix.

As performance measures for the trading rules we naturally use the fitness functions defined in Section 3. Since the null hypothesis is formulated in terms of ability to beat a benchmark, in the case of testing for directional change we take the natural benchmark as 50%. That is, $\varphi^1 = DC - 50$. For the case of the economic value fitness function we consider a zero return as the benchmark (due to the symmetry present on the foreign exchange market). Thus, $\varphi^2 = \log(R)$ and $\varphi^3 = \log(R^{TC})$ for models without and with transaction costs respectively.

Since our data is irregularly spaced and dependent we need to be careful exactly how we have carried out the re-sampling in both the pure price and order book cases.

Pure price information

The case, where technical indicators are based purely on the historical values of the exchange rate is relatively simple regarding the implementation of the bootstrap. To compute the Reality Check p -values, we generate 1000 independent block bootstrap re-samples and construct the empirical distribution consisting of 1000 realizations of V^* statistic. In particular, we build a sample of the one-period returns of the exchange rate from moving blocks of random length. The length of each block is geometrically distributed with probability 0.01 (see Politis and Romano (1994)) giving a mean block length of 100 transactions. Then the time series of the exchange rate levels is constructed from the sample of bootstrapped returns.

All order book information

When the trading rules are based on all order book information it becomes more complicated since it is necessary to resample the whole order book. Bootstrapping just the returns time series does not work in this case because the price levels are directly connected to their marks such as the best bid and offer levels, liquidity, depth etc and constructing price levels from bootstrapped returns would break this dependency. Hence, we resample the whole order book using fix length (for simplicity) blocks of 200 transactions and then construct returns of the exchange rate from its levels. In doing so we are faced, however, with possible jumps in price levels which would not be present in the original sample. These jumps would have a considerable impact on the cumulative returns and the genetic algorithm would concentrate on predicting the jumps and this fact can cause a bias of the p -values. To avoid this inconvenience we shift blocks of prices and bid and offer levels (the other order book information remains untouched) in such a way that the first price value of a new block coincides with the last price value of the previous block. This implies that since the number of observations is $n = 18065$ and the selected block length is equal to 200, we have manually set approximately 90 return values to be equal to 0. In the original data among 18065 observations, there

are about 5000 observations with zero return. As specified in Section 2), the investor does not trade until the exchange rate level goes out of the k -band. Therefore, we claim that this procedure will have little impact on our results but does enable us to bootstrap irregularly spaced dependent data from an order book.

For both pure price information and all order book information cases, the in-sample period has the same number of observations as the original – 9046.

Comparing our use of the Reality Check to the existing literature examining profitability of technical rules (for instance Sullivan, Timmermann and White (1999), Hsu and Kuan (2006)) we would claim that the use of the genetic algorithm should provide a much more reliable procedure than employing a fixed universe of technical rules. Indeed, the data-snooping analysis strongly depends on the particular set of possible alternative trading rules which could be used by the investor. Sullivan et al. (1999) consider 7,846 technical indicators while Hsu and Kuan (2006) expand this set up to 39,832 trading rules. However, the genetic programming technique allows us to consider many more strategies depending on the initial parameters of the algorithm (the number of repeats, initial population size, rules' depth, etc). On the one hand, it is impossible to calculate performance for all possible rules. At the same time, however, the Reality Check requires only the maximum of the difference in performance of the real and bootstrapped data. Hence, by setting the maximum of this difference as a fitness function of the algorithm we can simply generate an empirical distribution for the evaluating the p -values using the GP procedure. Plots of this distribution are presented below.

6 Results

Our aim is to find among the set of all trading rules those which have the best performance in the sense of predicting both correct directional change of the exchange rate and of economic value. We also consider the market with and without transaction costs. In addition we explore the uncertainty market timing issue by incorporating 5 levels of the inertia parameter k representing the investor's attitude to the uncertainty. We employ 3 different fitness functions and two different information sets – past price information and then order book information plus past prices. This immediately shows we have too many different cases to sensibly consider in detail so we will limit our discussion to drawing out several particular results.⁶

Using the genetic algorithm described in Section 3 we search for the best 20 rules in the sense of the percentage of correct directional predictions. We also report the average of the best 20 rules since this may provide both a more robust measure of performance

⁶The full set of results can be obtained from the authors on request.

and more closely reflect how traders use technical rules. In order to produce 20 rules the algorithm needed to be run approximately 25 times in each case since optimal rules that were found were not included twice in order to provide the 20 presented in the tables below. This indicates in the same manner the degree to which the algorithm has actually found the global optimum. Tables 1 – 5 report the performance of the best trading rules, their in-sample and out-of-sample percentage of correct directional predictions (columns 1 and 2) as well as their economic value (cumulative returns adjusted to a daily basis) with and without transaction costs (proportional with the rate $\theta = 0.0001$) (columns 3 and 4) for the five different values of inertia parameter k . The heading of each table indicates which fitness function has been used. Columns 5 and 6 report the results of the Pesaran-Timmermann (PT) test, columns 7 and 8 the Anatolyev-Gerko (AG) test and column 9 reports the p value corresponding to White’s reality check. The fitness function determines the performance criterion for the RC. A p value below 0.05 indicates rejection of null (at 95% of confidence) that there is no predictability or profitability in each case. Tables 6 – 10 contain the same information about the best 20 rules based both on all order book information and past price information⁷.

If we analyze the tables we can see taking Table 1 as an example that the fitness function used to select the optimal rules was directional change. The PT test (columns 5) clearly shows directional predictability as we reject the null of no predictability for all 20 rules at the 95% of confidence level including the best performing rule shown in row 1 and the average of all the rules shown in row 21. White’s Reality check confirms this as shown by the last column. There is no economic profitability under transactions costs but that is not surprising since the rules were not selected on that basis. As k increases through the following tables then if we look at table 3 when $k = 0.001$, this means that a price change has to move the third decimal point in the exchange rate to allow the trader to trade. Now we find clear predictability both in terms of sign and profitability for both the maximum rule and the average again supported by RC even though the fitness function for selected rules is directional change. The average returns for the max rule in this case with transaction costs are 7.37% on a daily basis. As k increases further, the number of transactions that are allowed can become very small (5239 for $k = 0$, 1494 for $k = 0.0005$, 738 for $k = 0.001$, 116 for $k = 0.005$ and 46 for $k = 0.01$ in our case) and the reliability of the inference for all tests becomes questionable. When $k = 0$ then the trader is allowed to trade at every instant which is not sensible and in this case it is not surprising that we can find no profitability from Table 1 (column 4) under transactions costs.

Tables 6 – 10 show the results from the same design with directional change as the

⁷As an in-sample period (search period) we use the data for Monday and Tuesday. In order to test the out-of-sample performances of the rules we consider the period from Wednesday.

fitness function but including the order book information in that available to the GA. Table 6 may be compared with Table 1. The results are generally worse and this result is reflected throughout the remaining exercises. Adding the order book information seems to create less reliability and stability in the results. We discuss possible reasons for this below once we have considered all the results.

We also repeat the same analysis with Economic Value as the fitness criterion for rule selection with and without transaction costs. In this case we can see from Table 11 (without transaction costs, $k = 0.001$) that the AG test indicates economic profitability which is supported by White's RC and the third column shows the daily returns that could be achieved by the max rule (4.484 %) and by the average of all the rules (2.19%). In Table 12 we can see significant profitability with $k = 0.005$ using order book information which is supported by all the tests of (4.418%) with the max rule and (1.299 %) under transactions cost – once again values that are lower than under the information set that just included prices.

It is in general difficult to beat the zero return benchmark (as well as buy and hold strategy⁸) when we select rules on the basis of transactions costs since buy and hold incurs transactions costs twice. However Table 13 which introduces transaction costs, with $k = 0.005$ shows significant profitability which is supported by the AG test for the max and average rules of roughly 4% a day with the RC significance levels around 7.5% and 8.95%.

Throughout all of these tables it is critical to notice the importance of the inertia parameter. It seems that either values of $k = 0.001$ or $k = 0.005$ deliver the best results fairly consistently. Table 14 collects this information together and shows the results for all fitness functions for the average rules at different values of k . This table together with Table 15 provides the critical summary of our results regarding market timing and inertia as captured here in the k parameter. Again if we track along the $k = 0.005$ line we will generally find clear directional predictability and profitability. The same holds for Table 15 which collects the same information together for the maximum rule. The same tables showing results for including order book information again indicate the slight reduction in performance that we find from including the structure of the order book in the informational set.

Table 16 and the following distributional plots indicate the probability of losing money, Ω being the ratio of probability above the break even point to that below it. This measure has been put forward as a general portfolio performance criterion superceding the Sharpe Ratio by Keating and Shadwick (2002). This is shown quite clearly in the figures that then follow for each case.

⁸We have also computed all the simulations using buy and hold as the benchmark and there is little difference between these results and the zero benchmark reported in the tables. Again full results can be provided by the authors on request.

In Table 17 we provide the results for the out of sample performance of several standard technical indicators for different values of k and it is clear their performance is weak in comparison.

Finally maybe one of the most important issues is how to apply the methodology described in this paper in practice. How to recognise, based on the in-sample performance, which of the 20 selected (best) rules will be profitable out-of-sample? One possibility is to take the rule with the maximum in-sample return, which however may not be optimal in many cases, and a more robust and stable choice is the average rule we have described above. This approach also has the disadvantage that it tries to make a prediction for the whole out-of-sample period at once. Perhaps more consistent with reality we have also considered the performance of only one step ahead predictions using a recursive procedure. Once we have got the in-sample dataset we run the GA to find the rule with the best in-sample performance and apply this rule to make a decision for the next period of time. After making the transaction we observe next period's price and update our information set using a rolling window procedure. Based on the updated in-sample dataset we repeat the GA in order to find the trading indicator for the next period and so on.

As an illustrative example consider the use of this recursive strategy with the economic value fitness function without transaction costs. The uncertainty bound is determined by the parameter $k = 0.005$ (this choice looks reasonable from the results reported above). The initial in-sample is considered to be Monday-Tuesday and we roll the in-sample window up to the last observation of Friday.

Since the GA is unable to find the global maximum of the fitness function and only approximate it to some extent, the results of the recursive procedure imply different trading rules for every separate recursive run through the data (even for the same dataset). Thus, the final return of the recursive procedure is a random variable because of the random mechanism built in the GA. Therefore, in order to get a more realistic picture of the recursive trading rule we provide 100 independent runs through the dataset for both pure price and all order book information strategies. The average daily return for the pure price information model is $\mu = 6.885\%$ and its standard deviation is $\sigma = 1.799$. The respective average and standard deviation from using the order book information are $\mu = 3.813\%$ and $\sigma = 2.131$. In the first case the hypothesis $H_0: \mu \leq 0$ is rejected with 95% of confidence while for the second case it is rejected only at 90% confidence level.

This reflects the same surprising result we found above with the static implementation of the method (that the performance of the strategy which exploits the order book information performs less well than that with just pure price information). Apart from the explanation that the market price acts as a sufficient statistic and so there is no need to use the structure of the order book it may also be that to predict future

prices the order book contains non-informative or redundant variables which have any little or no predictive power. We can see from the tables that the in-sample performance is usually better for the order book strategies and this seems to suggest that the GA has more to work on when constructing a “good” trading rule. However, its ability to forecast in-sample prices refers more to capturing the characteristics of a particular dataset rather than to its out of sample predictability⁹. Moreover, even for the in-sample period this ability does not appear to be very efficient as the implied trading rules look quite complicated and sophisticated unlike the best pure price rules which can often be very simple indeed. This may suggest the order book rules would not be robust. These sophisticated order book rules are in fact less stable during the genetic selection process because any small mutation can easily “kill” the rule. The probability that a simple rule will mutate is smaller as it is less sensitive and therefore they are more stable. The GA can at least keep their performance as a benchmark for genetic selection for a longer time. Complicated rules are destroyed more frequently and the GA has to re-start with building well performing trading rules from the very beginning. Hence, this process takes more time and machine resources and so is less likely to converge towards the optimum. In order to filter out useless variables by the GA, we would need to increase number of repetitions of the GA substantially and, probably, the population size.

Thus, there are two different ways as to how to use the order book information efficiently. The first is a machine based method – increase computer power, number of repetitions, computing time and the population size. The second is a human based method – very carefully select the variables which need to be included in the information set for the algorithm. Our analysis does show that the order book information does have some predictive power but it is not very efficient probably because of the unclear signals regarding predictability. Alternatively economic theory may have been shown to be correct and the market clearing price is in fact a sufficient statistic.

7 Conclusions

This paper has examined the predictability of exchange rates on a transaction level basis using both past transaction prices and the structure of the order book. Formal tests for the ability of genetically derived trading rules, that may be likened to technical rules, are applied to one week of tick-by-tick data on the USD-DM exchange rate drawn from Reuters DM2002 electronic trading system. The Pesaran-Timmermann test shows clear ability to predict directional changes in the exchange rate and the economic value of predictability taking account of transaction costs is shown to be sig-

⁹A similar problem affects the naive use of Neural Networks.

nificant out-of-sample using the Anatolyev-Gerko test. These conclusions rest critically however on the market timing decisions and the implied frequency of trades which are controlled by what we refer to as an inertia or uncertainty parameter which follows from the Bewley's preferences for decision-making under uncertainty. Some inertia in trading is critical to recover profitability. If the trading system is allowed to trade at every instant it clearly fails to show profitability but when trades are made only when prices changes are of a sufficient magnitude then significant profitability appears under transaction costs. These conclusions are confirmed using White's Reality Check. Somewhat surprisingly we do not find strong evidence that exploiting the order book structure aids predictability.

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8 List of Tables

Table 1: Trading rules based on pure price information: directional changes, $k = 0$

Technical rules	In-sam. DC, %	O-of-sam. DC, %	Returns, $\theta = 0$	Returns, $\theta = 10^{-4}$	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1. $(ret \leq minret10)$ or $(lagpr1 > avgpr5)$	55.35	52.90	5.786	-9.154	4.21	< 0.0001	2.47	0.0068	0.0175
2. $(ret < maxret10)$ and $(lagpr1 > min\{avgpr10, avgpr20\})$	55.20	53.61	7.231	-2.317	5.23	< 0.0001	3.06	0.0011	0.0065
3. $(ret < maxret10)$ and $(lagpr1 > avgpr5)$	55.08	53.67	8.208	-6.090	5.35	< 0.0001	3.49	0.0002	0.0055
4. $(ret \leq minret10)$ or $(lagpr1 \geq avgpr10)$	55.06	53.52	4.677	-6.345	5.12	< 0.0001	2.01	0.0222	0.0075
5. $(price \geq maxpr20)$ or $(maxret5 = lagret1)$ or $(avgret20 \leq maxret5)$ and $(price \geq avgpr20)$	55.00	53.88	-7.063	-12.569	5.62	< 0.0001	-3.49	> 0.5000	0.0055
6. $(lagpr1 \geq avgpr10)$ or $(lagpr1 > avgpr5)$	54.98	53.63	2.284	-8.082	5.30	< 0.0001	1.00	0.1587	0.0055
7. $(lagpr1 \geq avgpr20)$ and $(maxret5 = avgret5)$ or $(price \geq avgpr20)$	54.98	53.88	-8.089	-12.856	5.62	< 0.0001	-3.70	> 0.5000	0.0055
8. $lagpr1 > min\{avgpr10, lagpr2\}$	54.96	54.00	2.760	-8.768	5.83	< 0.0001	1.20	0.1151	0.0055
9. $(price \geq avgpr20)$ and $(maxret5 = lagret1)$ or $(price > avgpr20)$	54.94	53.84	-8.126	-12.938	5.56	< 0.0001	-3.71	> 0.5000	0.0055
10. $lagpr1 > min\{avgpr5, avgpr10\}$	54.93	53.58	2.272	-8.154	5.21	< 0.0001	0.99	0.1611	0.0065
11. $price > avgpr20$	54.93	53.84	-8.126	-12.938	5.56	< 0.0001	-3.71	> 0.5000	0.0055
12. $(price \geq avgpr20)$ or $(maxret5 = avgret5)$	54.91	53.73	-8.217	-13.278	5.39	< 0.0001	-3.76	> 0.5000	0.0055
13. $minpr20 < minpr10 \cdot lagret1$	53.90	52.77	-2.096	-12.556	4.01	< 0.0001	-0.93	> 0.5000	0.0024
14. $lagpr1 > min\{avgpr5, avgpr20\}$	54.89	53.46	2.657	-6.359	5.13	< 0.0001	1.17	0.1210	0.0075
15. $price \geq avgpr20$	54.89	53.83	-8.153	-12.963	5.53	< 0.0001	-3.73	> 0.5000	0.0055
16. $lagpr1 > avgpr20$	54.71	53.48	2.910	-2.701	5.03	< 0.0001	1.26	0.1038	0.0075
17. $(lagpr1 > avgpr5)$ or $(lagpr1 = avgpr10)$	54.69	53.40	3.742	-2.701	4.93	< 0.0001	1.61	0.0537	0.0085
18. $(price > avgpr10)$ or $(ret = minret20)$	54.69	54.98	3.742	-9.049	7.28	< 0.0001	-0.17	> 0.5000	0.0025
19. $lagpr1 > avgpr5$	54.64	53.34	3.730	-9.108	4.84	< 0.0001	1.61	0.0537	0.0105
20. $(price > avgpr20)$ or $(minpr10 > minpr20)$	54.60	52.42	-9.701	-13.766	3.53	0.0002	-4.51	> 0.5000	0.0305
21. Average	55.10	54.11	2.150	-6.123	5.98	< 0.0001	0.93	0.1762	0.0055

Best trading rules found by the GA based on the pure price information only. The fitness function is the percentage of the correct in-sample predictions of the exchange rate directional changes. Inertia parameter $k = 0$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample percentage of correct directional predictions are given in columns 2 and 3, their economic value (cumulative returns adjusted to a daily basis) with and without transaction costs (proportional with the rate $\theta = 0.0001$) are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 2: Trading rules based on pure price information: directional changes, $k = 0.0005$

	Technical rules	In-sam. DC, %	O-of-sam. DC, %	Returns, $\theta = 0$	Returns, $\theta = 10^{-4}$	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1.	$\text{avgret}_{10} > \text{minret}_{20} \cdot \text{maxret}_{20}$	56.01	51.28	6.040	3.133	1.07	0.1423	2.57	0.0051	0.2345
2.	$\text{avgret}_5 > \text{minret}_{20} \cdot \text{maxret}_{20}$	55.57	50.67	7.315	4.193	0.61	0.2709	3.10	0.0010	0.3675
3.	$(\text{minret}_{10} \geq \text{ret})$ or $(\text{avgpr}_{20} \cdot \text{lagret}_2 \cdot \text{maxret}_{10} \leq \text{lagpr}_1)$	56.60	50.87	4.629	-0.473	0.55	0.2912	2.02	0.0217	0.3115
4.	$(\text{minret}_{10} \geq \text{lagret}_2)$ or $(\text{avgpr}_{20} \cdot \text{ret} \cdot \text{avgret}_{20} \leq \text{lagpr}_1)$	55.72	54.04	6.728	1.692	3.25	0.0006	2.87	0.0021	0.0065
5.	$\text{minret}_{10} \geq \min\{\text{lagret}_2, \text{ret}\}$	56.16	51.95	6.261	1.308	1.35	0.0885	2.75	0.0030	0.1255
6.	$(\text{lagret}_1 \geq (\text{price} - \text{avgpr}_{20}) \cdot 1.743.99)$ or $(\text{maxret}_{10} = \text{avgret}_{20})$	54.99	51.35	9.878	6.894	1.36	0.0869	4.46	<0.0001	0.2215
7.	$(\text{price} < \text{avgpr}_{10})$ or $(\text{price} \cdot \text{minret}_{20} < \text{minpr}_5 \cdot \text{lagret}_1)$	55.13	50.34	6.081	2.536	0.72	0.2358	2.99	0.0014	0.4355
8.	$(\text{avgret}_{10} < \text{avgret}_5)$ or $(\text{avgpr}_5 > \text{avgpr}_{10} \cdot \text{maxret}_{20} \cdot \text{minret}_5)$	54.69	50.34	0.990	-3.196	0.71	0.2389	0.44	0.3300	0.4355
9.	$(\text{minret}_{10} \geq \text{ret})$ or $(\text{lagret}_1 \geq \text{lagret}_2)$	54.99	52.29	3.267	-1.362	2.21	0.0136	1.52	0.0643	0.0955
10.	$(\text{avgpr}_{10} \geq \text{price})$ or $(\text{maxret}_{10} > \max\{\text{avgret}_{10}, \text{ret}\})$	54.40	49.80	6.137	2.966	0.43	0.3336	3.38	0.0004	0.5565
11.	$(\text{minret}_{20} > \text{avgret}_{20} \cdot \text{minret}_{10})$ or $(\text{lagret}_1 \geq \text{lagret}_2)$	54.55	50.27	-2.792	-6.504	0.63	0.2643	-1.44	>0.5000	0.4455
12.	$(\text{minret}_{10} \geq \text{lagret}_1)$ or $(\text{maxret}_5 \cdot \text{minret}_{10} > \text{ret})$	55.57	53.90	5.381	0.168	2.95	0.0016	2.32	0.0102	0.0085
13.	$\text{avgpr}_5 > \text{avgpr}_{10} \cdot \text{maxret}_{20} \cdot \text{minret}_5$	54.40	52.15	5.909	2.349	1.47	0.0708	2.83	0.0023	0.1055
14.	$(\text{minret}_{10} \geq \text{ret})$ and $(\text{lagpr}_2 - \text{maxpr}_{10} \geq \text{maxret}_5 - \text{lagret}_2)$	54.99	51.55	4.727	0.977	0.92	0.1788	2.41	0.0080	0.1785
15.	$(\text{minret}_{10} = \text{minret}_5)$ or $(\text{lagpr}_1 > \text{lagpr}_2)$	54.40	50.61	1.714	-1.561	1.10	0.1357	0.87	0.1922	0.3805
16.	$(\text{avgpr}_{10} \geq \text{price})$ or $(\text{lagret}_1 > \text{avgret}_{20})$	54.25	50.67	4.189	0.995	1.17	0.1210	2.17	0.0150	0.3675
17.	$(\text{lagpr}_2 = \text{minpr}_5)$ or $(\text{ret} = \text{minret}_{10})$	54.25	51.68	6.172	1.575	1.07	0.1423	2.96	0.0015	0.1575
18.	$(\text{maxret}_{10} > \text{avgret}_{10} \cdot \text{ret})$ and $(\text{minret}_{10} = \text{minret}_5)$	54.25	51.14	3.813	-0.623	1.06	0.1446	1.67	0.0475	0.2595
19.	$(\text{lagret}_1 > \text{ret} \cdot 0.9994)$ and $(\text{lagpr}_1 > \text{maxpr}_{10} \cdot 0.9994)$ or $(\text{minret}_5 < 0.9994)$	53.81	53.70	10.212	5.792	3.54	0.0002	4.96	<0.0001	0.0105
20.	$(\text{avgret}_{10} < \text{avgret}_5)$ or $(\text{avgret}_{10} > \text{lagret}_2 \cdot \text{maxret}_{20})$	53.67	50.13	-1.159	-5.829	3.54	0.0002	4.96	<0.0001	0.4675
21. Average		58.50	51.95	6.559	3.062	1.28	0.1002	2.49	0.0064	0.1255

Best trading rules found by the GA based on the pure price information only. The fitness function is the percentage of the correct in-sample predictions of the exchange rate directional changes. Inertia parameter $k = 0.0005$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample percentage of correct directional predictions are given in columns 2 and 3, their economic value (cumulative returns adjusted to a daily basis) with and without transaction costs (proportional with the rate $\theta = 0.0001$) are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 3: Trading rules based on pure price information: directional changes, $k = 0.001$

	Technical rules	In-sam. DC, %	O-of-sam. DC, %	Returns, $\theta = 0$	Returns, $\theta = 10^{-4}$	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1.	(avgpr10 \geq maxpr10 \cdot ret) or (lagpr1 = avgpr10)	60.07	55.49	9.390	7.317	3.17	0.0008	4.52	<0.0001	0.0065
2.	avgpr10 \geq maxpr10 \cdot minret20	59.72	53.98	5.951	4.165	2.26	0.0119	2.57	0.0051	0.0325
3.	(price \leq minpr20) and (ret = minret10)	59.36	53.43	6.524	5.092	2.05	0.0201	3.71	0.0001	0.0545
4.	(lagpr1 \cdot lagret2 < avgpr10 \cdot avgret5) or (price < avgpr10)	59.36	50.69	2.015	0.255	0.25	0.4013	0.91	0.1814	0.3005
5.	(avgret20 \geq avgret10) or (price = minpr10)	59.36	52.34	5.302	3.292	1.44	0.0749	2.36	0.0091	0.1155
6.	(price < avgpr10) or (avgret20 \geq avgret10)	59.01	52.47	5.979	4.05	1.61	0.0537	2.77	0.0028	0.1025
7.	(lagpr1 \leq avgpr10) and (price \leq avgpr10)	59.01	50.82	1.619	-0.120	0.33	0.3707	0.73	0.2327	0.2775
8.	(lagpr1 \geq price) and (maxpr20 \cdot minret20 \geq price)	59.01	52.88	6.385	4.049	1.51	0.0655	2.73	0.0032	0.0785
9.	(price \cdot maxret20 \leq maxpr20) and (price \leq avgpr10)	58.66	52.88	7.707	5.553	1.50	0.0668	3.30	0.0005	0.0785
10.	(price = minpr20) or (lagpr1 = minpr20)	58.31	52.47	5.969	4.141	1.27	0.1020	2.59	0.0048	0.1025
11.	(lagpr1 \leq avgpr20) or (avgret20 > avgret10)	58.30	48.63	0.531	-1.295	-0.64	>0.5000	0.24	0.4052	0.6275
12.	avgpr10 \geq price	57.95	54.12	8.870	6.395	2.21	0.0136	3.73	0.0001	0.0295
13.	(minpr10 > avgpr10 \cdot avgret20) or (price < avgpr10)	57.95	53.98	8.826	6.366	2.14	0.0162	3.71	0.0001	0.0325
14.	price \leq minpr20	57.95	53.98	8.987	7.007	2.12	0.0170	3.93	<0.0001	0.0325
15.	(maxpr5 \cdot avgret5 < avgpr10) or (minret20 = ret)	56.89	54.95	7.784	5.312	2.65	0.0040	3.36	0.0004	0.0115
16.	(price \leq avgpr10) or (price \leq minpr5)	57.60	53.98	8.636	6.138	2.14	0.0162	3.63	0.0001	0.0325
17.	(lagpr2 \cdot lagret2 \geq minpr20) and (lagpr1 \cdot avgret5 \geq price)	57.60	53.16	7.288	4.500	1.69	0.0455	3.09	0.0010	0.0655
18.	price = minpr10	57.24	54.12	8.214	5.980	2.19	0.0143	3.52	0.0002	0.0295
19.	(minpr5 \geq price) or (avgpr5 \geq lagpr1)	56.54	53.02	3.749	1.613	1.73	0.0418	1.63	0.0516	0.0735
20.	(lagpr1 < avgpr5) or (avgret20 > avgret5)	55.83	49.73	0.726	-1.453	-0.09	>0.5000	0.32	0.3745	0.4465
21. Average		58.66	54.12	8.051	5.763	2.19	0.0143	3.42	0.0003	0.0295

Best trading rules found by the GA based on the pure price information only. The fitness function is the percentage of the correct in-sample predictions of the exchange rate directional changes. Inertia parameter $k = 0.001$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample percentage of correct directional predictions are given in columns 2 and 3, their economic value (cumulative returns adjusted to a daily basis) with and without transaction costs (proportional with the rate $\theta = 0.0001$) are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 4: Trading rules based on pure price information: directional changes, $k = 0.005$

Technical rules	In-sam. DC, %	O-of-sam. DC, %	Returns, $\theta = 0$	Returns, $\theta = 10^{-4}$	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1. $(\text{minret}20 = \text{ret})$ or $(\text{lagret}1 \leq \text{minret}20)$	84.00	60.38	4.085	3.711	2.21	0.0136	1.76	0.0392	0.0865
2. $(\text{minret}5 \cdot \text{maxret}10 \leq \text{avgret}5)$ or $(\text{minpr}20 = \text{lagpr}1)$	76.00	60.38	4.974	4.604	2.21	0.0136	2.21	0.0136	0.0865
3. $\text{minret}5 \geq \text{ret}$	76.00	72.64	9.634	9.145	5.44	<0.0001	4.19	<0.0001	0.0015
4. $\text{maxpr}5 \geq \text{max}\{\text{price}, \text{lagpr}2\}$	72.00	66.04	6.027	5.582	3.53	0.0002	2.63	0.0043	0.0185
5. $(\text{lagpr}2 \geq \text{maxpr}20 \cdot \text{minret}10)$ or $(\text{ret} = \text{minret}5)$	72.00	66.04	7.637	7.207	3.53	0.0002	3.35	0.0004	0.00185
6. $(\text{lagpr}1 = \text{minpr}10)$ or $(\text{lagpr}1 = \text{maxpr}5)$	72.00	42.45	-3.324	-3.627	-1.75	>0.5000	-1.53	>0.5000	0.8345
7. $(\text{ret} \leq \text{minret}10)$ or $(\text{avgpr}20 \geq \text{max}\{\text{avgpr}10, \text{lagpr}1\})$	72.00	64.15	6.356	5.981	3.13	0.0009	2.89	0.0019	0.0295
8. $(\text{max}\{\text{price}, \text{avgpr}20\} < \text{lagpr}1)$ or $(\text{maxret}5 = \text{lagret}1)$	72.00	69.81	8.085	7.639	4.70	<0.0001	3.59	0.0002	0.0045
9. $\text{lagpr}1 \geq \text{maxpr}5$	68.00	55.66	2.026	1.843	1.75	0.0401	1.13	0.1292	0.2225
10. $\text{price} < \text{maxpr}5$	68.00	67.92	8.212	7.751	4.01	<0.0001	3.54	0.0002	0.0125
11. $(\text{price} < \text{lagpr}2)$ and $(\text{lagpr}2 < \text{avgpr}5)$	68.00	64.15	4.847	4.491	3.45	0.0003	2.45	0.0071	0.0295
12. $(\text{price} < \text{avgpr}10)$ or $(\text{minpr}10 = \text{lagpr}1)$	68.00	61.32	5.565	5.220	2.47	0.0068	2.59	0.0048	0.0725
13. $(\text{ret} < \text{maxret}20)$ and $(\text{ret} \cdot \text{maxret}10 < \text{lagret}2)$	68.00	67.92	9.070	8.649	4.24	<0.0001	4.03	<0.0001	0.0125
14. $\text{maxpr}5 \cdot \text{minret}10 \leq \text{lagpr}2$	64.00	62.26	6.385	6.031	2.62	0.0044	2.83	0.0023	0.0595
15. $(\text{ret} \cdot \text{maxret}10 < \text{lagret}2)$ and $(\text{lagret}2 < \text{maxret}10)$	64.00	66.04	6.872	6.537	4.08	<0.0001	3.32	0.0005	0.0185
16. $(\text{ret} < \text{lagret}1)$ and $(\text{lagret}2 < \text{maxret}5)$	64.00	66.98	5.460	5.074	3.90	<0.0001	2.57	0.0051	0.0135
17. $(\text{ret} < \text{lagret}1)$ and $(\text{lagpr}2 < \text{maxpr}5)$	64.00	72.64	7.541	7.062	5.33	<0.0001	3.30	0.0005	0.0015
18. $(\text{ret} < \text{lagret}1)$ or $(\text{lagret}1 \leq \text{minret}20)$	64.00	66.98	5.956	5.561	3.85	0.0001	2.75	0.0030	0.0135
19. $(\text{ret} \leq \text{lagret}1)$ or $(\text{lagpr}1 \leq \text{min}\{\text{minpr}10, \text{avgpr}10\})$	64.00	61.32	4.091	3.752	2.50	0.0062	1.81	0.0351	0.0725
20. $\text{price} \leq \text{lagpr}2$	64.00	66.04	7.573	7.143	3.49	0.0002	3.21	0.0007	0.0185
21. Average	76.00	67.92	8.340	7.885	3.97	<0.0001	3.54	0.0002	0.0125

Best trading rules found by the GA based on the pure price information only. The fitness function is the percentage of the correct in-sample predictions of the exchange rate directional changes. Inertia parameter $k = 0.005$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample percentage of correct directional predictions are given in columns 2 and 3, their economic value (cumulative returns adjusted to a daily basis) with and without transaction costs (proportional with the rate $\theta = 0.0001$) are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 5: Trading rules based on pure price information: directional changes, $k = 0.01$

Technical rules	In-sam. DC, %	O-of-sam. DC, %	Returns, $\theta = 0$	Returns, $\theta = 10^{-4}$	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1. $(1.6369 > \text{avgpr}10 \cdot \text{ret})$ and $(\text{lagret}2 > = \text{avgret}5)$	100.00	56.41	1.536	1.414	0.79	0.2148	0.67	0.2514	0.2575
2. $(1.6369 > \text{avgpr}5 \cdot \text{ret})$ and $(\text{lagret}2 > = \text{avgret}5)$	100.00	56.41	1.536	1.414	0.79	0.2148	0.67	0.2514	0.2575
3. $(\text{price} \leq \text{maxpr}10 \cdot \text{avgret}10)$ and $(\text{maxret}10 > \text{lagret}1)$	100.00	38.46	-1.775	-1.886	-1.60	>0.5000	-0.98	>0.5000	0.7505
4. $\text{lagret}2 > \text{avgret}5$	83.33	46.15	-2.262	-2.39	-0.48	>0.5000	-1.01	>0.5000	0.5565
5. $\text{maxret}5 < \text{maxret}10$	83.33	56.41	1.498	1.383	0.88	0.1894	0.65	0.2578	0.2575
6. $(\text{avgpr}5 > \text{lagpr}2)$ and $(\text{lagret}1 < \text{maxret}20)$	83.33	61.54	0.585	0.458	1.53	0.0630	0.26	0.3974	0.1525
7. $\text{minret}5 > (0.167 + \text{maxpr}5) \cdot 0.556$	83.33	61.54	2.064	2.003	1.47	0.0708	0.90	0.1841	0.1525
8. $(\text{ret} \leq \text{lagret}1)$ and $(\text{avgret}5 < \text{avgret}10)$	83.33	66.67	3.966	3.862	2.63	0.0043	1.84	0.0329	0.0845
9. $\text{avgpr}5 > \text{lagpr}1$	83.33	58.97	-0.451	-0.610	1.16	0.1230	-0.22	>0.5000	0.1985
10. $\text{maxret}10 > \text{lagret}1$	83.33	35.90	-2.186	-2.284	-2.27	>0.5000	-1.29	>0.5000	0.8065
11. $\text{lagret}2 = \text{maxret}5$	83.33	51.28	0.897	0.817	0.08	0.4681	0.49	0.3121	0.4055
12. $\text{avgpr}10 \leq \text{minpr}5$	83.33	43.59	-1.156	-1.228	-1.43	>0.5000	-0.66	>0.5000	0.6205
13. $(\text{lagpr}2 > \text{lagpr}1)$ and $(\text{avgpr}10 \geq \text{avgpr}5)$	66.67	53.85	-0.404	-0.517	0.47	0.3192	-0.22	>0.5000	0.3055
14. $\text{minret}20 < \text{minret}10$	66.67	53.85	0.372	0.299	0.49	0.3121	0.24	>0.5000	0.3055
15. $\text{lagret}1 < 1$	66.67	51.28	0.388	0.254	0.15	0.4404	0.17	0.4325	0.4055
16. $\text{price} > \text{maxpr}10$	66.67	51.28	-0.055	-0.062	0.00	0.5000	0.00	0.5000	0.4055
17. $\text{minret}10 = \text{avgret}5$	66.67	51.28	-0.055	-0.061	0.00	0.5000	0.00	0.5000	0.4055
18. $\text{avgpr}10 \geq \text{lagpr}1$	66.67	66.67	0.786	0.619	2.20	0.0139	0.35	0.3632	0.0845
19. $\text{lagret}2 = \text{avgret}10$	66.67	51.28	-0.055	-0.062	0.00	0.5000	0.00	0.5000	0.4055
20. sell	66.67	51.28	-0.055	-0.061	0.00	0.5000	0.00	0.5000	0.4055
21. Average	83.33	64.10	2.310	2.208	2.27	0.0116	1.11	0.1335	0.1105

Best trading rules found by the GA based on the pure price information only. The fitness function is the percentage of the correct in-sample predictions of the exchange rate directional changes. Inertia parameter $k = 0.01$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample percentage of correct directional predictions are given in columns 2 and 3, their economic value (cumulative returns adjusted to a daily basis) with and without transaction costs (proportional with the rate $\theta = 0.0001$) are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 6: Trading rules based on all order book information: directional changes, $k = 0$

	Technical rules	In-sam. DC, %	O-of-sam. DC, %	Returns, $\theta = 0$	Returns, $\theta = 10^{-4}$	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1.	(bestbid > avgpr20) or (bestbid > price) or (bestbid > bestbid2)	58.61	57.30	6.378	-5.628	10.70	< 0.0001	2.61	0.0045	< 0.001
2.	(maxpr20 < bestoff) or (bestbid > avgpr20) or (bestbid > price)	58.61	57.05	6.307	-3.00	10.32	< 0.0001	2.60	0.0047	< 0.001
3.	(bestbid > min{avgpr20, price}) or (offcount < 0.4376 + lagpr2)	58.07	56.80	6.056	-2.923	10.01	< 0.0001	2.51	0.0060	< 0.001
4.	(bestbid > avgpr20) or (bestbid > price)	57.93	56.76	6.247	-2.748	9.95	< 0.0001	2.59	0.0048	< 0.001
5.	(bestbid2 < bestbid) or (minpr5 < bestbid)	57.84	56.64	4.809	-7.517	9.71	< 0.0001	1.98	0.0239	< 0.001
6.	bestbid > min{depthbid1, offcount, minpr5, avgpr20}	57.60	56.45	4.770	-5.067	9.45	< 0.0001	1.98	0.0239	< 0.001
7.	(maxpr5 ≥ avgpr20) and (bestoff ≥ maxpr5)	57.35	56.84	4.571	-3.750	10.36	< 0.0001	1.96	0.0250	< 0.001
8.	(bestoff = maxpr5) or (bestoff > maxpr10) or (4.3234 ≥ bidcount1 · minret20)	57.29	56.93	8.130	-2.763	10.14	< 0.0001	3.31	0.0005	< 0.001
9.	(bestoff ≥ avgpr20) and (bestoff ≥ maxpr5)	57.10	56.91	4.976	-4.467	10.26	< 0.0001	2.09	0.0183	< 0.001
10.	(5 > depthbid) or (bestbid > bestbid2) or (maxpr10 ≤ max{lagret2 · max{bestbid2, bestoff}, bestbid})	57.06	55.55	3.871	-6.979	8.14	< 0.0001	1.61	0.0537	< 0.001
11.	(bestoff = maxpr5) or (bestoff > maxpr10)	56.97	57.07	8.135	-2.662	10.41	< 0.0001	3.33	0.0004	< 0.001
12.	(maxpr10 ≤ bestoff) or (ret ≤ minret5)	56.95	56.26	9.653	-3.880	9.20	< 0.0001	3.93	< 0.0001	< 0.001
13.	(maxpr10 > lagpr1) or (min{maxpr10, depthhoff} ≤ bestoff) or (bidcount · depthbid ≤ min{time2, 5 + bestbid4} · (9.3 - lagpr2))	56.87	57.07	9.737	-0.552	10.32	< 0.0001	3.93	< 0.0001	< 0.001
14.	minpr5 < bestbid	56.75	56.07	6.324	-5.207	8.85	< 0.0001	2.59	0.0048	< 0.001
15.	(bestbid > minpr20) or (bestoff1 - bidcount2 ≤ 0.14 + max{liqoff2, $\frac{\text{bidcount}^2}{4.38}$ })	56.56	55.20	2.864	-4.045	8.33	< 0.0001	1.31	0.0951	< 0.001
16.	maxpr10 ≤ bestoff	56.29	56.85	6.261	-2.858	10.33	< 0.0001	2.66	0.0039	< 0.001
17.	(bestoff ≥ maxpr20) or (offcount2 < 1.5)	56.25	55.10	2.188	-4.491	8.46	< 0.0001	1.06	0.1446	< 0.001
18.	(bestoff ≥ maxpr20) and (liqoff · max{time1, time2} ≤ avgret5 · avgret10 · depthhoff2)	56.21	55.16	4.367	-2.428	8.57	< 0.0001	2.08	0.0188	< 0.001
19.	(bestoff > avgpr5) and (bestoff > avgpr20)	56.17	55.27	0.676	-6.816	7.70	< 0.0001	0.28	0.3898	< 0.001
20.	bestoff ≥ maxpr20	56.15	55.16	4.367	-2.428	8.57	< 0.0001	2.08	0.0188	< 0.001
21.	Average	58.78	57.30	5.821	-3.202	10.72	< 0.0001	2.40	0.0082	< 0.001

Best trading rules found by the GA based on the all order book information. The fitness function is the percentage of the correct in-sample predictions of the exchange rate directional changes. Inertia parameter $k = 0$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample percentage of correct directional predictions are given in columns 2 and 3, their economic value (cumulative returns adjusted to a daily basis) with and without transaction costs (proportional with the rate $\theta = 0.0001$) are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 7: Trading rules based on all order book information: directional changes $\alpha = 0.0005$

Technical rules	DC, %	DC, %	$\theta = 0$	$\theta = 10^{-4}$	stat.	p-value	stat.	p-value	White's p-value
1. (price < bestoff) and (min{3.61 + offcount2, 2 · bestoffq1 - lagpr2 + depthbid2 } < depthoff)	60.24	52.86	1.103	-3.133	2.55	0.0054	0.47	0.3192	0.0055
2. (price < bestoff) and (depthoff ≥ 14)	59.06	53.13	3.529	-0.722	2.72	0.0033	1.48	0.0694	0.0025
3. (maxret5 · 4.0661 - quant1 - bestoffq2 · bestbidq < 2.1426) and ((bestoff1 ≥ maxpr20) or (bestbid > minpr5))	59.06	54.00	3.411	-0.604	2.97	0.0015	1.50	0.0668	0.0015
4. ((time1 ≤ bestoffq2 + max{bestoffq2, maxpr10}) or (bestoffq2 ≥ bestcount2) or (lagret1 ≥ bestbidq1)) or (time1 ≥ ret)	58.76	48.22	-0.167	-4.744	-1.56	0.9418	-0.07	>0.5000	0.5915
5. (bestbid) or (time2 · 4.5848 ≤ bestoffq2)	58.47	52.72	1.635	-2.473	2.39	0.0084	0.70	0.2420	0.0055
6. (avgpr5 ≥ avgpr20 · min{minret10, $\frac{\text{depthoff}}{\text{lagpr2}}$ } · maxret20) or (depthoff ≥ max{bidcount2, maxret20} · lagpr1 · bestbid2)	58.47	49.83	4.098	1.731	0.43	0.0336	2.03	0.0212	0.2445
7. (bestoffq2 ≥ 3) or (quant1 / (max{bestoffq, quant} - 3.2) > 2.99) or (3.1 ≤ bestoffq1)	58.32	50.10	1.198	-3.210	0.20	0.4207	0.51	0.3050	0.1895
8. (price ≤ bestoff1) and (bidcount > bestoff1)	58.03	50.44	6.019	2.332	0.87	0.1922	2.81	0.0025	0.1495
9. (maxpr10 ≤ bestoff1) or (price ≤ bestoff1)	57.44	50.50	6.422	2.776	0.94	0.1736	3.00	0.0013	0.1425
10. (minret10 ≤ lagpr1 - lagpr2) or (9.2395 ≤ max{min{liqid, 8.10}, 7.3} - quant1 - depthoff2 + quant6.77)	57.14	51.98	2.921	-1.476	1.75	0.0401	1.24	0.1075	0.0245
11. (liqid1 ≤ lagpr1 - lagpr2) or (9.2395 ≤ max{min{liqid, 8.10}, 7.3} - quant1 - depthoff2 + quant6.77)	57.14	48.49	-4.297	-5.797	-0.79	>0.5000	-2.74	>0.5000	0.5235
12. (min{8.219, bestoff - minpr5 , quant} ≥ liqoff) and (bestbidq2 < 8.6459) and (5.504 < offcount)	57.00	51.92	1.609	-1.295	2.03	0.0212	0.72	0.2358	0.0255
13. (min{depthoff2, 2.136} ≤ quant2) or (depthbid1 < depthoff2 - bestoff1)	57.00	48.69	-3.464	-5.546	-0.64	>0.5000	-1.62	>0.5000	0.4735
14. (bestoff2 + bidcount2 < offcount1) or (bidcount1 · liqid ≥ 6.31 · bestoff2 · min{offcount1, bestoff1} · liqoff)	56.84	49.02	0.099	-1.719	-0.33	0.6293	0.03	0.4880	0.4025
15. (min{bestoff - minpr5, quant} ≥ liqoff) and (bestbidq2 < 8.6459)	56.85	51.92	2.065	-0.799	2.18	0.0146	0.93	0.1762	0.0255
16. (time1 ≥ ret) and (depthoff1 > max{bestbidq + offcount, 9.87, offcount + max{bestbidq, minpr20 + ret + 0.17}}) and (bestbidq2 ≥ ret)	56.84	49.97	1.719	-2.718	0.10	0.4602	0.72	0.2358	0.2135
17. (min{max{bestoffq2, 6.057}, quant2} ≥ 2.809) or (4.3 ≤ bestoffq1 + bestoffq2)	56.70	50.24	2.113	-2.269	0.21	0.4168	0.88	0.1894	0.1725
18. price < bestoff	56.55	53.40	5.924	1.426	3.00	0.0013	2.48	0.0066	0.0015
19. (min{bestoffq1, 8.29} > 4.295 - max{bestbidq, bestbidq2}) or (offcount > max{max{bestbidq, bestbidq2} · bestbid1, [0.485 - depthbid1]})	56.41	50.58	-0.403	-4.455	0.52	0.3015	-0.17	>0.5000	0.1315
20. ((offcount1 > time2) and (bestoffq1 > price)) or (max{depthbid2, bestoffq2} < offcount1)	56.26	49.63	-0.944	-4.948	-0.23	>0.5000	-0.40	>0.5000	0.3705
21. Average	64.51	51.31	3.791	0.918	1.88	0.0301	1.91	0.0281	0.0655

Best trading rules found by the GA based on the all order book information. The fitness function is the percentage of the correct in-sample predictions of the exchange rate directional changes. Inertia parameter $k = 0.0005$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample percentage of correct directional predictions are given in columns 2 and 3, their economic value (cumulative returns adjusted to a daily basis) with and without transaction costs (proportional with the rate $\theta = 0.0001$) are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 8: Trading rules based on all order book information: directional changes, $k = 0.001$

	Technical rules	In-sam. DC, %	O-of-sam. DC, %	Returns, $\theta = 0$	Returns, $\theta = 10^{-4}$	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1.	$((\max\{\text{depthoff2} + \text{bestoffq} - \text{quant} \cdot \text{offcount}\} - \text{depthbid2} \geq 4.03) \text{ or } (\text{quant1} > \text{avgpr10})$ or $(\text{bestoffq} - \text{quant} \geq 4.03) \text{ or } (\text{liquof2} \geq \text{avgret10})$ and $(\text{time2} < \text{depthbid2})$	63.25	45.82	-1.366	-2.964	-2.13	>0.5000	-0.63	>0.5000	0.7505
2.	$(\text{bestoffq} = \text{offcount})$ or $(\text{quant2} \geq \text{bestoff}) \text{ or } ((\text{bestbid1} = \text{minpr10}) \text{ or } (\text{bestoffq} = \text{bidcount2}))$ and $(\frac{\text{offcount}}{\text{bestoff}} > \text{bestoff1})$	62.54	44.58	-1.097	-3.165	-2.83	>0.5000	-0.49	>0.5000	0.8735
3.	$((\text{time} \leq \text{avgpr5})$ and $(\text{bidcount2} \geq \frac{5.52}{\text{time} \cdot \text{bestoffq1}})$ and $(\text{bestbidq2} \geq \text{avgret10})$) or $(\text{offcount} < \text{minpr5})$ or $((\text{time} < \text{bidcount2})$ and $(\text{quant1} \geq \text{lagpr1}))$	61.13	46.36	-4.426	-6.269	-2.23	>0.5000	-1.96	>0.5000	0.6765
4.	$(\text{quant1} \geq \text{avgpr10})$ or $((4.39 < \text{bestbidq}/1.115)$ and $(\text{time2} < \text{bestbidq2}))$	60.78	46.50	1.079	-1.206	-1.82	>0.5000	0.46	0.3228	0.6525
5.	$(\text{quant} > 1)$ or $(\text{offcount1} \geq \text{depthbid})$	60.78	46.63	0.156	-1.958	-1.73	>0.5000	0.06	0.4671	0.6305
6.	$(4 < \text{bestbidq})$ or $(\text{quant1} > 2.8)$ or $(\text{depthbid1} - \text{quant1} \leq \text{depthoff1})$ or $(4.54 \leq \text{bestbidq} - \text{avgret5})$	60.78	48.01	-0.016	-0.958	-0.93	>0.5000	-0.02	>0.5000	0.4175
7.	$(\text{minpr5} = \text{bestbid1})$ or $(\text{quant} > \text{bestbid})$	60.42	47.33	0.254	-1.803	-1.26	>0.5000	0.11	0.4562	0.5335
8.	$(\text{avgpr10} \geq \text{price})$ and $((\text{time2} < \text{depthbid})$ or $(6 \geq \text{bidcount1}))$	60.42	54.18	9.084	6.632	2.28	0.0113	3.70	0.0001	0.0025
9.	$(\text{quant2} \geq \text{avgpr20})$ and $(\min\{\text{avgpr20}, \text{price}\} < \text{lagpr2})$	60.42	47.87	1.468	-1.133	-1.10	>0.5000	0.52	0.3015	0.4405
10.	$(\text{avgpr10} > \max\{\text{bestoff1}, \text{time}\})$ or $(\text{avgpr10} < \text{quant2})$	60.42	46.91	0.276	-2.117	-1.53	>0.5000	0.11	0.4562	0.5965
11.	$(\text{depthoff} > 7.26 + \text{depthbid1})$ or $(\text{bestoff} < \text{quant2})$	60.42	47.60	0.544	-0.715	-1.11	>0.5000	0.26	0.3974	0.4875
12.	$(\text{avgpr10} > \text{time})$ or $(\text{avgpr10} < \max\{\text{quant}, \text{quant2}\})$	60.07	45.68	-0.528	-2.816	-2.20	>0.5000	-0.23	>0.5000	0.7655
13.	$(\text{time} < \text{bestbid})$ or $(\text{bestoff} < \text{quant2})$	60.07	45.68	-0.528	-2.816	-2.20	>0.5000	-0.23	>0.5000	0.7655
14.	$(\text{avgpr10} > \text{time})$ or $(1 < \text{quant})$	60.07	45.68	-0.528	-2.816	-2.20	>0.5000	-0.23	>0.5000	0.7655
15.	$(\text{quant2} > 1)$ or $(\text{minpr20} > \text{bestbid})$	60.07	46.36	-1.880	-4.136	-1.82	>0.5000	-0.82	>0.5000	0.6765
16.	$(\text{quant1} \geq \text{avgpr5})$ or $(\text{lagpr2} > \text{time1})$ or $(5.82 \geq \text{bidcount2})$	60.07	46.23	-1.539	-3.308	-1.94	>0.5000	-0.74	>0.5000	0.7015
17.	$(\text{quant1} \geq \text{time} - \frac{0.892}{\text{minpr10}})$ or $(\text{maxpr5} < \text{quant})$	60.07	45.68	-0.528	-2.816	-2.20	>0.5000	-0.23	>0.5000	0.7655
18.	$(\frac{5.76}{\min\{2.76, \text{avgret20}\} \cdot \text{bestbid}} > \text{bidcount2})$ or $(\text{quant1} > \text{bestbid1})$	59.36	45.95	-2.906	-5.196	-2.05	>0.5000	-1.26	>0.5000	0.7285
19.	$(\text{time2} + \text{maxpr10} - \frac{\text{maxret10}}{8.02} \leq 8.81 \cdot \text{bestbidq1} + \text{depthbid1})$ and $(\text{avgpr20} < \text{quant})$	59.01	46.23	-0.012	-2.428	-1.97	>0.5000	-0.01	>0.5000	0.7015
20.	$(\text{quant} \geq \text{lagret2} + \min\{\frac{\text{offcount2}}{\text{offcount} - \text{price}}, \max\{\text{lagret1}, \text{time1}\}\})$ and $(7.35 \leq \text{offcount})$	58.66	45.95	-1.624	-3.783	-2.11	>0.5000	-0.69	>0.5000	0.7285
21.	Average	59.72	46.36	0.222	-2.161	-1.83	>0.5000	0.09	0.4641	0.6765

Best trading rules found by the GA based on the all order book information. The fitness function is the percentage of the correct in-sample predictions of the exchange rate directional changes. Inertia parameter $k = 0.001$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample percentage of correct directional predictions are given in columns 2 and 3, their economic value (cumulative returns adjusted to a daily basis) with and without transaction costs (proportional with the rate $\theta = 0.0001$) are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 9: Trading rules based on all order book information: directional changes, $k = 0.005$

Technical rules	In-sam. DC, %	O-of-sam. DC, %	Returns, $\theta = 0$	Returns, $\theta = 10^{-4}$	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1. $(1 < \text{bestbidq1})$ and $(\text{bestoffq} \geq \text{avgret20} + \text{quant2})$	85.19	47.27	0.430	0.156	-0.46	>0.5000	0.24	0.4052	0.5885
2. $(\text{quant} < \text{bestoffq})$ and $(\text{bestbidq} \leq \min\{\text{bestbidq2}, \text{depthbid1}, \text{bestoffq}\})$	85.19	51.82	-0.145	-0.450	0.65	0.2578	-0.06	>0.5000	0.3325
3. $(\text{quant2} < \text{bestoffq})$ and $(\text{liqbid} \geq \text{bestbid1})$ or $(\text{bestbid1} < \text{bestbidq1})$	85.19	50.00	1.522	1.184	0.21	0.4168	0.73	0.2327	0.4360
4. $(\text{bestbid2} - \text{maxret10}) \cdot (\text{bidcount2} + \text{bestbidq}) < \text{offcount}$ and $(\text{bestoffq} > \text{quant1})$	85.19	53.64	2.272	1.959	0.99	0.1611	0.98	0.1635	0.2545
5. $(\text{liqoff2} \leq 0.14 \cdot \text{offcount2} - \min\{\text{liqbid2}, \max\{\text{bestbid1}, \text{time1}, 4.15\}\})$ and $(\text{quant2} < \text{bestoffq})$	85.19	53.64	0.709	0.307	1.00	0.1587	0.31	0.3783	0.2545
6. $(\text{avgret5} < \text{bestbidq1})$ and $(\max\{-\max\{\text{bestoffq}, \text{avgret5} - \text{liqbid1}\} \cdot \text{quant2}, \text{bestoffq} + (\text{maxpr5} - \text{quant}) \cdot \text{quant2}\} > \text{maxpr10})$	85.19	52.73	2.258	1.877	0.79	0.2148	1.02	0.1539	0.2935
7. $(\text{liqoff2} < \text{liqbid2})$ or $(\text{avgpr20} > \text{avgpr10})$ and $(\max\{\text{avgpr20}, 3.5433 - \min\{\text{bestoffq}, 2.0178\}\} < \text{bestbidq1})$	85.19	50.91	1.445	1.127	0.41	0.3409	0.64	0.2611	0.3775
8. $(\text{liqoff2} < \text{liqbid2})$ or $(\text{avgpr20} > \text{avgpr10})$ and $(\text{maxpr5} < \text{bestbidq1})$	81.48	50.91	0.895	0.580	0.41	0.3409	0.40	0.3446	0.3775
9. $(\text{bestbidq2} \leq 6)$ and $(\text{quant1} \leq \text{bestoffq} \cdot \text{minret10})$	81.48	49.09	-0.314	-0.672	0.00	0.5000	-0.13	>0.5000	0.4905
10. $(\text{quant} < \text{bestoffq})$ and $(\text{bestbidq} \leq \text{bestoffq})$	81.48	52.73	0.934	0.558	0.79	0.2148	0.41	0.3409	0.2935
11. $(\text{bestoffq} \geq 3.8 - \min\{1.15, 3.5 - \text{quant}\})$ or $(2 > \text{bidcount2})$	81.48	51.82	0.097	-0.296	0.58	0.2810	0.05	0.4801	0.3325
12. $(\text{depthoff2} \leq \text{bestbidq2})$ or $(\text{bestoffq} - \text{avgret10} > 1.35)$ or $(\text{depthoff2} \leq \text{avgpr20})$	81.48	54.55	0.936	0.550	1.16	0.1230	0.40	0.3446	0.2205
13. $(3 \geq \text{bestbidq})$ and $(\text{quant1} < \text{bestoffq})$	81.48	52.73	1.072	0.722	0.79	0.2148	0.47	0.3192	0.2935
14. $(\text{avgret10} < \text{bestoffq})$ and $(\text{minret5} < \text{bestoffq2})$	81.48	50.91	0.308	-0.079	0.38	0.3520	0.13	0.4483	0.3775
15. $(\text{avgret10} \leq \text{quant2})$ and $(\text{quant2} < \text{bestoffq})$	81.48	53.64	2.646	2.270	0.99	0.1611	1.11	0.1335	0.2545
16. $(\text{bestoffq} \geq \text{liqoff})$ and $(\text{bestoffq} > \text{quant1} + \text{minret5})$	81.48	50.91	0.430	0.056	0.38	0.3520	0.18	0.4286	0.3775
17. $(\text{bestoffq} > \max\{\text{quant}, 2\})$	77.78	53.64	0.980	0.597	0.98	0.1635	0.42	0.3372	0.2545
18. $\text{bestoffq} > \text{bestbidq2}$	77.78	57.27	1.761	1.375	1.74	0.0409	0.74	0.2296	0.1425
19. $(\text{lagpr2} > \text{price})$ or $(5.69 - 2.866 \cdot \text{bestoffq} > \text{maxret10})$	77.78	55.45	3.405	3.295	2.50	0.0062	3.11	0.0009	0.1925
20. $(\text{maxret10} > \text{depthoff2})$ or $(3 \leq \text{bestoffq})$	77.78	54.55	-0.040	-0.419	1.16	0.1230	-0.01	>0.5000	0.2205
21. Average	85.19	47.27	-0.968	-1.337	-0.38	>0.5000	-0.41	>0.5000	0.5885

Best trading rules found by the GA based on the all order book information. The fitness function is the percentage of the correct in-sample predictions of the exchange rate directional changes. Inertia parameter $k = 0.005$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample percentage of correct directional predictions are given in columns 2 and 3, their economic value (cumulative returns adjusted to a daily basis) with and without transaction costs (proportional with the rate $\theta = 0.0001$) are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 10: Trading rules based on all order book information: directional changes, $k = 0.01$

Technical rules	In-sam. DC, %	O-of-sam. DC, %	Returns, $\theta = 0$	Returns, $\theta = 10^{-4}$	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1. (offcount > 6) and (offcount2 ≤ 8)	100.00	50.00	-0.915	-0.935	0.07	0.4721	-3.68	>0.5000	0.4315
2. (max{time - 2.5, maxret20} < $\frac{\text{offcount2} + s_4}{\text{avgret10}}$) and (offcount < 9)	100.00	50.00	-0.128	-0.141	-1.02	>0.5000	-0.73	>0.5000	0.4315
3. (liqoff2 - offcount1 > -8.9) and (hidcount2 > 7)	100.00	52.38	0.149	0.122	0.10	0.4602	0.61	0.2709	0.3025
4. offcount = offcount1	100.00	50.00	-0.025	-0.212	-0.09	>0.5000	-0.01	>0.5000	0.4315
5. (bestbid > bestbid2) or ((quant2 ≥ lagret1) and (lagpr2 ≥ bestoffq1))	100.00	38.10	-0.806	-0.905	-1.65	>0.5000	-0.43	>0.5000	0.9325
6. (offcount < 9) and (time < time1)	100.00	47.62	-0.312	-0.385	-0.28	>0.5000	-0.40	>0.5000	0.5725
7. time1 > avgr20 · time	100.00	35.71	-2.670	-2.806	-1.97	>0.5000	-1.20	>0.5000	0.9655
8. (bestbid > bestbid2) or (bestbid > avgr5)	100.00	28.57	-4.328	-4.475	-3.04	>0.5000	-1.87	>0.5000	>0.999
9. bestoff2 = bestoff	100.00	52.38	0.178	0.104	0.59	0.2776	0.23	0.4090	0.3025
10. ($\frac{0.3 \cdot (\text{quant2} - \text{bestbidq1}) + 3.52}{3.8} \leq \text{maxpr20}$) or (bestoff2 > bestoffq1)	100.00	47.62	1.264	1.163	-0.22	>0.5000	0.58	0.2810	0.5725
11. (quant < $\frac{\text{depthbid1}}{3.8}$) and (avgr10 < bestbid1)	100.00	50.00	0.072	0.012	0.20	0.4207	0.05	0.4801	0.4315
12. (2.52 ≤ bestoffq) or (max{liqoff2, bestbid1} > maxpr5)	100.00	59.52	1.817	1.702	1.59	0.0559	0.78	0.2177	0.0465
13. bestoffq1 - liqbid1 < bestoffq	100.00	54.76	2.680	2.591	1.13	0.1292	2.33	0.0099	0.1915
14. (bestoff2 ≤ bestoff) or (liqoff2 > avgr10)	100.00	40.48	-1.781	-1.931	-1.22	>0.5000	-0.76	>0.5000	0.8755
15. 8 ≥ offcount2	83.33	45.24	-0.823	-0.869	-0.65	>0.5000	-0.73	>0.5000	0.6885
16. lagret2 > time	83.33	50.00	-0.099	-0.145	0.10	0.4602	-0.04	>0.5000	0.4315
17. (time ≤ avgr10) and (0.23 > liqoff2)	83.33	50.00	-0.099	-0.145	0.10	0.4602	-0.04	>0.5000	0.4315
18. bestoffq1 ≤ minpr10	83.33	45.24	0.846	0.732	-0.55	>0.5000	0.36	0.3594	0.6885
19. minpr5 < min{lagpr1, bestbid}	83.33	57.14	3.741	3.582	0.99	0.1611	1.67	0.0475	0.1065
20. (depthoff2 ≤ 6.54) or (offcount2 < maxpr20 · 5.37)	83.33	45.24	-0.823	-0.869	-0.65	>0.5000	-0.73	>0.5000	0.6885
21. Average	100.00	47.62	-0.985	-1.024	-0.77	>0.5000	-2.27	>0.5000	0.5725

Best trading rules found by the GA based on the all order book information. The fitness function is the percentage of the correct in-sample predictions of the exchange rate directional changes. Inertia parameter $k = 0.01$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample percentage of correct directional predictions are given in columns 2 and 3, their economic value (cumulative returns adjusted to a daily basis) with and without transaction costs (proportional with the rate $\theta = 0.0001$) are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 11: Trading rules based on pure price information: economic value, no-transaction costs, $k = 0.001$

	Technical rules	In-sam., Ret., %	Out-of-sam., Ret., %, $\theta = 0$	O-of-s, Ret., $\theta = 10^{-4}$	DC, %	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1.	$(\max_{pr10} - \text{avgret5} + \max_{ret5} \leq \max_{pr20})$ or $(\max_{pr10} - \text{avgret5} + \min_{ret10} \leq \text{avgpr20})$	3.781	6.049	4.484	51.92	0.98	0.1635	2.61	0.0045	0.0025
2.	$(\min_{pr10} = \text{lagpr1})$ or $(\min_{ret20} \geq \text{ret})$	3.574	4.581	2.633	52.88	1.51	0.0655	2.29	0.0110	0.0115
3.	$(\max_{ret10} \cdot \text{avgpr20} \geq \max_{pr5})$ or $(\text{avgpr5} = \text{lagpr2})$ or $(\text{avgpr5} = \text{avgpr10})$	3.567	1.473	-0.077	51.10	0.70	0.2420	0.64	0.2611	0.0775
4.	$\text{avgpr20}^2 \cdot \text{lagpr2} > \min_{pr5} \cdot \max_{pr5}^2$	3.465	6.909	5.191	53.16	1.66	0.0485	2.97	0.0015	0.0015
5.	$(\text{price} = \min_{pr20})$ or $(\min\{\text{lagpr1}, \text{avgpr5}\} = \min_{pr20})$	3.452	6.013	4.170	52.61	1.35	0.0885	2.62	0.0044	0.0025
6.	$(\text{avgpr10} = \text{avgpr5})$ or $(\min\{\text{price}, \text{lagpr1}\} = \min_{pr20})$	3.400	5.339	3.494	51.92	0.98	0.1635	2.32	0.0102	0.0065
7.	$(\min\{\text{price}, \text{lagpr1}\} = \text{avgpr10})$ or $(\min\{\text{price}, \text{lagpr1}\} = \min_{pr20})$	3.287	6.012	4.170	52.61	1.35	0.0885	2.61	0.0045	0.0025
8.	$(\min_{ret20} = \text{lagret1})$ or $(\text{price} \cdot \max_{ret5} \leq \text{avgpr10})$	3.282	2.001	0.061	51.10	0.54	0.2946	0.88	0.1894	0.0515
9.	$(\text{lagret1} = \min_{ret20})$ or $(\text{ret} = \min_{ret10})$	3.264	4.346	2.164	53.16	1.65	0.0495	2.01	0.0222	0.0125
10.	$(\text{avgret10} < \text{avgret20})$ or $(\text{price} = \min_{pr20})$	3.262	5.390	3.379	52.34	1.41	0.0793	2.39	0.0084	0.0065
11.	$(\text{lagret1} = \min_{ret10})$ or $(\text{ret} = \min_{ret20})$	3.252	6.350	4.043	55.63	3.08	0.0010	2.93	0.0017	0.0175
12.	$(\text{lagpr2} = \text{avgpr5})$ or $(\min_{ret10} \geq \text{ret})$	3.204	6.251	3.911	54.26	2.32	0.0102	2.93	0.0017	0.0025
13.	$(\text{avgret10} < \text{avgret20})$ or $(\min\{\text{avgret10}, \text{lagret1}^2, \text{ret}\} \leq \text{avgret20})$	3.029	1.287	2.570	51.10	0.80	0.2119	2.08	0.0188	0.0885
14.	$(\text{lagret1} = \min_{ret10})$ or $(\text{ret} = \min_{ret10})$	3.006	5.397	2.973	54.26	2.26	0.0119	2.39	0.0084	0.0065
15.	$\min_{ret10} = \min\{\text{ret}, \text{lagret1}\}$	3.006	5.397	2.973	54.26	2.26	0.0119	2.39	0.0084	0.0065
16.	$(\min_{pr10} = \min_{pr20})$ and $(\text{ret} \leq \min\{\min_{ret10}, \frac{\text{avgret5}}{\text{lagret1}}\})$	2.890	5.874	4.235	52.06	1.05	0.1469	3.20	0.0007	0.0025
17.	$(\text{ret} \leq \min_{ret10})$ and $(\min_{pr10} = \min_{pr5})$	2.864	6.172	4.383	53.43	1.94	0.0262	3.24	0.0006	0.0025
18.	$(\min_{ret10} \geq \text{ret})$ and $(\text{price} \leq \text{avgpr10})$	2.839	6.602	4.694	53.98	2.27	0.0116	3.33	0.0004	0.0025
19.	$(\text{avgret10} \leq \text{avgret20})$ or $(\text{ret} \leq \min_{ret10})$	2.791	3.068	0.960	50.55	0.44	0.3300	1.38	0.0838	0.0235
20.	$\text{ret} \leq \min_{ret10}$	2.645	6.387	4.225	53.30	1.78	0.0375	3.13	0.0009	0.0025
21. Average		3.555	4.150	2.190	52.75	1.42	0.0778	1.88	0.0301	0.0125

Best trading rules found by the GA based on the pure price information only. The fitness function is the cumulative return for 3 days trading. Inertia parameter $k = 0.001$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample economic value (cumulative returns adjusted to a daily basis) are given in columns 2 and 3, the economic value with transaction costs (proportional with the rate $\theta = 0.0001$) and their percentage of correct directional predictions are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Genko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 12: Trading rules based on all order book information: economic value, no-transaction costs, $k = 0.005$

	Technical rules	In-sam., Ret., %	Out-of-sam., Ret., %, $\theta = 0$	O-of-s, Ret., $\theta = 10^{-4}$	DC, %	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1.	(bestoffq1 \geq lagret2) and (bestoffq1 \geq ret) and (bestoffq - ret \geq ret)	4.198	4.774	4.418	59.09	2.20	0.0139	1.99	0.0233	0.0305
2.	(bestoffq $>$ bestbidq2) or (bestbidq2 \geq min{max{bidcount, quant2}, max{bidcount, quant2} - 4.89 })	3.971	3.876	3.530	58.18	1.98	0.0239	1.63	0.0516	0.0505
3.	(offcount1 - time $<$ bestbidq2) or (bestbidq2 $<$ bestoffq)	3.639	1.675	1.432	54.55	1.40	0.0808	0.79	0.2148	0.1815
4.	((time - bestoffq1 - avgret20) - 7.88) $>$ bestbidq2 and (bestoffq \geq maxret20) and ((time \leq maxret20) or (depthoff $>$ liqoff))	3.596	2.606	2.279	59.09	2.20	0.0139	1.12	0.1314	0.0835
5.	((liqoff1 \leq 0.24) and ((min{avgret20, quant2} = bestbidq2) or (minret5 $>$ bestoffq))) or (bestoffq \geq max{quant, bestbidq, bestbid})	3.546	3.738	3.379	56.36	1.54	0.0618	1.55	0.0606	0.0525
6.	((quant1 $<$ min{8.14, bestoffq}) or (2.9 $<$ bestbid - 1.7) and (3.08 \geq bestbidq))	3.546	1.072	0.722	52.73	0.79	0.2148	0.47	0.3192	0.2015
7.	(quant1 $<$ bestoffq) and ((avgret10 + bestbidq) \cdot maxpr10 \leq 8.27)	3.546	1.221	0.858	52.73	0.78	0.2177	0.53	0.2981	0.1985
8.	(bestbidq2 \cdot minret20 $<$ 5.04) and (quant2 $<$ bestoffq)	3.545	-0.362	-0.703	49.09	0.00	0.5000	-0.15	$>$ 0.5000	0.3625
9.	(max{quant2, price} $<$ min{bestoffq, 3.38} - avgret5) or (max{bestbid1, quant2} $<$ min{bestoffq, 8.7, time1})	3.537	0.519	0.144	51.82	0.58	0.2810	0.23	0.4090	0.2435
10.	(bestoffq \geq bestbidq2) and (4.63 \cdot bestoffq + quant $>$ 8.7)	3.531	1.754	1.395	57.27	1.55	0.0606	0.75	0.2266	0.1665
11.	(5.41 \leq bestbidq1 \cdot bestoffq) and (bestbidq1 \leq 3.08 + maxpr5)	3.518	1.318	1.062	50.00	0.23	0.4090	0.71	0.2389	0.1915
12.	(bestbidq1 $>$ bestbid \cdot 6.96) or (bestoffq \geq max{ $\frac{\text{bestbidq2} \cdot \text{maxpr10}}{\text{time}}$, avgpr20})	3.517	1.805	1.432	56.36	1.56	0.0594	0.77	0.2206	0.1395
13.	(-5.94 \cdot bestbid1 $>$ -0.069 - bestbidq1) or (avgret10 $<$ avgret20) or (3 \leq bestoffq)	3.301	-0.139	-0.464	50.91	0.41	0.3409	-0.07	$>$ 0.5000	0.3185
14.	((4.09 \leq bestoffq) and (min{minret5, liqoff} $>$ time2)) or (bestoffq \geq max{bestoff, bestbidq, quant2})	3.225	1.640	1.289	54.55	1.15	0.1251	0.69	0.2451	0.1845
15.	(9.87 $<$ bestbidq1) or (bestoffq $\geq \frac{\text{bestoff1} + \text{bestbidq1}}{\min\{\text{bestbidq1}, \text{bestoff2} + \frac{\text{liqoff}}{\text{maxpr5}}\}}$)	3.212	1.782	1.403	56.36	1.54	0.0618	0.75	0.2266	0.1695
16.	(5.9 \geq max{bestoffq1, 1.9 \cdot quant1}) and ((bestoff1 $<$ bestoffq) or (quant $>$ 2 \cdot price))	3.212	1.839	1.520	56.36	1.39	0.0823	0.80	0.2119	0.1375
17.	(bestoffq \geq min{bestbidq2, depthbid}) and (bestoffq $>$ 1))	3.209	1.829	1.476	57.27	1.74	0.0409	0.78	0.2177	0.1395
18.	(min{3.22, quant2} $<$ max{quant2, bestoffq})	3.200	0.727	0.318	51.82	0.38	0.3520	0.30	0.3821	0.2195
19.	quant2 \geq bestoffq \cdot (ret - 2.41) + 4.94	3.175	1.575	1.183	56.36	1.35	0.0885	0.66	0.2546	0.1905
20.	(bestbidq = bestoffq1) and (liqoff + bestoffq1 $>$ bestoffq2)	3.164	-2.100	-2.257	46.36	-0.84	$>$ 0.5000	-1.28	$>$ 0.5000	0.4785
21. Average		3.868	1.664	1.299	54.55	1.15	0.1251	0.70	0.2420	0.1825

Best trading rules found by the GA based on the all order book information. The fitness function is the cumulative return for 3 days trading. Inertia parameter $k = 0.005$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday - Friday. The average rule gives buy signal if more than 9 of best 19 rules give buy signal and sell otherwise. The in-sample and out-of-sample economic value (cumulative returns adjusted to a daily basis) are given in columns 2 and 3, the economic value with transaction costs (proportional with the rate $\theta = 0.0001$) and their percentage of correct directional predictions are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Genko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 13: Trading rules based on pure price information: economic value, transaction costs
 $\theta = 0.0001, k = 0.005$

	Technical rules	In-sam., Ret., $\theta = 10^{-4}$	Out-of-s., Ret., $\theta = 10^{-4}$	Out-of-s., Ret., $\theta = 0$	DC, %	P-T stat.	P-T p-value	A-G stat.	A-G p-value	White's p-value
1.	$(\text{lagpr1} > \text{avgret20} \cdot \text{minret10})$ and $(\text{minpr20} > \text{price} \cdot \text{minret10})$	5.847	4.427	5.808	61.32	2.45	0.0071	2.69	0.0036	0.0065
2.	$(\text{minret20} = \text{ret})$ or $(\text{lagret1} - \text{minret5} + \text{minret20} = \text{minret10})$	5.562	3.346	3.726	58.49	1.78	0.0375	1.61	0.0537	0.0165
3.	$(\text{ret} = \text{minret20})$ or $(\text{avgret10} < \text{avgret20})$	5.287	2.843	3.179	58.49	1.80	0.0359	1.37	0.0853	0.0265
4.	$(\text{maxpr5} = \text{lagpr1})$ or $(\text{minret10} = \max\{\frac{\text{minpr20}}{\text{lagpr2}}, \text{minret5} \cdot \text{minret5}\})$	5.133	0.608	0.869	54.72	1.02	0.1539	0.38	0.3520	0.1335
5.	$\frac{6.55}{\text{maxpr20}} \geq 0.719 + \text{price} + \text{minpr10}$	5.129	2.436	2.477	52.83	1.39	0.0823	3.70	0.0001	0.0375
6.	$(\text{minpr5} = \text{lagpr2})$ and $(\text{minpr20} = \text{lagpr2})$ or $(\text{minret20} = \text{minret5})$	4.361	2.289	2.617	53.77	0.79	0.2148	1.14	0.1271	0.0395
7.	$\text{ret} = \text{minret20}$	4.324	7.518	7.912	67.92	4.41	<0.0001	4.04	<0.0001	0.0015
8.	$(\text{avgret10} < \text{avgret20})$ or $(\text{avgret20} < \text{avgret5})$	3.943	-0.763	-0.624	50.00	0.00	0.5000	-0.56	>0.5000	0.3005
9.	$(\text{avgret5} \geq \text{lagret2})$ and $(\text{avgret5} \geq \text{ret})$	3.785	4.148	4.475	58.49	1.96	0.0250	2.08	0.0188	0.0065
10.	$(1 \leq \text{avgret10})$ and $(\text{avgret20} \leq \text{lagret1})$ and $(\text{minpr5} \leq \text{lagret2} \cdot \text{lagpr1})$	3.664	-3.887	-3.662	45.28	-1.10	>0.5000	-1.93	>0.5000	0.5555
11. Average		6.252	3.743	4.111	60.38	2.19	0.0143	1.77	0.0384	0.0125

Best trading rules found by the GA based on the pure price information only. The fitness function is the cumulative return for 3 days trading under proportional transaction costs, $\theta = 0.0001$. Inertia parameter $k = 0.001$. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. The average rule gives buy signal if more than 4 of best 9 rules give buy signal and sell otherwise. The in-sample and out-of-sample economic value (cumulative returns adjusted to a daily basis) with transaction costs are given in columns 2 and 3, the economic value without transaction costs and percentage of correct directional predictions are given in columns 4 and 5. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 14: Average rules based on pure price information

Fitness function: directional changes

k	In-sample, Dir. change, %	Out-of-sample, Dir. Ch., %	Daily return, %, $\theta = 0$	Daily return, %, $\theta = 10^{-4}$	P-T statistic	P-T p-value	A-G statistic	A-G p-value	White's p-value
0	55.10	54.11	2.150	-6.123	5.98	<0.0001	0.93	0.1762	0.0055
0.0005	58.50	51.95	6.559	3.062	1.28	0.1002	2.49	0.0064	0.1255
0.001	58.66	54.12	8.051	5.763	2.19	0.0143	3.42	0.0003	0.0295
0.005	76.00	67.92	8.340	7.885	3.97	<0.0001	3.54	0.0002	0.0125
0.01	83.33	64.10	2.310	2.208	2.27	0.0116	1.11	0.1335	0.1105

Fitness function: cumulative returns, no-transaction costs

k	In-sample, Daily ret., %, $\theta = 0$	Out-of-sample, Daily ret., %, $\theta = 0$	Daily return, %, $\theta = 10^{-4}$	Dir. change, %	P-T statistic	P-T p-value	A-G statistic	A-G p-value	White's p-value
0	5.654	8.327	-10.267	51.00	1.44	0.0749	3.51	0.0002	<0.001
0.0005	3.460	6.676	1.833	51.75	1.31	0.0951	2.84	0.0023	0.0025
0.001	3.555	4.150	2.190	52.75	1.42	0.0778	1.88	0.0301	0.0125
0.005	1.813	8.690	8.198	69.81	4.48	<0.0001	3.71	0.0001	<0.001
0.01	1.645	1.447	1.359	51.28	0.20	0.4207	0.65	0.2578	0.0505

Fitness function: cumulative returns, $\theta = 0.0001$

k	In-sample, Daily ret., %, $\theta = 10^{-4}$	Out-of-sample, Daily ret., %, $\theta = 10^{-4}$	Daily return, %, $\theta = 0$	Dir. change, %	P-T statistic	P-T p-value	A-G statistic	A-G p-value	White's p-value
0	1.500	2.850	3.531	50.87	1.50	0.0668	1.89	0.0294	0.15355
0.0005	0.638	0.039	2.818	50.87	0.56	0.2877	1.23	0.1093	0.3205
0.001	2.614	3.594	5.828	52.61	1.34	0.0901	2.68	0.0037	0.0215
0.005	6.252	3.743	4.111	60.38	2.19	0.0143	1.77	0.0384	0.0125
0.01	1.045	-1.495	-1.383	43.59	-0.80	>0.5000	-0.69	>0.5000	0.4125

Average of best 20 trading rules found by the GA for different fitness functions based on the pure price information. Column 1 contains different values of inertia parameter. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. Fitness functions are percentage of correct directional changes and economic value (cumulative returns adjusted to a daily basis) both with and without transaction costs ($\theta = 0.0001$). Columns 2 and 3 provide the in-sample and out-of-sample of a correspondent fitness function and columns 3 and 4 out-of-sample of two other performance measures. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 15: Maximum in-sample performance rules based on pure price information

Fitness function: directional changes

k	In-sample, Dir. change, %	Out-of-sample, Dir.Ch., %	Daily return, %, $\theta = 0$	Daily return, %, $\theta = 10^{-4}$	P-T statistic	P-T p-value	A-G statistic	A-G p-value	White's p-value
0	55.35	52.90	5.786	-9.154	4.21	<0.0001	2.47	0.0068	0.0175
0.0005	56.01	51.28	6.040	3.133	1.07	0.1423	2.57	0.0051	0.2345
0.001	60.07	55.49	9.390	7.317	3.17	0.0008	4.52	<0.0001	0.0065
0.005	84.00	60.38	4.085	3.711	2.21	0.0136	1.76	0.0392	0.0865
0.01	100.00	56.41	1.536	1.414	0.79	0.2148	0.67	0.2514	0.2575

Fitness function: cumulative returns, no-transaction costs

k	In-sample, Daily ret., %, $\theta = 0$	Out-of-sample, Daily ret., %, $\theta = 0$	Daily return, %, $\theta = 10^{-4}$	Dir. change, %	P-T statistic	P-T p-value	A-G statistic	A-G p-value	White's p-value
0	6.562	8.689	8.905	51.48	2.15	0.0158	3.67	0.0001	<0.001
0.0005	4.569	6.233	2.477	52.62	1.89	0.0294	2.74	0.0031	0.0045
0.001	3.781	6.049	4.484	51.92	0.98	0.1635	2.61	0.0045	0.0025
0.005	3.292	0.644	0.550	53.77	1.49	0.0681	0.53	0.2981	0.1265
0.01	1.707	-1.062	-1.095	48.72	-0.05	>0.5000	-1.31	>0.5000	0.3525

Fitness function: cumulative returns, $\theta = 0.0001$

k	In-sample, Daily ret., %, $\theta = 10^{-4}$	Out-of-sample, Daily ret., %, $\theta = 10^{-4}$	Daily return, %, $\theta = 0$	Dir. change, %	P-T statistic	P-T p-value	A-G statistic	A-G p-value	White's p-value
0	1.671	3.930	6.291	50.48	0.97	0.1660	3.54	0.0002	0.1275
0.0005	1.244	4.632	4.873	51.48	1.99	0.0233	2.63	0.0043	0.0205
0.001	4.319	3.676	5.012	53.30	2.05	0.0201	3.17	0.0008	0.0215
0.005	5.847	4.427	5.808	61.32	2.45	0.0071	2.69	0.0036	0.0065
0.01	1.667	-0.292	-0.239	48.72	-0.11	>0.5000	-0.20	>0.5000	0.2405

Maximum in-sample performance of best 20 trading rules found by the GA for different fitness functions based on the pure price information. Column 1 contains different values of inertia parameter. In-sample period: Monday and Tuesday, out-of-sample: Wednesday – Friday. Fitness functions are percentage of correct directional changes and economic value (cumulative returns adjusted to a daily basis) both with and without transaction costs ($\theta = 0.0001$). Columns 2 and 3 provide the in-sample and out-of-sample of a correspondent fitness function and columns 3 and 4 out-of-sample of two other performance measures. Columns 6 and 7 report the statistic and its p-value of the Pesaran-Timmermann (PT) test, columns 8 and 9 contain the statistic and its p-value of the Anatolyev-Gerko (AG) test and column 10 reports the p-value corresponding to White's reality check. The fitness function determines the performance criterion for the RC. A p-value below 0.05 indicates rejection of null of no predictability at 95% of confidence.

Table 16: Robustness Check

Pure Price Information

k	$P\{DC \geq 50\%\}$	Ω_{DC}	$P\{r \geq 0\}$	$P\{r \geq r_{BH}\}$	Ω_{EV}	$P\{r_{TC} \geq 0\}$	$P\{r_{TC} \geq r_{BH}\}$	Ω_{TC}
0	0.943	83.384	0.956	0.974	152.380	0.534	0.607	1.327
0.0005	0.744	4.508	0.939	0.946	36.118	0.571	0.620	1.871
0.001	0.799	7.689	0.915	0.931	43.846	0.798	0.811	9.265
0.005	0.831	14.035	0.893	0.911	26.625	0.869	0.870	15.960
0.01	0.813	6.461	0.753	0.789	6.087	0.731	0.760	5.655

All Order-Book Information

k	$P\{DC \geq 50\%\}$	Ω_{DC}	$P\{r \geq 0\}$	$P\{r \geq r_{BH}\}$	Ω_{EV}	$P\{r_{TC} \geq 0\}$	$P\{r_{TC} \geq r_{BH}\}$	Ω_{TC}
0	0.975	261.221	0.912	0.914	39.415	0.681	0.693	3.882
0.0005	0.825	9.203	0.872	0.881	17.734	0.640	0.683	2.620
0.001	0.787	84.811	0.870	0.873	14.355	0.677	0.723	4.086
0.005	0.815	6.837	0.834	0.850	12.539	0.775	0.768	5.823
0.01	0.759	3.553	0.731	0.765	4.535	0.674	0.715	3.231

$P\{DC \geq 50\%\}$ denotes the probability of predicting more than 50% of directional changes, $P\{r \geq 0\}$ and $P\{r_{TC} \geq 0\}$ are the probabilities of non-losing money by the best GA trading rule without and with transaction costs ($\theta = 0.0001$) respectively, $P\{r \geq r_{BH}\}$ and $P\{r_{TC} \geq r_{BH}\}$ are the probabilities of beating the buy-and-hold strategy without and with transaction costs respectively. Ω statistics are the ratios of probability above the break even point to that below it. The statistics are calculated using the bootstrap approach.

Table 17: Standard Rules

Trading rules	Performance measure	$k = 0$	$k = 0.0005$	$k = 0.001$	$k = 0.005$	$k = 0.01$
MA Oscillator	DC	52.21	50.87	50.41	50.94	43.59
	R	-0.088	-0.720	0.003	-0.032	0.067
	R^{tc}	-3.472	-3.223	-1.512	-0.345	-0.087
Variable length MA Oscillator	DC	50.04	48.99	49.18	50.00	48.72
	R	0.055	0.055	0.055	0.055	0.055
	R^{tc}	0.048	0.048	0.048	0.048	0.048
Filter Rule	DC	49.67	50.27	50.00	46.23	41.03
	R	-2.908	-2.908	-2.908	-2.908	-2.908
	R^{tc}	-2.953	-2.953	-2.953	-2.953	-2.953
Breakout Rule	DC	49.96	51.01	50.82	50.00	51.28
	R	-0.055	-0.055	-0.055	-0.055	-0.055
	R^{tc}	-0.062	-0.062	-0.062	-0.062	-0.062
Bollinger Band	DC	51.56	52.89	51.79	50.00	48.72
	R	1.309	1.795	1.122	0.055	0.055
	R^{tc}	1.275	1.761	1.102	0.048	0.048
Aroon Oscillator	DC	48.58	50.00	49.45	46.23	43.59
	R	-1.757	-1.327	-1.327	-1.298	-1.306
	R^{tc}	-1.797	-1.353	-1.353	-1.324	-1.333

Performances of some standard technical indicators for three fitness functions: percentage of directional changes and economic values without and with transaction costs ($\theta = 0.0001$). The results are provided for 5 different values of inertia k parameter.

Bootstrap distributions

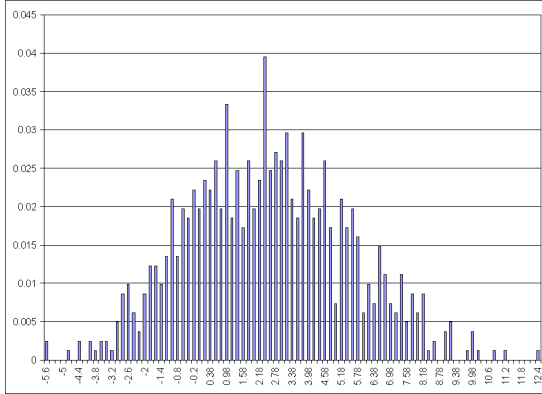


Figure 3: Bootstrap distribution of maximum of DC based on pure price information net of 50%. $k = 0.001$

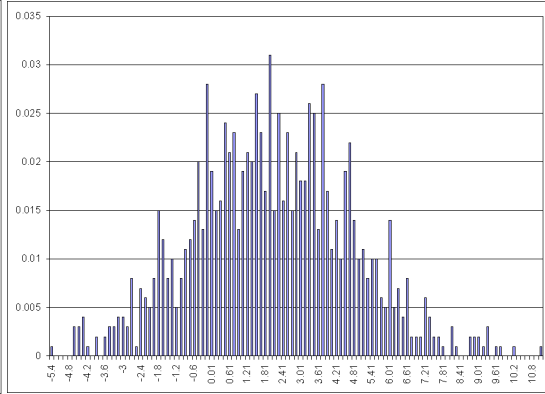


Figure 4: Bootstrap distribution of maximum of DC based on order book information net of 50%. $k = 0.001$

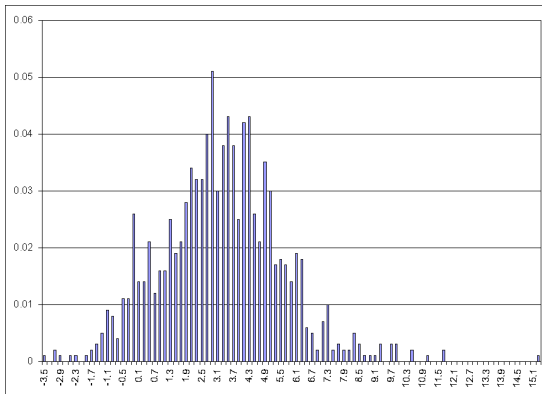


Figure 5: Bootstrap distribution of maximum of R based on pure price information net of buy-and-hold. $k = 0.001$

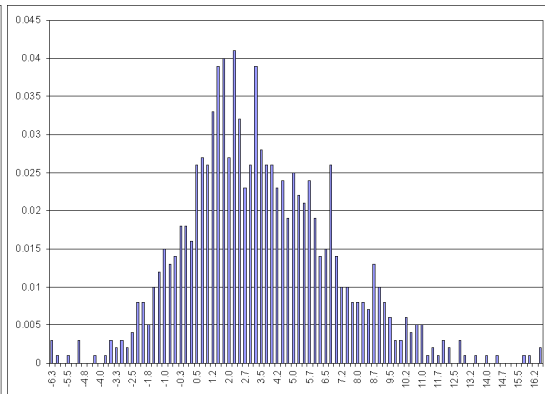


Figure 6: Bootstrap distribution of max of R based on order book information net of buy-and-hold. $k = 0.001$

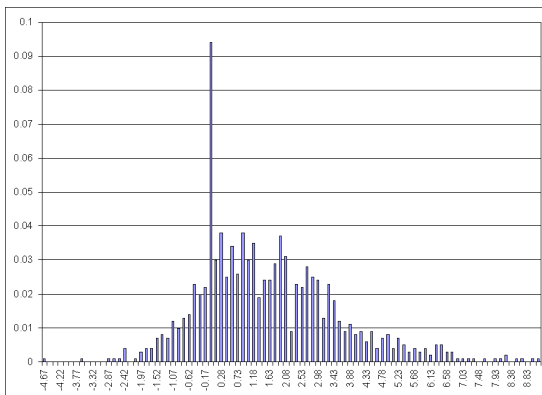


Figure 7: Bootstrap distribution of max of R^{TC} based on pure price information net of buy-and-hold, $\theta = 0.001$. $k = 0.001$

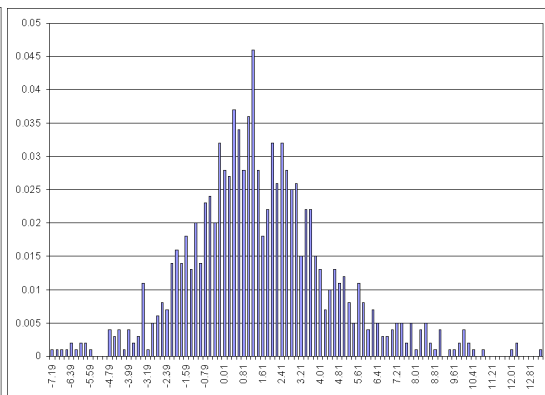


Figure 8: Bootstrap distribution of max of R^{TC} based on order book information net of buy-and-hold, $\theta = 0.0001$. $k = 0.001$

Appendix

8.1 Pesaran-Timmermann Test

The Pesaran-Timmermann statistic is used to test the null of no market timing or that the proportion of correct predictions equals the proportion which can be expected under the null of independence between the realised and predicted values. Let e_t be the realised value of the exchange rate and z_t – its forecast. Define the probabilities

$$\begin{aligned} P_{11} &= P(z_t < 0, e_t < 0), & P_{12} &= P(z_t < 0, e_t \geq 0), \\ P_{21} &= P(z_t \geq 0, e_t < 0), & P_{22} &= P(z_t \geq 0, e_t \geq 0). \end{aligned}$$

The diagonal elements of this contingency table provide the proportion of correct predictions. P_{ij} denotes the probability of a realisation in the cell of the i 'th row and j 'th column of the contingency table. In general, the Pesaran-Timmermann test considers a number of categories ($i, j \in \{1, \dots, m\}$); we only need to consider $m = 2$. Denote by $P_{i0} = \sum_{j=1}^m P_{ij}$ the probability of cells in the i 'th row and $P_{0j} = \sum_{i=1}^m P_{ij}$ the probability of cells in the j 'th column. The null hypothesis is expressed as

$$H_0 : \sum_{i=1}^m (\hat{P}_{ii} - \hat{P}_{i0}\hat{P}_{0i}) = 0$$

The test is based on the standardised statistic

$$s_n = \sqrt{n} V_n^{-\frac{1}{2}} S_n \stackrel{a}{\sim} N(0, 1),$$

where n is the number of observations, and

$$\begin{aligned} S_n &= \sum_{i=1}^m (\hat{P}_{ii} - \hat{P}_{i0}\hat{P}_{0i}) \\ V_n &= \left(\frac{\partial f(\mathbf{P})}{\partial \mathbf{P}} \right)'_{\mathbf{P}=\hat{\mathbf{P}}} (\hat{\Psi} - \hat{\mathbf{P}}\hat{\mathbf{P}}') \left(\frac{\partial f(\mathbf{P})}{\partial \mathbf{P}} \right)_{\mathbf{P}=\hat{\mathbf{P}}} \end{aligned}$$

$\hat{\Psi}$ is an $m^2 \times m^2$ diagonal matrix with $\hat{\mathbf{P}}$ as its diagonal elements,

$$\left(\frac{\partial f(\mathbf{P})}{\partial \mathbf{P}} \right)_{\mathbf{P}=\hat{\mathbf{P}}} = \begin{cases} 1 - P_{0i} - P_{i0} & \text{for } i = j \\ -P_{j0} - P_{0i} & \text{for } i \neq j \end{cases}$$

When $m = 2$ this test is asymptotically equivalent to the Henriksson-Merton test of market timing (see Henrikson and Merton (1981)).

8.2 Anatolyev-Gerko Test

The Anatolyev and Gerko (Anatolyev and Gerko (2005)) test of mean predictability is based on both market timing and a trading rule. Essentially this is a Hausman

test that compares two estimates of mean returns from a simple trading rule, both of which will be consistent under the null of no predictability but will differ under the alternative.

Let r_t be the observed log-returns of the exchange rate and \hat{r}_t be their forecasts for $t = 1, \dots, n$. The forecasts depend on the past information $\mathcal{F}_{t-1} = \{r_{t-1}, r_{t-2}, \dots\}$. Let the trading rule of the investor be based on the forecast variable \hat{r}_t , in particular, the investor takes a long position in USD if $\hat{r}_t \geq 0$ and a short position in dollars if $\hat{r}_t < 0$. Then the one-period return from using the trading strategy is $R_t = \text{sign}(\hat{r}_t) \cdot r_t$. The null hypothesis is conditional mean independence so that $H_0: E(r_t | \mathcal{F}_{t-1}) = \text{const}$ or that \hat{r}_t and r_t are independent. The expected one-period return $E(R_t)$ can be consistently estimated under the null by two estimators:

$$A_n = \frac{1}{n} \sum_t R_t$$

and

$$B_n = \left(\frac{1}{n} \sum_t \text{sign}(\hat{r}_t) \right) \left(\frac{1}{n} \sum_t r_t \right).$$

A_n estimates the average return from using the trading strategy whereas B_n estimates the average return from using the benchmark strategy that issues buy/sell signals randomly with probabilities corresponding to the proportion of buys and sells implied ex post by the trading strategy. When r_t is predictable investing in the trading strategy will generate higher returns than the benchmark and the difference between A_n and B_n will be sizable. The variance of the difference $A_n - B_n$ is

$$V = \text{Var}(A_n - B_n) = \frac{4(n-1)}{n^2} p_{\hat{r}}(1-p_{\hat{r}}) \text{Var}(r_t),$$

where $p_{\hat{r}} = \text{Pr}\{\text{sign}(\hat{r}_t) = 1\}$. The estimator for the variance is $\hat{V} = \frac{4}{n^2} \hat{p}_{\hat{r}}(1-\hat{p}_{\hat{r}}) \sum_t (r_t - \bar{r})^2$ with $\hat{p}_{\hat{r}} = \frac{1}{2} \left(1 + \frac{1}{n} \sum_t \text{sign}(\hat{r}_t) \right)$. The excess profitability statistic is then given by

$$EP = \frac{A_n - B_n}{\sqrt{\hat{V}}} \xrightarrow{d} N(0, 1)$$

under the null hypothesis.

8.3 White's Reality Check

The main idea behind the Reality Check is as follows; let φ_k , ($k = 1, \dots, M$) denote the performance measure of the k -th trading rule relative to some benchmark performance or rule. The aim is to test whether there is a rule within the population that delivers superior performance to the benchmark. The null hypothesis is then stated as;

$$H_0: \max_{k=1, \dots, M} \varphi_k \leq 0.$$

in other words there is no rule that delivers positive returns relative to the benchmark i.e. beats the benchmark. To test this null, we need the distribution under the null, White (2000) suggested using the stationary bootstrap method of Politis and Romano (1994) to estimate the distribution of the test statistic $V = \max_{k=1, \dots, M} \varphi_k$. If we denote by $\varphi_{k,j}^*$ the performance measure of the k -th trading rule calculated using j -th bootstrap sample. The empirical distribution can be obtained using bootstrap realizations

$$V_j^* = \max_{k=1, \dots, M} (\varphi_{k,j}^* - \varphi_k), j = 1, \dots, B.$$

It shown in White (2000) that the distributions of V and V^* are asymptotically equivalent. Comparing the value of the statistic V with the quantiles of the empirical distribution of V^* we obtain the Reality Check p -values which are suitable for testing the null hypothesis.

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