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Foreign Exchange Trading with Adaptive Computational Learning

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Outline

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1 Motivation

• Increasing evidence that markets are predictable
  • Lo & McKinley (2000) state that rather than being a symptom of inefficiency predictability in the financial markets is the “oil that lubricates the gears of capitalism”

• Most technical traders are active in the FX markets and at high frequency
  • Daily vs high frequency Neeley (1999)
  • Equities vs FX Taylor & Allen (1992)
  • Asset allocation vs trading Dempster & Jones (2001)
Previous Work

- Previous work examining single popular indicators does not find evidence of profit opportunities e.g. Dempster & Jones (1999)
- Neeley, Weller & Dittmar (1997) found out-of-sample annual excess returns in the 1-7% range in currency markets against the dollar during 1981-1995
- Dempster et al (2001) found significant out-of-sample annual returns up to about 2bp slippage using various computational learning methods
Price and Quantity Analysis

• Project with HSBC
  Can customer order flows and the limit order book provide additional information useful in predicting FX rates a few days in advance

• Exploratory
  Initially six months of data to mid August 2002
  Eighteen months of data to mid November 2003 currently being analysed
Literature Review

- Macroeconomic fundamentals based modelling of FX timeseries has been shown not to fit empirical evidence at horizons of less than one year Meese & Rogoff (1983a, 1983b)

- Increasing interest in microstructure based approaches Lyons (2001)

- Published work on orders and transaction flows in equity markets Farmer and Lillo (2003) but much less published for FX due to lack of data
The Global FX Market
Average Market Spreads on EURUSD

Source: Stacy Williams
HSBC Investment Bank
2 Problem Definition

• Intelligent Trading System
  • Trading systems generate buy rules, sell rules and exit rules
  • Rules are defined as a mapping between states and actions
  • States are defined as a combination of indicators (which can be technical/fundamental/order flow/order book/composite)

• Key Features of an Intelligent Trading System
  • Learning & discovery
  • Adaptation
  • Explanation
The System in a ‘Live’ Trading Context

Market

Live Data Feed

Database

Active Cash Management Filter

Strategies

Bid Formulation

Algorithms
Adaptive Trading

- Strategies are combinations of indicators drawn from the world of technical and customer order analysis
- Best performing strategies are selected using computational learning techniques
- System can be overlaid by simple cash/risk management filters
- Adaptation is achieved in several ways:
  - Online learning
  - Re-mining at set intervals
  - Profitability dependent time intervals
    - (e.g. if portfolio loses money for $n$ consecutive periods)
The Need For High Frequency Data

• To simulate the actions of traders
  • ‘desk traders’ watch the markets ‘tick by tick’ and apply the concepts of technical analysis at frequencies much higher than ‘daily’
• Trade entry and exit strategies
  • Even technical traders who look for patterns in daily data alone often use tick data for confirmatory entry signals
  • The vast majority of traders place stops in the markets alongside their trades to manage downside risk and such stops are activated at ‘tick’ level
• In general realism
Data

• 4 years of high frequency (1 minute) midpoint quote data from Bank of America

• Currencies: GBPUSD, USDCHF and USDJPY

• Frequencies: 15 minute, 1 hour, 2 hour, 4 hour and 8 hour

• Dates: January 1995 to December 1998 (1995 used for first in-sample learning period)
Objective Function

• Simulate simple trader in single currency pair
  • Trades by drawing on a credit line, converting, holding and then converting back and accumulating any profit/shortfall in domestic currency (dollars)
  • Can borrow $1 (or equivalent) in either currency
  • Cumulated profit or loss at end of sample period is objective value

• Transaction costs (due to bid-ask spread and slippage) charged at 0, 1, 2, 4 and 10 basis points of amount exchanged
More Formally…

• With transaction cost $c$ exchange rates (expressed per unit of home currency) of $F_t$ at trade entry and $F_{t'}$ at trade exit drawing on a credit line of $C$ units of home currency and taking a long position in the foreign currency will yield a return per unit of home currency of

$$\left[ \frac{F_t}{F_{t'}} (1-c)^2 - 1 \right]$$

• If a short position is taken in the foreign currency then $C/F_t$ units of foreign currency are drawn from the credit line and the return per unit of home currency is

$$\left[ (1-c) - \frac{F_{t'}}{F_t} \frac{1}{(1-c)} \right]$$
Objective Function

- Indicator signals over time a stochastic process $s$ with state space $S$ driven by the exchange rate process $F$
- Solve the stochastic optimization problem defined by the maximisation of expected return over the trading horizon net of transaction costs

$$\mathbb{E} \sum_{i=1}^{N_T} r_i (F_{t_i}, F'_{t_i})$$

- The statistics of the processes $F$ and $s$ are entirely unknown
- Computational learning methods attempt to find approximate solutions by discovering a (feedback) trading strategy $\phi: S \times \{1,s\} \rightarrow \{1,s\}$ that maps the current market state $s_i$ and position to a new position
Technical Indicators

• A number of popular indicators used as inputs:
  • Adaptive Moving Average
  • Bollinger Bands
  • Commodity Channel Index
  • Momentum Oscillator
  • Moving Average Convergence/Divergence
  • Moving Average Crossover
  • Price Channel Breakout
  • Relative Strength Index
  • Stochastics
  • Wilder’s Time/Price SAR
  • Williams’ Percent R
Problem Definition

- Technical and other indicators together define market state
- System attempts to learn what trading action to take in each state
  Two possibilities examined:
  - **2-way system**: Always in the market (long/short positions)
  - **3-way system**: Can take neutral positions (out of the market)
- **Train on 12-month moving window then 1 month out-of-sample trading**
3 Computational Learning Techniques

- **Reinforcement learning** attempts to learn a behaviour without direct ‘supervision’
- Reinforcement learning attempts to discover which trading action to take in each market state (as defined by indicators) by receiving rewards with aim to maximise total reward
- Reward function is increase in wealth
- Makes multiple passes through in-sample period refining its actions each time
- Uses Watkins’ **Q-learning** algorithm so rewards ‘trickle down’ to actions that caused them
Reinforcement Learning

• Learning while interacting with the environment

• RL methods estimate value functions (defined in terms of total reward) based upon previously learned estimates

\[
Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[ r_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t - a_t) \right]
\]
Evolutionary Learning

- Genetic algorithm evolves trading rules
- Rules are represented as binary trees
  - Terminals are indicators (MO, PCB, MAX, etc.)
  - Non-terminals are Boolean functions (AND, OR, XOR)
  - Together represent simple functions (e.g. IF MO AND PCB THEN LONG)
- Rule is executed at each time step to get position at next time step making many passes (generations) through in-sample data
- Best in-sample performing rule (on raw return) is used out-of-sample
Evolutionary Reinforcement Learning (ERL)

- RL was prone to overfitting when given too many inputs Dempster et al (2001)
- Can we use a GA to constrain the inputs to RL?
Recurrent Reinforcement Learning

- RL learns indirectly from optimising a performance function of the output signals
- **Recurrent reinforcement learning** (RRL) feeds back the output signal to the system making a **single pass** through the data
- **Feedback** creates awareness of the system (output) state and a stabilising effect (cf. control theory)
- Structure of the system is a simple neural network which is able to approximate an optimal nonlinear feedback function with high precision while remaining mathematically tractable
- The performance function is again cumulative net profit and the feedback signal is current position
4 Results

Reinforcement vs Evolutionary Learning
Comparison of Methods Results

- Returns are broadly similar at 0bp & 1bp slippage

- At higher slippage values GA is able to trade profitably at up to 4bp whereas RL is unable to trade profitably beyond 1bp

- RL suffers from overfitting the in-sample data

- ERL system overcomes this issue and obtains the highest returns at 4bp in 2 of the 3 currencies studied
Frequency Effect

• As slippage increases monthly dealing adapts to frequency

• Rather than constrain the frequency artificially in the pre-processing step the algorithm should be left to choose its own trading frequency by feeding it with the highest frequency data available
Should We Optimize Parameters?

• Technical indicators attempt to capture similar dynamics
• By optimizing parameters the correlation between the indicators increases significantly
• Thus information content for the learning methods decreases and performance declines
3-way ERL System Results

Hybrid System 3way: 15 minute trading

Percent Annual Return

0bp 1bp 2bp 4bp 10bp

GBPUSD

USDCHF

USDJPY

GBPUSD

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Evolutionary RL System – USDCHF 2-way
15 minute at 2bp
Significance Test

• We utilize a simple non-parametric binomial test Dempster and Jones (2001)

• Null hypothesis: out-of-sample cumulative trading profits and losses are periodically sampled from a continuous time stationary ergodic process with state distribution having median zero

• Under this null hypothesis profits and losses are equally likely

• It follows that over n monthly periods, the number of profitable months $n^+$ is binomially distributed with parameters $n$ and $\frac{1}{2}$

• We use a two-tailed test of the hypothesis that median profit and loss is non-zero with the statistic $n^+$
Evolutionary RL System – USDCHF 2-way 15 minute at 2bp

The p-value for this test was 0.9082

n = 36  n⁺ = 22
Optimizing Risk Adjusted Return

• RL techniques typically require immediate rewards
  • RL runs into difficulty associating delayed negative feedback with the states that caused them
  • Difficult to incorporate drawdown or Sharpe ratio as these are not instantaneous measures

• Evolutionary RL system is ideally suited to solve this
  • Introduction of risk adjusted optimization moved to the GA layer where it is straightforward to incorporate
  • GA fitness function maximizes some measure of risk-adjusted reward over the evaluation period
  • RL optimization remains as discussed earlier
# Risk Adjusted Return Results

- Risk adjustment of the performance function improves returns although they remain broadly in line with the previous
- **Sharpe Ratios** of two ERL systems – optimization of drawdown adjusted return and total return

<table>
<thead>
<tr>
<th>Sharpe Ratios</th>
<th>GBP/USD</th>
<th>USD/CHF</th>
<th>USD/JPY</th>
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</thead>
<tbody>
<tr>
<td>Drawdown Adjusted Return (0bp)</td>
<td>2.33</td>
<td>2.3</td>
<td>1.84</td>
</tr>
<tr>
<td>No Risk Adjustment (0bp)</td>
<td>2.21</td>
<td>2.22</td>
<td>1.82</td>
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<td>Drawdown Adjusted Return (1bp)</td>
<td>1.46</td>
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<td>0.41</td>
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<tr>
<td>No Risk Adjustment (1bp)</td>
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<tr>
<td>Drawdown Adjusted Return (2bp)</td>
<td>0.79</td>
<td>0.4</td>
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<tr>
<td>No Risk Adjustment (2bp)</td>
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<tr>
<td>Drawdown Adjusted Return (4bp)</td>
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<tr>
<td>No Risk Adjustment (4bp)</td>
<td>-0.04</td>
<td>0.16</td>
<td>0.12</td>
</tr>
</tbody>
</table>
Risk Management

• Risk Adjusted Optimization
  • Sharpe ratio optimization
  • Sterling ratio optimization (drawdown adjusted)

• Overlaying Cash Management
  • Stop loss overlay
  • Trailing stop overlay
Indicator Based RRL Preliminary Results

- 15-minute GBP USD midpoint quote data (Bank of America)
- 1994-09-07 until 1999-09-07
- 402% cumulative profit at 3bp
- Price based RRL *Moody-Gold (2003)* 330% profit at 3bp
- Indicators utilized
  - Moving Average Crossover
  - RSI
  - Commodity Channel Index
  - Percent R
  - Price Channel Breakout
  - Stochastics
Volume Data

- 5 ¾ months of order book and order flow data
- Currencies: GBPUSD, EURUSD and USDJPY
  - USDJPY was not considered for the order book due to errors in the data
- Intraday order book/flow data but for this pilot study was aggregated into daily
- Dates: March 1, 2002 – August 19, 2002
- In-sample period: 1st March – 30th May (65 data pts)
- Out-of-sample: 1st of June – 19th August (58 data pts)
Order Flow Data

• Customer order flows - from accepted quotes

• Represent inventory ‘shocks’ to the market

• Internal HSBC trading desks excluded

• Know the type of customer but not the reason for the order although some categorisation has been done by HSBC
Customer Orders

- Reasons for orders include:
  - Payments for goods & services
  - Overseas investment - capital projects or markets
  - Exposure hedging - commercial or investment institution
  - Central bank intervention
  - Speculation - hedge funds
Order Flow Data

- HSBC broke down transactions into several categories
- These categories were used to derive the indicators:
  - Net daily transactions in that currency pair (1 if positive volume, 0 if negative)
  - Net retail transactions
  - Retail speculative transactions
  - Retail nonspeculative transactions
  - Net institutional transactions
  - Institutional speculative transactions
  - Institutional nonspeculative transactions
  - Net speculative transactions
  - Net nonspeculative transactions
Order Book Data

- Daily **snap-shot** at start of London trading
- Limit orders from customers
- Order price outside the current bid-ask spread - so cannot be executed immediately
- Distribution of orders above and below the current price
- ‘Take profit’ orders and ‘stop loss’ orders
- Expect only orders ‘near’ the current price to have an effect and to contain useful information for prediction
Order Book Data

• For each day the following **indicators** are generated:
  • Net customer sales for stop-loss orders where the price is more than 0.0% and less than or equal to 0.5% from the current spot
  • Net customer sales for stop-loss orders where the price is more than 0.5% and less than 1% from the current spot
  • Net customer sales for stop loss orders where the price is between 0 and 1% (i.e. the sum of the former two)
  • These are calculated for all orders and for **take-profit** orders both for the whole order book as at the time of the snapshot of the book and for new orders only
  • The total number of indicators derived from the order book is 12
ERL System Parallelization

- GA is of order $O(2^n)$ in inputs thus for every additional indicator the searchspace doubles
- Large number of indicators makes parallelization critical
Performance Over Time

- Cumulative return over the out-of-sample period of EURUSD at 2bp slippage and GBPUSD at 4bp
Order Flow Indicators used by ERL

• EURUSD: No consistency appears in indicators chosen
  • Due to low correlations we expect combinations of indicators to change

• GBPUSD: Consistency emerges across the slippage values
  • Retail, nonspeculative institutional and speculative institutional are consistently selected

• USDJPY:
  • Appears to consistently choose nonspeculative retail (a highly correlated indicator)
  • Despite high correlations system often stays out of the market - even in-sample
Conclusions

• Results show significant promise in approach
  • We demonstrate that order book and order flow based trading can significantly improve the results

• Feeding in technical indicators is often important - but not in isolation - rather in addition to order book or flow information
Current Work

• Finegrain indicators for trade size

• Examine rolling in-sample/out-of-sample with a one week rolling out-of-sample period as this is the timescale used at HSBC

• Recently received more data from HSBC which is currently being analysed

• Multicurrency trading