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Modelling the Global FX Market

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Outline

1  Introduction
2  The Global FX Market
3  Structure of the FX Market
4  Modelling Trading Agents
5  Modelling Market Makers
6  Conclusions and Future Directions
1 Introduction

- 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 With Computational Learning

- Previous work examining single popular indicators finds no evidence of profit opportunities e.g. Dempster & Jones (1999)

- Neeley, Weller & Dittmar (1997) found out-of-sample annual 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
Literature Review

- **Macroeconomic fundamentals** based models of FX timeseries do not fit empirical evidence at horizons of less than one year  Meese & Rogoff (1983)

- Increasing interest in *microstructure* based approaches  Lyons (2001)


2 The Global FX Market
Turnover 2001

Latest Bank for International Settlements FX market survey was conducted in April and June 2001

Average daily FX market turnover $1.2 trillion

Swaps 55%, Spot 34%, Outright Forward 11%

Spot daily turnover about $400 billion
FX Market Turnover by Currency

EuroDollar easily the most traded currency pair with 30% of global turnover and probably higher now

DollarYen next with 20%

SterlingDollar was 11%

Further 5% of turnover in the crosses between these currencies - mainly the EuroYen and SterlingEuro crosses

All other currencies and their crosses together accounted for about a third of global FX turnover
FX Market Concentration

- Global FX trading is highly concentrated

- In 2001 there were almost 2000 institutions active in the FX market

- But just 30 of those accounted for 35% of global turnover

- In last three years this concentration into fewer banks has continued and 20 banks now account for 40% of turnover

- Next survey later this year - 2004
Inter-Bank FX Market

- EBS and Reuters (D-2000/3000) are the inter-bank systems
- In 2001 they accounted for just under 40% of spot inter-bank trading
- Now - 2004 - they account for over 90% of all inter-bank FX
- Over 97% in the three major currency pairs: EuroDollar DollarYen and SterlingDollar
- 85% to 90% of spot FX turnover is inter-dealer and 10% to 15% is customer trades
FX Market Structure

- Customers can interact with the global FX market only through market participants: the FX market makers
- Customers deal with more than one market maker
- Market makers deal with each other to clear excess inventory
- Proprietary traders are usually within banks - and so deal primarily with their own bank’s market maker (often at reduced spreads) - or directly with EBS/Reuters
- Also deal with other banks’ market makers
Global Market: EUR/USD Spread and Volume

Source: Stacy Williams, HSBC Investment Bank

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Global Market: Average GBPEUR Liquidity by Rate

Source: Stacy Williams, HSBC Investment Bank
Customer Terminology Example

- Customers leave **limit orders** with market makers:
  - Two types: *Take Profit* orders and *Stop Loss* orders
  - These have very different effects when they are activated by a price move in the market. A *take profit* order acts in the **opposite direction** to the market move that triggers it, a *stop loss* order acts in the **same direction** as the market move that triggers it
  - An example will make the difference clear. We will use the DollarYen exchange rate: the price of a dollar in terms of Yen
Customer Terminology Example

- A customer has bought dollars at a price of 100 Yen; if the price rises to 105 there will be a profit. If the customer leaves a limit order to sell the dollars at a price of 107 Yen this would be a take profit order. When there is a rise in the market price the order is to sell. The resulting transaction acts in the opposite direction to the move that triggered it.

- If the customer had again bought dollars at a price of 100 Yen but the price was now 95 a limit order could be left to close the position – that is to sell the dollars – if the price fell to 92. This would stop the loss getting any bigger and is thus known as a stop-loss order. In this case a fall in the market price triggers a sell and so the order acts in the same direction as the move that triggered it.
3 Structure of the FX Market

• Both EBS and Reuters provide double auction markets (buy and sell markets) in virtually all currency pairs.

• However, the market has segmented: EBS has the greatest turnover and liquidity in EuroDollar and DollarYen while Reuters is the main market for SterlingDollar and for the Euro against non-Dollar currencies.
FX Market Terminology

- **Bid**: Price market maker will pay to buy the currency
- **Ask (or Offer)**: Price at which market maker will sell the currency
- **Depth**: Total amount available at a particular price
- **Regular Amount**: A characteristic size set for each currency pair - typically 20 million dollars
- **Regular Price**: The price nearest the best price at which the regular amount is available to deal
  - Note the depth profile is usually bimodal with peak depth at prices a few pips worse that the best prices
FX Market Makers Private Information

• Market makers have private information

1. Order flow from their own customers:
   • Direction
   • Size
   • Type of customer

2. Their own customer order book:
   • Type of order
   • Price
   • Size
   • Type of customer
FX Market Makers Limited Information

- Market makers see limited information on EBS or Reuters
  1. Best bid and offer price
  2. Size at best bid (offer) but only if not regular
  3. Price where bid (offer) first goes regular (or best price if regular at best)
  4. Every transaction showing only restricted information:
     1. Price
     2. If buyer or seller initiated (if hit ask or bid)

Note, size of transaction is NOT shown
EBS Screen
4 Modelling Trading Agents

Two approaches:

1. Model customers (traders) as active agents and treat the global FX market (the market makers and their interactions) as a ‘black box’

   This is the trading-model approach: given a time series of market prices and related data what are optimal trading rules for the trading agents

2. Model the market makers as active agents and treat the customers as a stochastic source of orders

   This takes the continuous double auction model that has been applied in equity markets and applies it to the more complicated problem of the FX market with market maker agents between the customers and the price setting mechanism
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
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)
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

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

- 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 $\phi: \Sigma \times \{1,s\} \rightarrow \{1,s\}$ that maps the current market state $s_t$ and position to a new position
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
Trading Agent Models

- Three computational learning techniques are used to model traders:
  - Evolutionary learning: Genetic algorithms (GA) and genetic programs
  - Evolutionary reinforcement learning: Value function learning (ERL)
  - Reinforcement learning: Policy function learning (PRL)

- All techniques are dynamically adapted in a rolling window framework which ensures optimal learning behaviour of the agents
Trading Agent Information

• Past price data is fed into the learning system. The system will try to exploit (non-linear) serial dependencies in the spot price timeseries

• Technical indicators are calculated and fed in as well: they try to capture some property of the stochastic price process that can be exploited in trading

• The addition of these technical indicators on recent intraday data increased profitability by up to 30% per year
Modelling Trading Agents: GA model

- **Genetic algorithm** tries to find an optimal combination of trading rules by ‘evolving’ a population of rules by multiple passes through the in-sample data

- Set of **possible rules** derived from the technical indicators is $O(2^n)$

- **GA results on EUR-USD:**
  - On all frequencies for 0bp slippage: trading is profitable
  - On 1min and 5min for 1bp slippage: trading is profitable
  - Otherwise at realistic slippages: GA fails

- This moderate performance can be understood given the limited information value of technical indicators not supplemented by any other information
Proprietary Trading Agent Information

- Order book and order flow information fed into the ERL system

- Order book and order flow data is a market maker’s private proprietary information

- Indicators are calculated from the order book and order flow data to capture its properties most relevant to our artificial traders
Modelling Proprietary Trading Agents: ERL model

- Superior performance is expected given the use of non-public information. This is not a violation of weak and semi-strong form of the Efficient Market Hypothesis since private (insider) information is received
- On major currency pairs trading was profitable even after accounting for 10bp spreads
Evolutionary RL System – USDCHF 2-way 15 minute at 2bp
Significance Test

- We utilize a simple nonparametric 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 Dempster, Evstigneev & Schenk Hoppe (2003)

- 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

n = 36
n⁺ = 22

The p-value for this test was 0.9082
Modelling Proprietary Trading Agents: PRL model

- **Reinforcement learning** learns behaviour indirectly without direct ‘supervision’ by optimising a performance function of the trading signals.

- **Policy reinforcement learning (PRL)** learns the policy function that makes trading decisions **online** based on the supplied state information and the feedback rule using a simple **multilayer perceptron** neural network.

- Information supplied to this trading agent is past **price data and technical indicators**.

- Feeding in **order book and order flow data**: work in progress.
PRL Model Features

- Recurrent input is achieved by feedback of the trading signal into the system which creates awareness of the system (output) state -- a stabilising effect in control theory  Mood (1999)  Gold (2003)

- Agent looks simultaneously at different time-frames in an attempt to uncover patterns in the past prices or indicator values

- Trading activity is restricted when spreads were high i.e. during non-active periods in the market

- Low market liquidity also increases the order execution time and thus decreases profitability

- Stop-loss rules achieve risk reduction at the expense of decreased profits
PRL Model Results

• **Profitable** trading in major currency pairs at **realistic spreads**:
  - 2bp for EUR-USD
  - 3bp for USD-GBP

• Even **profitable** at **higher spreads**:
  - 3bp for EUR-USD
  - 4bp for USD-GBP

• With **realistic stop-losses**:
  - 20bp

• Even **profitable** with **stop-losses tight**:
  - 5bp
Modelling Trading Agents: PRL Model Results

- EURUSD:
  - 1min frequency
  - Jan 1999 to Jan 2002
  - 2bp slippage
  - stop-loss 20bp
  - yearly return 153%

Out-of-sample cumulative profits on EUR/USD at 1bp one-way spread.

Cumulative Profit (%)
Modelling Trading Agents: PRL Model Results

- GBPUSD:
  - 1min frequency
  - July 1991 to Dec 1999
  - 4bp slippage
  - stop-loss 20bp
  - yearly return 84%
PRL Model Daily Trading Results

• For daily trading technical indicators do not enhance performance on current EURUSD data

• At 20.3% per annum using 25 days past returns profits nearly triple over those at 7.5% using 3 days past returns

• Using 3 days past returns and customer order flows nearly doubles per annum profit at 14.1% but using 25 days past returns profits are reduced

• Adding technical indicators to past returns at daily frequency with or without order flows reduces trading profits – to make losses using 3 days past returns
5 Modelling Market Makers

- The model of the FX market shown earlier provides a structure for simulation
- Treat market makers as the active agents with customer order flow exogenously determined
- Treat customers as generating an initially fixed sequence of orders
- How should market makers respond?
Market Maker
(Inventory)

Market Maker
(Inventory)

Market Maker
(Inventory)

Customer Orders

Place Order

Hit Order

Best Bid & Ask

Regular Amount

Buy Orders

Sell Orders

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Market Maker Behaviour

• What is optimal market maker behaviour?

• Model market maker actions – conditional on:
  • ‘Public’ market information
  • ‘Public’ events
  • Private market information
  • Private events
Market Maker Actions

• Take a bid/ask price by hitting limit order of size $S$
• Place a limit buy/sell order at price $P$ of size $S$
• Cancel some or all (size $S$) of an existing buy/sell order
• Change existing buy/sell order to new price and size $P$ and $S$
• Do nothing at this time
• Modelling market reaction in terms of spread as a random walk between two partially absorbing barriers
Market Maker Public Information

- Best bid and ask prices (and so spread)
- Size at best bid and best ask
- Regular bid distance from best bid
- Regular ask distance from best ask
- Volatility of best prices
- Short-term technical indicators (trend, etc.)
- Inter-dealer activity in number (not size) of trades and buy/sell balance
Market Maker Public Events

- Best bid price changes
- Best ask price changes
- Liquidity at best bid changes
- Liquidity at best ask changes
- Regular bid price changes
- Regular ask price changes
Market Maker Private Information

- **Inventory**
- **Customer deals:** net buy/sell balance
- **Customers deals:** volume (both number and size)
- **Structure of customer limit orders**
- **Own limit orders with inter-dealer market**
Market Maker Private Events

- **Buy** (from us) order executed with customer

- **Sell** (to us) order executed with customer

- **Other market maker** hits our limit buy/sell order (event also known to the other MM)
Market Maker Stylized Behaviour

- Market makers are risk averse but must deal continuously to generate revenues.

- Continuous small profits on small trades – e.g. 10 million dollars – are preferable to occasional large profits on big trades with related losses!

- Large customer orders in inventory are dealt as many small trades Lyons (2001).

- Prices and amounts of bid and ask quotes are asymmetric depending on both the current market and customer order inventory.

- Gaming behaviour as for example bidding when selling off inventory is standard.

- The interdealer market is mean reverting on very short time scales as a result creating opportunities for proprietary traders.
Market Maker Model

- **MM action** conditional on events and information

- Optimisation methods:
  - Machine learning
    - Genetic Algorithms
    - Genetic Programs
    - Reinforcement Learning (various variants)
  - Agent Models
Conclusions & Directions for Future Work

- Have shown profitable automated FX trading agents at realistic transaction costs
- Proprietary trading indicators tested with PRL algorithm
- Detailed simulation modelling of the customers – market maker – interbank trading system in progress
- Detailed simulation modelling of the market makers actions in the entire two layer global FX market in progress
- Investigation of other agent based alternatives