Multiscale Analysis of Foreign Exchange Order Flows and Technical Trading Profitability

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Order flows and causality

- Foreign exchange (FX) order flows are “signed” transaction volumes.
- They are signed according to the initiator of the trade – positive for buy orders and negative for sell orders.
- More FX buying volume than selling volume over a period of time indicates a positive pressure on the price.

Order flows and causality

- The major assumption underlying FX market microstructure models is that exchange rate movements are driven by order flow.
- Order flow allows the wider market to learn about dispersed private information -- it represents the conduit through which information becomes embedded within market prices.

Order flows and causality

- In rational markets, ***aggregate*** order flow should reflect innovations in dispersed information, rather than being the result of “momentum” (or “feedback”) trading strategies followed by ***some*** FX traders.
- Positive (negative) feedback trading is systematic buying (selling) in response to price increases, and selling (buying) in response to price decreases.

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Order flows and causality

- Recent FX market microstructure literature has reported that currency order flows are powerful determinants and predictors of exchange rate returns.
- Note: the linear estimate of the size of price effects would be biased if causality runs from price to order flow.

Order flows and causality

- Only a select few papers have directly tested the causality assumption in FX markets and the evidence is mixed.
- Evans and Lyons (2002) and Killeen et al. (2006) find the assumption appropriate.
- Sager and Taylor (2008), Marsh and O'Rourke (2005), Boyer and van Norden (2006) and Gradojevic and Neely (2009) reveal reverse causality effects.

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Order flows and causality

- All of the above papers focus on testing the causality assumption at one particular data frequency (typically daily).
- In financial markets, the data generating process (DGP) is a complex network of layers with each layer corresponding to a particular frequency – need to account for intra- and inter-frequency dynamics (Dacorogna et al., 2001).

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Primary objective…

- By using a test for causality in the frequency domain from Breitung and Candelon (2006), this paper provides a complete inter-frequency characterization of the DGP governing the causality relationship between order flows and the CAD/USD exchange rate returns (1994-2005):
  - To investigate whether both the existence and direction of causality is frequency-dependent.

Secondary objectives…

- To investigate potential links between reverse causality and technical trading activities at various frequencies:
  - Is technical trading a type of “irrational” behavior that governs feedback trading?

Secondary objectives…

- To study the impact of financial versus non-financial order flows on technical trading activities.
- To use order flows for technical trading rule calculations (much like the volume could be used in technical trading; e.g., “on-balance” volume indicator in Neely et al. 2010) and test the profitability of such strategies at different time horizons.
- For instance, in equity markets, high recent volume and price increases indicate an uptrend – buy signal.

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Causality in the frequency domain

- To test the hypothesis that *y* does not cause *x* at frequency ω the following null hypothesis is used:

$$M_{y \to x}(\omega) = 0$$

- The VAR equation for x_t can be written as

$$x_t = a_1 x_{t-1} + \ldots + a_p x_{t-p} + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \varepsilon_{1t}.$$

- The null hypothesis is equivalent to the linear restriction

$$H_0 : R(\omega)\beta = 0,$$

- where

$$\beta = \left[\beta_1, \ldots, \beta_p\right]' \quad R(\omega) = \begin{bmatrix} \cos(\omega) & \cos(2\omega) & \ldots & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & \ldots & \sin(p\omega) \end{bmatrix}$$

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Causality in the frequency domain

- Recall that in the complex form x_t and y_t can be written as $x_t = Ae^{i\omega t} = A(cos(\omega t) + isin(\omega t))$ and $y_t = Be^{i\omega t} = B(cos(\omega t) + isin(\omega t))$, where i is the imaginary unit.
- The test statistic is asymptotically distributed as the χ^2 with two degrees of freedom so the 5% critical value is 5.99.

Data

- The data is at a daily frequency, from the Bank of Canada, between October 10, 1994 and September 30, 2005: 2,798 observations of daily returns and order flows.
- The order flow data are aggregate daily trading flows (in Canadian dollars) for eight major Canadian commercial banks:
- Commercial client transactions (CC) include all transactions with resident and non- resident non-financial customers.

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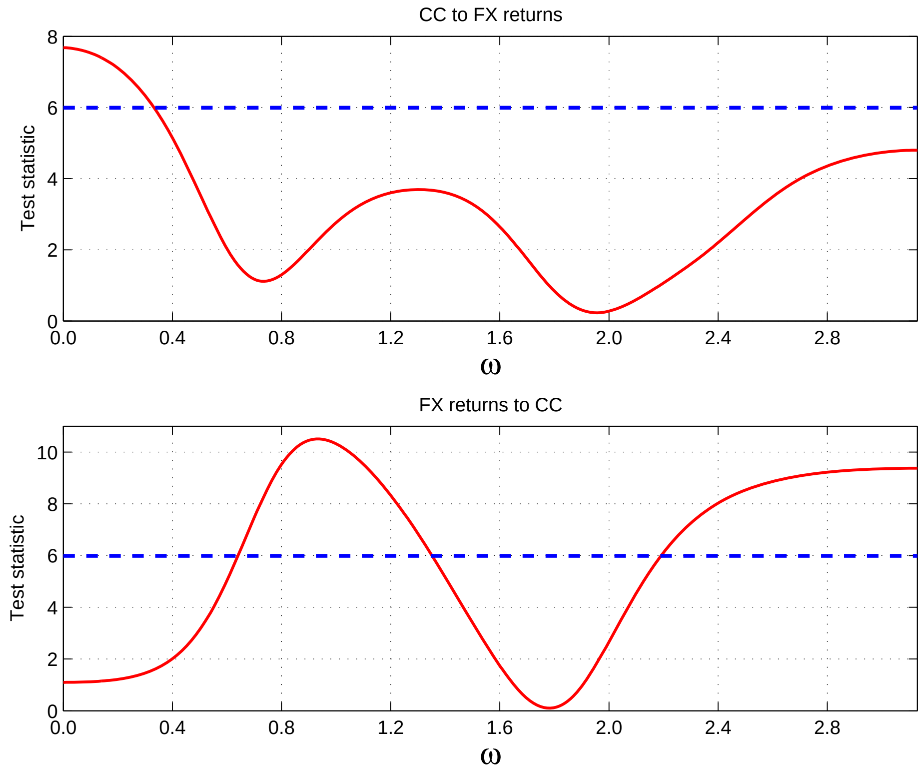
Data

- Foreign institution transactions (FD) include all transactions with foreign financial institutions, such as FX dealers.
- The CC transactions are motivated by trades in real goods and services, while the FD transactions are motivated by international portfolio considerations.
- These order flows represent approximately 40-60% of all Canada/U.S. dollar transactions.

Results: multiscale causality



Top panel: Causality tests (non-financial order flows to FX returns). **Bottom panel**: Causality tests (FX returns to non-financial order flows). The values of the χ^2 test statistic are given by a solid line. The 5% critical value (5.99) that is given by a horizontal dashed line. **The null hypotheses** are 1) that non-financial order flow does not cause FX returns at frequency ω (**top**) and 2) that FX returns do not cause non-financial order flow at frequency ω (**bottom**).

Results: multiscale causality

- CC->FX: the null hypothesis of no causality is rejected when $\omega<0.35$ which corresponds to frequencies with a wavelength of roughly more than four weeks (20 days = $2\pi/\omega$) – this range of frequencies in line with the theory.
- FX->CC: No stable pattern. **Significant short-run feedback.** For cycles longer than 12-13 days ($\omega=0.5$), no feedback effects.
- Linear exchange rate models that employ non-financial order flows produce unbiased estimates of the size of price effects at medium to long horizons.

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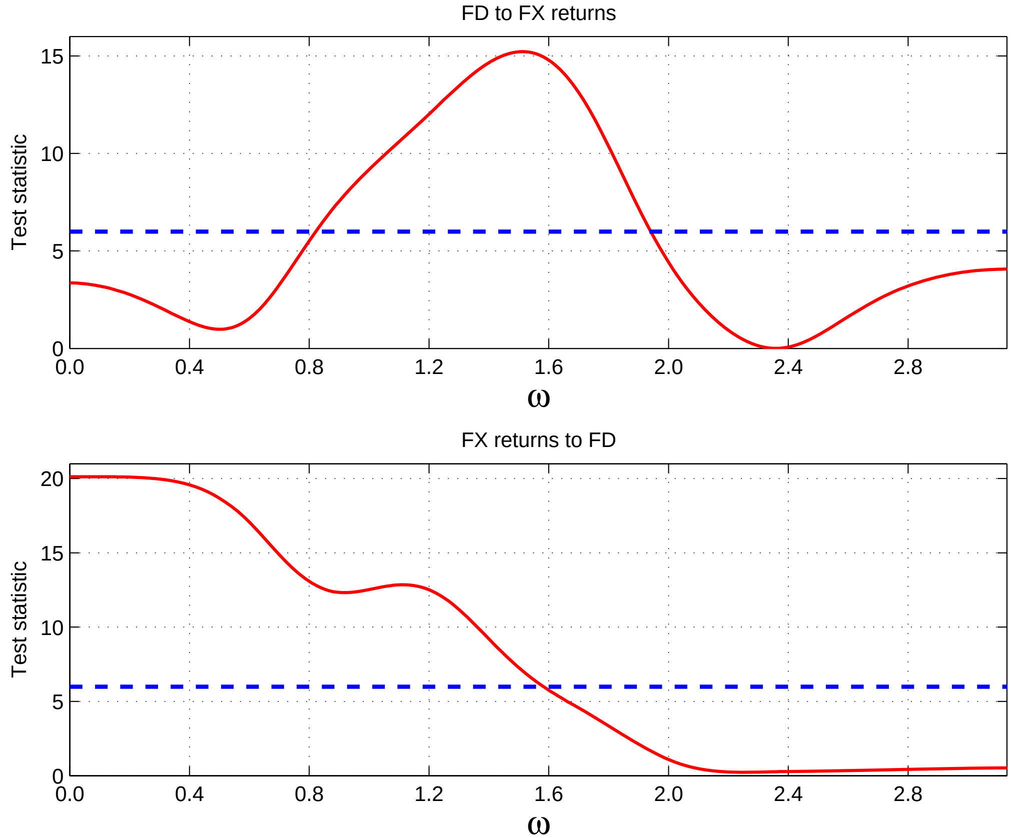
Results: multiscale causality



Top panel: Causality tests (financial order flows to FX returns). **Bottom panel**: Causality tests (FX returns to financial order flows). The values of the χ^2 test statistic are given by a solid line. The 5% critical value (5.99) that is given by a horizontal dashed line. **The null hypotheses** are 1) that financial order flow does not cause FX returns at frequency ω (**top**) and 2) that FX returns do not cause financial order flow at frequency ω (**bottom**).

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Results: multiscale causality

- FD->FX: No stable pattern. FD not very informative.
- Financial order flow is a poor predictor of exchange rate returns.
- FX->FD: **Significant feedback for cycles longer than 4 days** (ω<1.6).
- Sub-period analysis:1994-1997 period was in line with the causality assumption for both order flow types.
- This period was characterized by stable exchange rates.

Results: technical trading

- Three variants of two technical trading rules are calculated with the Canada/U.S. dollar exchange rate (return), the non-financial order flows, (CC) and the financial order flows (FD).

- The technical trading rules are calculated at the daily, weekly, bi-weekly, and monthly frequencies.

- The following table presents the profits from the moving average rules (MACO) and trading range break-out (TRBO) rules on the three data sets.

Results: technical trading

Profits generated after transaction costs:

	MACO (1,50)	MACO (10,50)	MACO (5,50)	TRBO (5)	TRBO (10)	TRBO (20)	Average
Daily Data							
Return	-4.31%	-0.40%	-0.49%	-3.04%	-1.11%	1.09%	-0.55%
CC	-4.42%	1.21%	1.59%	-3.57%	-0.50%	1.56%	-0.09%
FD	-5.76%	-1.32%	-0.58%	-4.68%	-1.61%	-0.36%	-1.22%
Weekly							
Return	-1.30%	0.53%	0.62%	-0.88%	-0.07%	1.26%	-0.38%
CC	0.90%	1.76%	1.83%	1.48%	1.50%	1.90%	0.65%
FD	-7.00%	5.44%	1.11%	-5.84%	1.33%	2.88%	-2.84%
Bi-weekly							
Return	-0.95%	-0.13%	1.05%	-0.35%	0.69%	1.51%	0.10%
CC	1.38%	1.66%	1.85%	1.64%	1.74%	1.21%	0.95%
FD	0.03%	-0.03%	-0.01%	0.54%	0.67%	0.16%	0.05%
Monthly							
Return	0.25%	1.13%	1.52%	0.72%	1.03%	0.64%	0.67%
CC	1.14%	1.55%	0.95%	1.37%	1.25%	1.02%	0.89%
FD	0.15%	-0.01%	-0.01%	0.49%	0.08%	0.14%	0.12%

Results: technical trading

- Note that, even after accounting for transaction costs, substantial excess returns can be found for all three time series.

- However, the results are mixed regarding the profitability of technical trading rules with order flow data.

Results: technical trading

- Note that the bi-weekly and monthly frequency generated larger profits than the daily and weekly frequencies.

- Accordingly, no evidence of a relationship between technical trading profits and reverse causality across time scales is found.

- Interestingly, FD order flow produced some encouraging findings (red circles) that potentially link the technical trading of financial institutions at longer horizons to reverse causality.

Results: technical trading

- However, trading rules were more profitable with CC data than either the FD data or return data.
- Accordingly, it appears that there is more technical trading information content in the trades of non-financial customer (e.g., Canadian corporations) than in the trades of financial customers (e.g., foreign dealers).

Conclusions and summary

- In contrast to the microstructure theory, the evidence shows that both the existence and direction of the causal relationship depends on the customer (order flow) type, frequency, and time period.
- In general, non-financial order flows are informative in the medium to long run, while financial order flows are good predictors of exchange rates over a narrow range of frequencies with wave-lengths between 3 and 8 days.

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Conclusions and summary

- We do not find any robust evidence for the multiscale dependency of reverse causality on the technical trading profitability or trading intensity.
- These findings suggest that feedback trading effects cannot be explained by the predominant activity of technical traders and that “liquidity provision” might be responsible for the presented evidence of reverse causality in the Canada/U.S. dollar market.

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Conclusions and summary

- It is worthwhile to note the striking result that technical trading rules that employ both order flow types can be profitable, and that the profits from the technical trading rules increase as the frequency of the data decreases.
- Furthermore, we demonstrate the superiority in profitability of non-financial order flows.

Fuzzy Logic, Trading Uncertainty and Technical Trading

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Outline

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- Two approaches: *charting* (identifies geometric patterns in the history of prices) and *technical indicators* (mechanically applies mathematical trading rules constructed from past and present prices) (see surveys by Irwin and Park, 2007, Menkhoff and Taylor, 2007 and Neely and Weller, 2010).

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- The success of technical trading violates the weak form of the efficient market hypothesis, which states that past prices should not assist traders in earning unusually high returns.

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- *Sentiment-oriented technical traders* are order anticipators who exploit predictable price patterns caused by uninformed traders (front-run the uninformed traders and trade before they trade!).
- In this paper, we interpret the activity of sentiment-oriented technical traders as ‘uncertainty reduction’ while the uninformed traders are considered pure technical traders who employ simple technical indicators.

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- We address the uncertainty in decision-making which arises if there is an insufficient knowledge about the appropriateness of the trading model - trading (model) uncertainty.
- We employ fuzzy logic to address and partially reduce two implications of trading uncertainty: market timing ("when to trade") and order size ("how to trade").

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- We directly compare the efficacy of standard technical indicators and ‘fuzzy technical indicators’ for high-frequency (one-minute) EUR-USD exchange rates in 2005.
- Also, we develop five testable hypotheses that involve the relationship between high-frequency profitability and volatility (hypotheses 1-3), and the ranking of the trading strategies (hypotheses 4 and 5).

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- Also, we develop five testable hypotheses that involve the relationship between high-frequency profitability and volatility (hypotheses 1-3), and the ranking of the trading strategies (hypotheses 4 and 5).
- From the market microstructure perspective, we argue that fuzzy logic-based technical trading mimics the behavior of sentiment-oriented technical traders.

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- Information granules such as “high speed”, “significant risk” or “strong sell” can be processed using fuzzy logic.
- Fuzzy logic can help traders control for the uncertainty aspect of employing technical indicators that are in essence discrete buy or sell trading signals.

- Any fuzzy model has three main components: (1) fuzzy “rule base” in the form of a set of “if-then” rules (expert knowledge about the model), (2) fuzzification module that transforms the explanatory variables (inputs) into fuzzy variables, and (3) defuzzification module that converts the conclusion from the fuzzy domain into the dependent variable (output).

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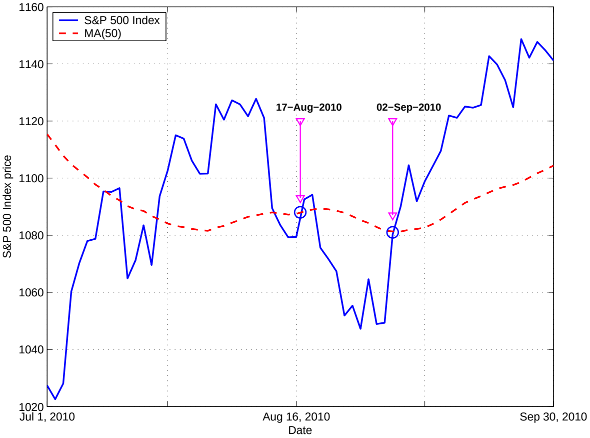
- The rules can, for instance, state that "if the long moving average is $<$LARGE$>$ and the short moving average is $<$VERY SMALL$>$, then the technical trading signal is $<$STRONG SELL$>$."

The following example will illustrate fuzzy decision-making (‘fuzzy technical indicators’) and compare it with the standard moving average technical indicators approach:



(Daily closing prices and MA(50) for the S&P-500 Index from July 1, 2010 to September 30, 2010)

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- On September 2nd, 2010, fuzzy logic realizes the larger discrepancy between the S&P-500 Index value and MA(50) and generates a ‘STRONG BUY’ recommendation (i.e., invest roughly 92% of your current endowment).

- Our model has two inputs - MA(50) and daily closing price - both fuzzified on the interval [0, 1] into the following five triangular fuzzy membership functions: “VERY SMALL,” “SMALL,” “MEDIUM,” “LARGE,” and “VERY LARGE”.

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- The rule base contains $5^2 = 25$ rules that compare all possible combinations of the two inputs and produce the appropriate outputs.

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- Let's consider a signal x_t with a known frequency ν. In the frequency domain, this signal can be written as

$$x_t = e^{i2\pi\nu t}$$

$$MA(50) = y_t = \frac{1}{50}(x_t + x_{t-1} + \ldots + x_{t-49}) = H(\nu)e^{i2\pi\nu t}$$

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- $H(\nu)$ is the *frequency response function* or the *transfer function* of the MA(50) filter:

$$H(\nu) = G(\nu)e^{i\theta\nu}$$

  where $G(\nu)$ is called the *gain function* and θ is the phase angle.

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- When $\theta \neq 0$ there will be a change in the phase known as the *phase shift*.
- For MA(50), $H(\nu)$ can be written as

$$H(\nu) = \frac{e^{-i\pi\nu 49}}{50}\left(\frac{\sin(\pi\nu 50)}{\sin(\pi\nu)}\right) = e^{-i\pi\nu 49}G(\nu)$$

which shows that there exists a *phase shift* and that the phase is $49\pi\nu$.

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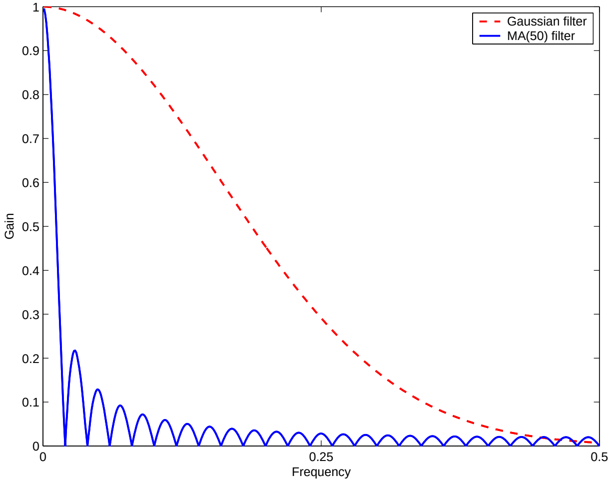
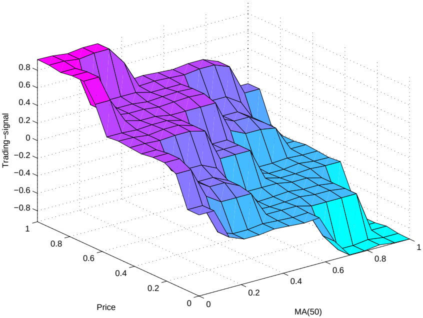
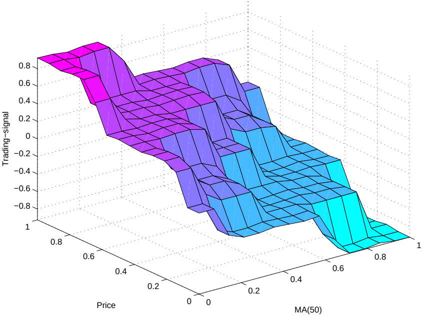
- The fuzzy Gaussian filter used in the current paper has such a capability (see figure).

Gain functions

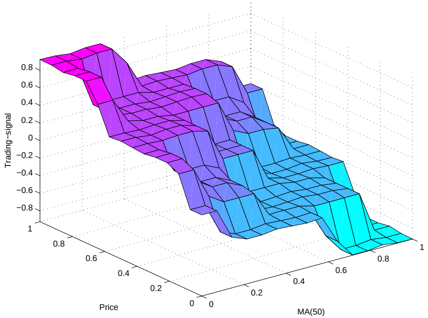




- Fuzzy rule base generates a continuous decision surface in a form of mapping from the inputs to the output.



- Fuzzy rule base generates a continuous decision surface in a form of mapping from the inputs to the output.
- It accounts for the distance between the inputs and produces a trading signal that identifies the exact fraction of the funds that are to be allocated to a position.



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- It accounts for the distance between the inputs and produces a trading signal that identifies the exact fraction of the funds that are to be allocated to a position.
- The distance between the price and MA(50) is viewed as a measure of uncertainty which increases as the distance decreases.

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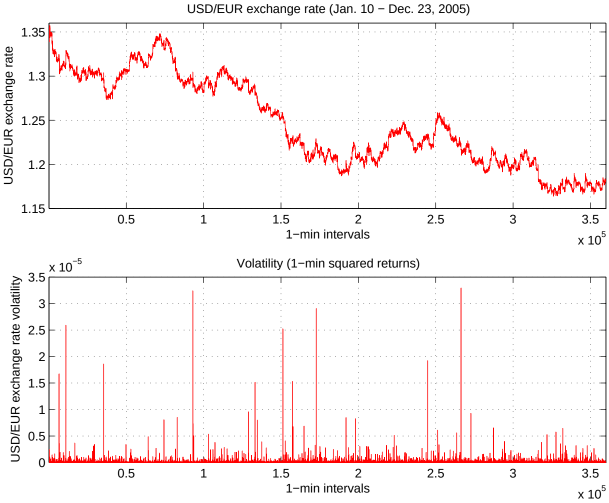
USD/EUR exchange rate (Jan. 10 − Dec. 23, 2005)
USD/EUR exchange rate
1.35
1.3
1.25
1.2
1.15
0.5
1
1.5
2
2.5
3
3.5
1−min intervals
x 10^5
Volatility (1−min squared returns)
x 10^−5
USD/EUR exchange rate volatility
3.5
3
2.5
2
1.5
1
0.5
0
0.5
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- 5: Fuzzy technical indicators and pure technical indicators dominate the buy-and-hold strategies, irrespective of volatility.

Results

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- All tables include two basis points transaction costs for a one-way trade, which is realistic for large transactions

Conditional mean returns for the moving average rules:

Sample (date)	Statistic	Mon	Tue	Wed	Thu	Fri
Jan 10-July 8, 2005	Fuzzy	6.11	12.67	13.37	14.90	16.65
	Pure	6.07	5.61	-4.39	-0.99	-4.82
	Buy&Hold	-8.52	-5.88	1.17	-21.45	-0.27
	(t-stat)	(0.01)	(2.22)	(3.74)	(5.47)	(3.14)
	[W]	[0.62]	[0.03]	[0.00]	[0.00]	[0.00]
	Volatility	4.88	6.43	7.36	7.13	8.31
July 11-Dec 23, 2005	Fuzzy	4.52	10.04	6.74	10.73	13.98
	Pure	4.47	-0.91	4.27	-5.79	-4.37
	Buy&Hold	-2.12	-0.99	12.54	7.87	-17.52
	(t-stat)	(0.89)	(2.67)	(0.86)	(2.87)	(3.15)
	[W]	[0.36]	[0.00]	[0.35]	[0.00]	[0.00]
	Volatility	6.01	7.70	7.64	8.25	7.95

Conditional mean returns for filter rules:

Sample (date)	Statistic	Mon	Tue	Wed	Thu	Fri
Jan 10-July 8, 2005	Fuzzy	0.34	3.40	7.52	7.13	10.57
	Pure	-1.17	-1.84	-3.19	-5.45	-6.62
	Buy&Hold	-10.19	-5.74	-3.23	-21.61	-4.18
	(t-stat)	(1.64)	(1.15)	(2.45)	(5.88)	(7.56)
	[W]	[0.42]	[0.07]	[0.00]	[0.00]	[0.00]
	Volatility	4.88	6.43	7.36	7.13	8.31
July 11-Dec 23, 2005	Fuzzy	4.25	5.36	8.01	9.61	8.13
	Pure	-3.71	-12.13	-6.08	-10.09	-4.91
	Buy&Hold	-3.51	-1.06	7.79	6.89	-18.09
	(t-stat)	(2.23)	(3.09)	(8.50)	(8.30)	(2.43)
	[W]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]
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- The tables demonstrate the validity of the five Hypotheses.
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- Fuzzy reasoning might be able to explain the behavior (and success) of sentiment-oriented technical traders – it mimics the learning process and the implementation of trading strategies for such traders.

Conclusions

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- We find an increased dominance of the fuzzy approach on more volatile days of the week (Fridays and Thursdays), but not as much on Mondays, which are found the least volatile in the data.
- We conclude that the success of our fuzzy uncertainty reduction technique stems from its two important properties: 1) smooth decision surface and 2) reduction in trading costs.

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- Extension 1: fuzzify alternative technical indicators such as the trading range break-out rules, momentum rules or rules based on volume.

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- Extension 3: understand the role of volatility better – present the volatility input to the fuzzy controller and expand the rule base with more complex fuzzy rules of the following nature: “if the long moving average is $<$LARGE$>$, and the short moving average is $<$VERY SMALL$>$, and the volatility is $<$VERY SMALL$>$ then the technical trading signal is $<$SELL$>$.”

Thank you!
Questions/Discussion?