Investigating FX-Market Efficiency with Support Vector Machines.

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Exchange Rate Forecasting.
Content:

- Description of general project
- Introduction
  - Markets and computational complexity
  - Motivation
- Procedure
- SVM’ as a tool
- Results
- Conclusions

Exchange Rate Forecasting.
Description of project:

Investigations are part of project

Intelligent Systems in Finance (ISF)

Goals:

- Investigate complexity of financial decision problems
- How parameters and structural properties influence complexity?
- Develop tools (based on ideas from machine learning) for this problems.

Applications:

Risk management, credit risk, operational risk, FX markets, stock markets, business process optimization

Participants:

GILLARDON AG financial software, entory AG, BMW Group, University Newcastle, University Karlsruhe (Institute AIFB, Graduate School IME)

Foreign Exchange Market.
Introduction.

The Foreign Exchange (FX or FOREX) market is the market where exchange rates are determined.

- Exchange rates are the mechanisms by which world currencies are tied together in the global marketplace, providing the price of one currency in terms of another.
- Primary functions:
  - Transfer of purchasing power
  - Hedging of foreign exchange risk
- Five groups of market participants: International banks, bank customers, non-bank dealers, brokers, central banks
- Four major markets: spot, forward (futures), options, and swaps.
- Market activities: arbitrage, speculation, hedging

Foreign Exchange Market.
History.

The Foreign Exchange (FX or FOREX) market is the market where exchange rates are determined.

- Following WW II, the world's major currencies were fixed relative to the USD. Changes were rare and the result of sustained imbalances in global capital flows.
- Since 1973 these currencies have been floating and attempts to explain and predict their movements have been largely unsuccessful.
- Currently the foreign exchange (FX) market is the largest financial market in the world operating 24 hours a day, 7 days a week (mainly in Tokyo, London, and New York).
- Average trading volume in 2004 was 1.9 trillion USD per day

Exchange Rate Forecasting.
Introduction.

Forecasting financial time series is an important and complex problem.

- **Important:**
  - Theoretical research: numerous approaches from various disciplines, such as macroeconomics, statistics, financial theory, cognitive sciences and machine learning.
  - Practice: banks, hedge fonds, industrial corporations, private investors.
- **Complex:**
  - **FX markets** show key common elements of complex systems: feedback, non-stationarity, many interacting agents, adaptation, evolution, open system.
  - Nobody yet knows how to describe mathematically the time evolution of such complex systems in a general but useful way.
  - Modern Finance Theory assumes that efficient market hypothesis holds. However, it is still an open question to which degree FX markets can be predicted.

Why computational complexity matters?

There are some provable results on computational complexity of markets in general and decision problems in Economics:

- Computation of economic concepts (winning strategies, equilibria, …)
- Prediction of markets becomes more complex with the growing number of strategies
- Arbitrage opportunity for exchange markets
- Decision problems in risk management (credit risk: portfolio problems, operation risk different decision problems)

The high complexity (computational as well as dynamic) of many economic systems is one of the main reasons why often we have to use heuristics to support economic decisions.

Exchange Rate Forecasting.

Introduction – back to real life

Complexity matters in Economics and it prevents easy solutions, efficient algorithms to solve the problems and often even efficient algorithms to approximate optimal solutions.

But nevertheless in real life

decisions have to be made!

- **We need the right tools to support our decision making.**
- **Complexity is an argument to help us to choose the right tools to support our decisions.**
- **By considering the results on complexity we know that it is suitable to use heuristics, which are able to handle problems of high dimensionality, e.g. some tools from machine learning, as SVM's.**

Foreign Exchange Risk .
Does it matter?

Risk management theory suggests that it is optimal for a firm to manage its risks, simply, if the benefits of risk management exceed the costs of managing the risks.

- Modigliani and Miller (1958): Under perfect capital markets firms need not manage their financial risks. Investors can do it for themselves.
- In the last two decades, academics have challenged the Miller-Modigliani hypothesis in its pure form and demonstrated that hedging can sometimes add value:
  - Information asymmetry (Froot et al. 1993)
  - Differential transaction costs (Stulz 1985)
  - Costs of financial distress (Shapiro and Titman 1985)
  - Progressive corporate taxes (Smith and Stulz 1985)
  - Financing investments (Myers 1977)
- Empirical examination of hedging theories has been affected by the general unavailability of data on hedging activities
- Empirical studies used survey data to examine the determinants of derivatives use (e.g. Nance, Smith, and Smithson 1993, etc.)

Foreign Exchange Risk .
Does it matter?

Germany
Auto Manufacturing

Deutsche Bank

10/15/2003

German Autos

Dollar Pains

USD currency effect - Sensitivity to USD/EUR and to net USD exposure

(€m)		Net USD Exposure				
		5,500	6,000	6,296	6,500	7,000
	1.15	-527	-569	-594	-611	-653
	1.20	-584	-634	-665	-685	-736
USD/EUR	1.25	-635	-694	-729	-754	-813
	1.30	-683	-750	-786	-817	-884
	1.40	-768	-849	-892	-929	-1,010

Source: DrKW Equity research, BMW Group

Dresdner Kleinwort Wasserstein

Foreign Exchange Risk .

Does it matter?

German newspaper headlines regularly stress the importance of currency effects on corporate earnings statements.

“Währungsrisiken verursachen den größten Teil des Dasa-Verlusts“ (FAZ, 12.9.1995, S.21)

“Starker Euro frisst VW Gewinn”;…ähnlich ergeht es Firmen wie Siemens, Philips, Total Fina, Elf, Boss, Altana und Unilever“ (FTD 8.5.2003)

“…Dollar-Schwäche hat mit dazu beigetragen, dass der Konzern [VW] in Nordamerika einen Verlust von mehr als 900 Millionen Euro einfuhr.“ (FAZ, 3.6.2004, S.21)

“Währungverluste knabbern am Konzerngewinn“ (HB, 7.5.1996, S.19)

“Lufthansa fliegt höheren Gewinn ein – Ergebnis wird aber durch Währungsverluste belastet“ (SZ, 22.5.1996)

“Fatale Folgen – Der Höhenflug des Euro drückt auf den Gewinn vieler Unternehmen und kostet Wirtschaftswachstum. “ (Capital, 2/2004, S.12 ff.)

“Schwacher Dollar hinterlässt Bei Autoherstellern tiefe Spuren“ (FAZ, 9.12.2004)

“Schwacher Dollar Lässt BMW Umsatz schrumpfen“ (FTD, 28.1.2004, S.9)

Foreign Exchange Risk .
Does it matter?

As business becomes more global, foreign exchange risks are considered as the most costly type of corporate risk.

Factors	% 4 or 5	% 4 or 5	N
Foreign exchange risks		53%	239
Strategic risks		47%	232
Financing risk		40%	233
Competitive risks		39%	237
Failure of company projects		36%	236
Execution risks		35%	231
Reputational risks		33%	232
Commodity price risks		32%	238
Operational risks		31%	232
Interest rate risks		31%	239
Credit risks		28%	237
Regulatory or government risks		26%	238
Loss of key personnel		26%	235
Property and casualty risks		22%	236
Litigation risks		21%	233
Natural catastrophe risks		17%	237
Employee misdeeds		13%	234
Terrorism risks		13%	235
Political risks		11%	238
Pension or healthcare shortfalls		10%	228
Weather risks		9%	235

Servaes and Tufano (2006): “The Theory and Practice of Corporate Risk Management Policy”

Foreign Exchange Risk .
Does it matter?

Although foreign exchange risk has top priority, corporations seem to have either…

- …not found a recipe yet to cope with adverse exchange rate fluctuations or…
- …or that the methods applied do not provide sufficient protection against currency risks.

Foreign Exchange Risk Management.
What can be done?

There are different (contradicting) objectives and different strategies to choose from.

Common Goals of FX Managements

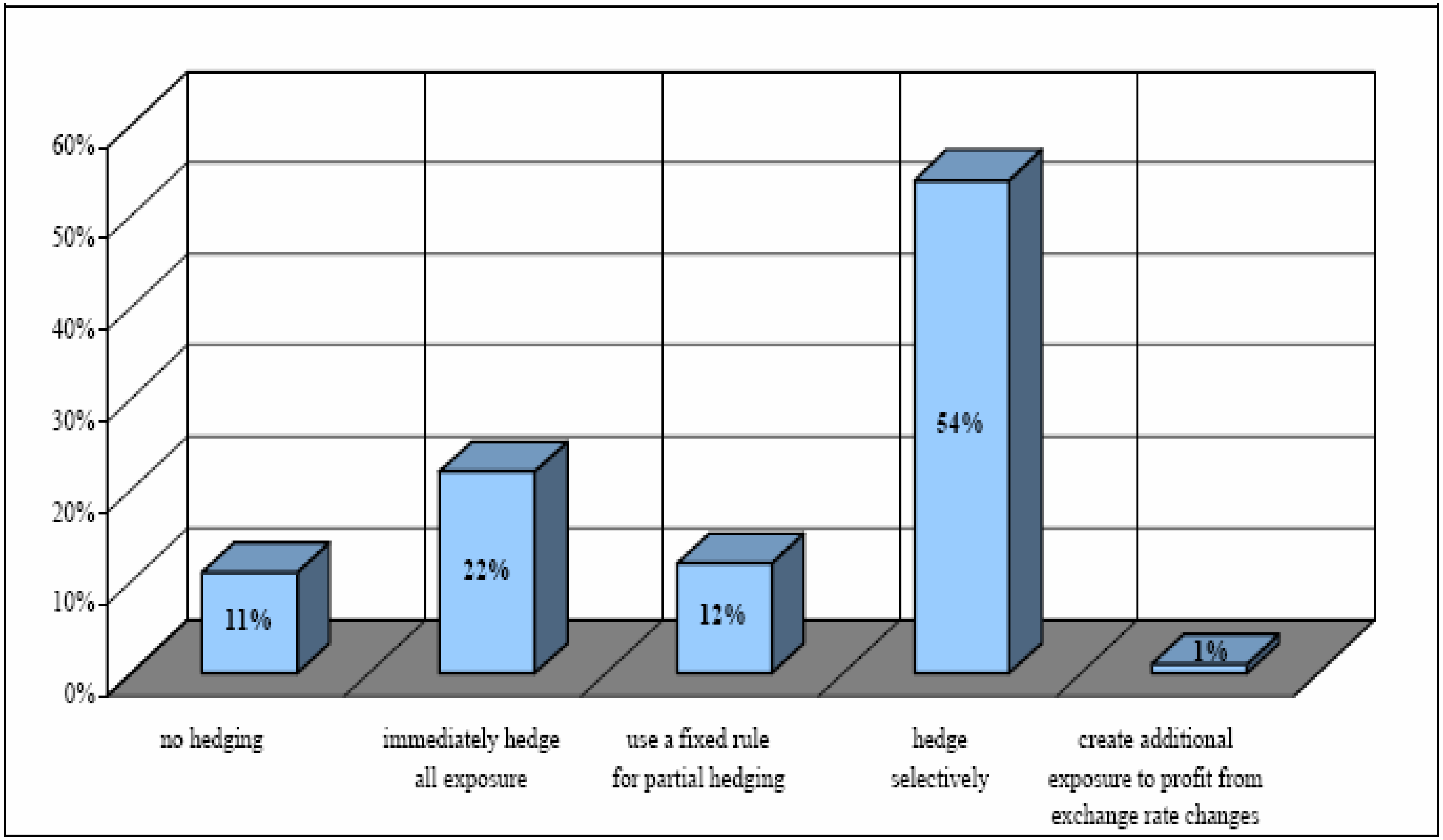
- Increasing Planning Stability
- Reducing Earnings Risk
- Taking Advantage of Opportunities
- Minimizing Transaction Costs

Alternative Strategies

- 0% Hedging (Spot Strategy)
- 100% Hedging
- Fixed rule for Partial Hedging
- Selective Hedging
- Create Additional Exposure (Speculation)

Foreign Exchange Risk Management.
What can be done?

The majority of German firms follows a selective hedging strategy.



Glaum (2000): "Foreign Exchange Risk Management in German Non-Financial Corporations"

Selective Hedging:

- Hedge only those positions for which a currency loss is expected.
- Leave open positions for which a currency gain is expected.

Foreign Exchange Risk
What can be done?

Most companies incorporate a certain degree of flexibility in their hedging strategy.

- Risk-averse hedging behaviour implies eliminating all foreign exchange risk as soon as it arises.
- The majority of corporations are neither risk-averse nor risk-taking, but find themselves somewhere in between the two extremes.
- Consequently, the majority of corporations seems to be confident enough in their ability to predict foreign exchange rate movements!
- But: foreign exchange market is generally known to be highly efficient!
- 2 Questions:
  - How can market efficiency be tested? Is there a risk premium in the market?
  - What is an appropriate overall approach for building a decision-support model?

Foreign Exchange Market Efficiency
Definition

Fama (1970, 1991) defines a market to be efficient if prices in that market fully reflect all the available and relevant information.

- Intuition: if market processes information immediately, price changes can only be caused by the arrival of new information. However, since future information cannot be predicted, it is also impossible to predict future price changes.
- 3 types of efficiency:
  - **Weak-form** efficiency: No investor can earn excess returns by developing trading rules based on historical price or return information.
  - **Semi-strong-form** efficiency: No investor can earn excess returns by developing trading rules based on publicly available information.
  - **Strong-form** efficiency: No investor can earn excess returns using any information, whether publicly available or not.

Foreign Exchange Market Efficiency

Traditional tests

Standard Finance approaches focus on the notion of a bias in the forward rate.

- Covered Interest Rate Parity (CIP):

  $$f_t^k - s_t = i_{t,k} - i_{t,k}^*$$

- Uncovered Interest Rate Parity (UIP):

  $$E(s_{t+k}) - s_t = i_{t,k} - i_{t,k}^*$$

  $$s_{t+k} - s_t = \alpha + \beta\left(f_t^k - s_t\right) + \mu_{t+k}$$ ("Fama regression")

- "Forward bias puzzle": negative value of β (Froot and Thaler 1990)
- Explanations:
  - Risk-averse market participants?

    $E(s_{t+k}) - f_{t,k} - \rho_{t,k} = 0$ (Engel 1992)
  - Risk-neutral but irrational market participants? (Lewis 1990)
  - Risk-averse and irrational market participants? (Froot 1987)

Exchange Rate Forecasting
Motivation of our work

The following analysis is motivated by the work of…

[Kamruzzaman and Sarker 2003]:

- Applied SVM regression to predict a set of Australian FX rates.
- It was found that Gaussian RBF and Polynomial kernels appear to be a better choice than Linear or Spline kernels.

[Francois, Wertz and Verleysen 2005]:

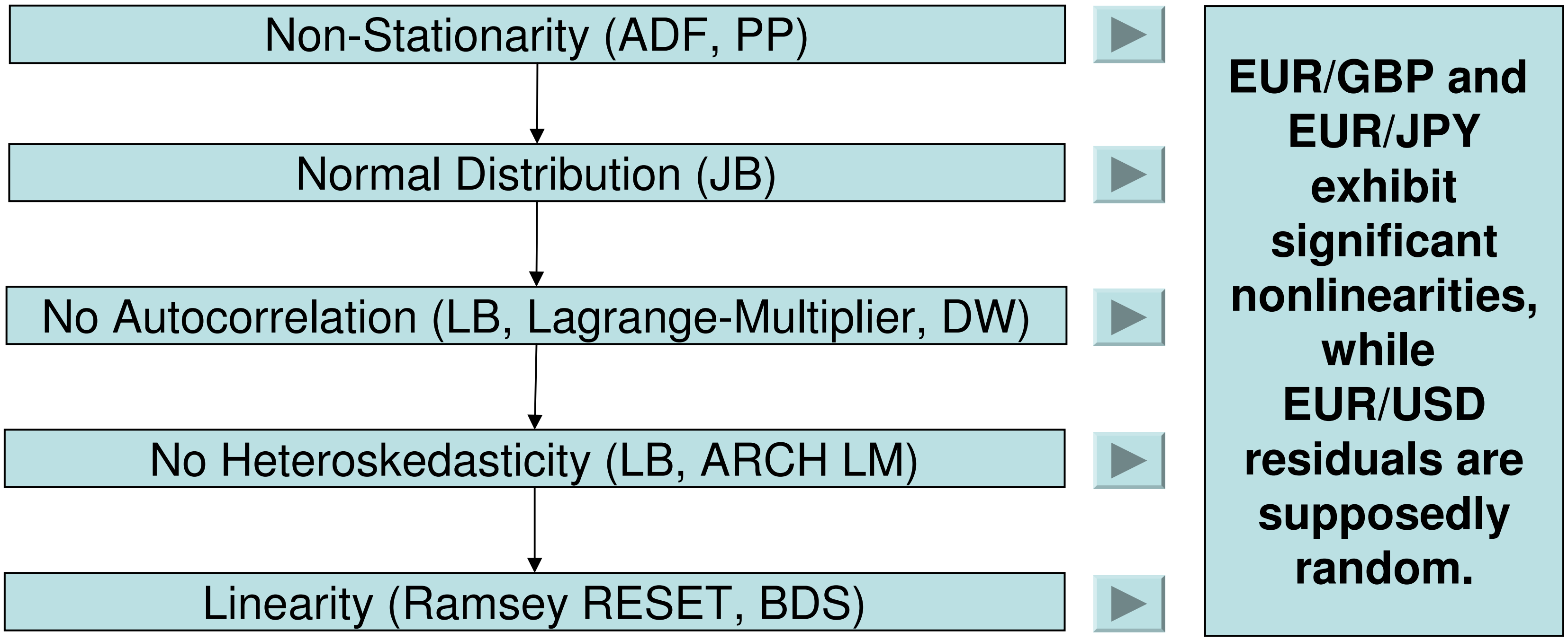
"Gaussian kernels are adequate measures of similarity when the representation dimension of the space remains small, but that they fail to reach their goal in high dimensional spaces. We suggest the use of p-Gaussian kernels that include a supplementary degree of freedom in order to adapt to the distribution of data in high dimensional problems."

➔ Are SVM's useful for predicting FX rate returns?
➔ What sort of kernel should be chosen?
➔ Do p-Gaussian kernels improve forecasting quality empirically?

Time Series Analysis.
Stylized Facts.

Analyzing statistical properties of exchange rate data makes sense for two reasons:

- Understanding the degree of randomness
- Building benchmark models



➔ It remains to be seen how well SVM models will be able to exploit nonlinearities and compare to linear benchmark models.

Data Selection.
Procedure.

The procedure of obtaining an explanatory dataset of input instances is divided into two phases.

Phase 1: Data Collection

- Stock Market Price Indices
- 3-Month Interest Rates
- 10-Year Government Bond Yields
- 10-Year Government Bond Spreads
- Prices of Silver, Gold and Platinum
- Price of Brent Crude Oil
- Diverse Metals and Agricultural Commodities as being traded on the LME

In-sample: 01.01.1997 – 31.08.2003 (1739 obs.), Out-of-sample: 01.09.2003 -31.12.2004 (350 obs.)

Phase 2: Dimensionality Reduction

Granger Causality Tests
PCA

EUR/GBP: 3 FX Rates, 4 Stock Ind., 2 Government Bonds, Platinum, Nickel.

EUR/JPY: EUR/CHF, IBEX, 5 Government Bonds, UK Bond Spreads, Australian 3-month Interest Rate, Silver.

EUR/USD: AUD/USD, SPX, Copper, 2 Metals, 2 Agricultural Commodities.

Foreign Exchange Market Efficiency.
Trading with Support Vector Machines (SVM).

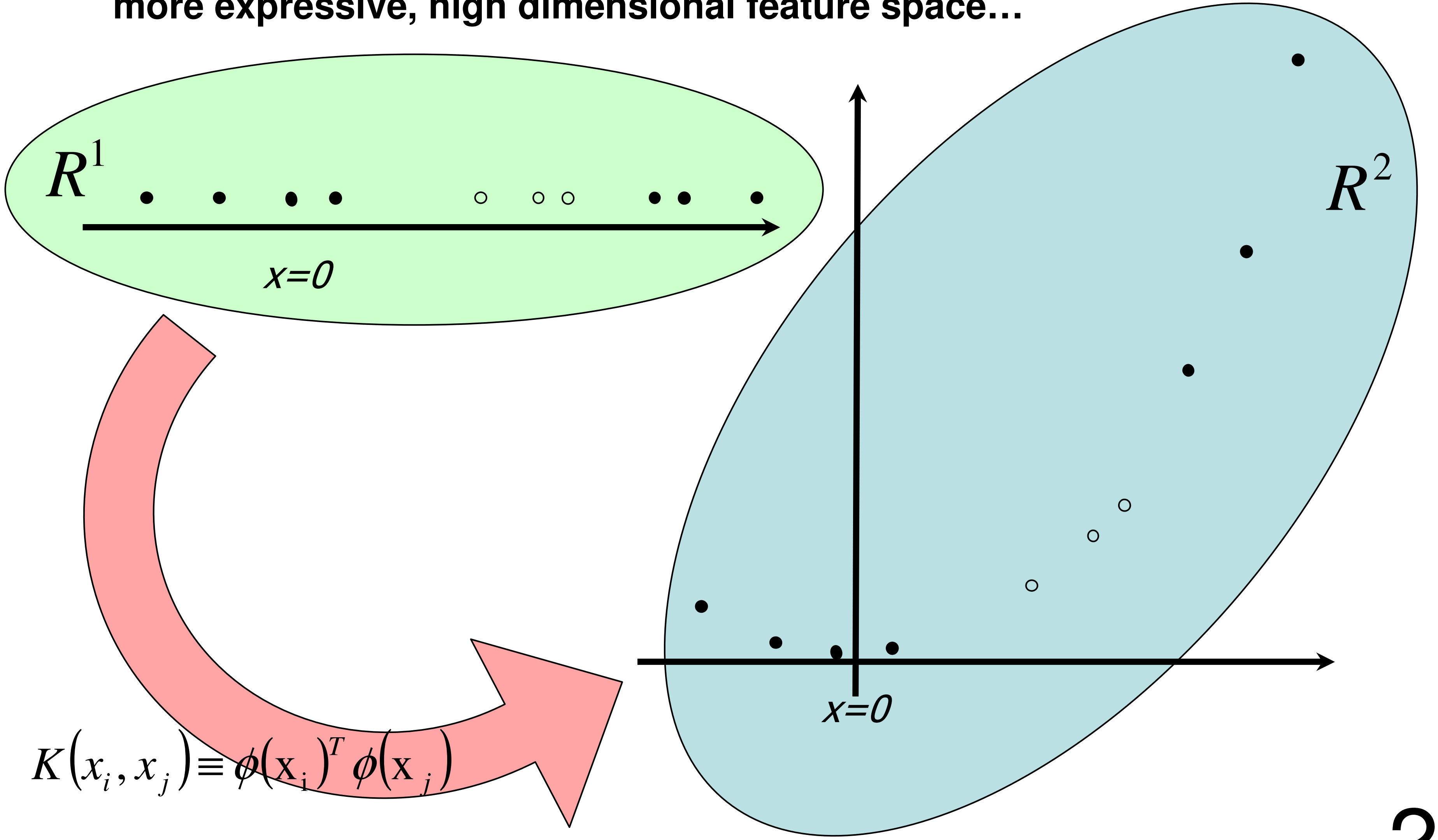
Support Vector Machines (SVM) are a new kind of supervised learning system that map the input dataset via kernel into a high dimensional feature space in order to enable linear data classification and regression.

- Introduced by Boser, Guyon, and Vapnik (1992)
- SVM has proven to be a principled and very powerful method that in the few years since its introduction has already outperformed many other systems in a variety of applications, e.g.
  - text categorization
  - image processing
  - hand-written digit recognition
  - bioinformatics problems
  - time series prediction
- We examine the general ability of SVM's to correctly classify daily EUR/GBP, EUR/JPY, and EURUSD exchange rate returns.

Support Vector Machines.
Basic Idea.

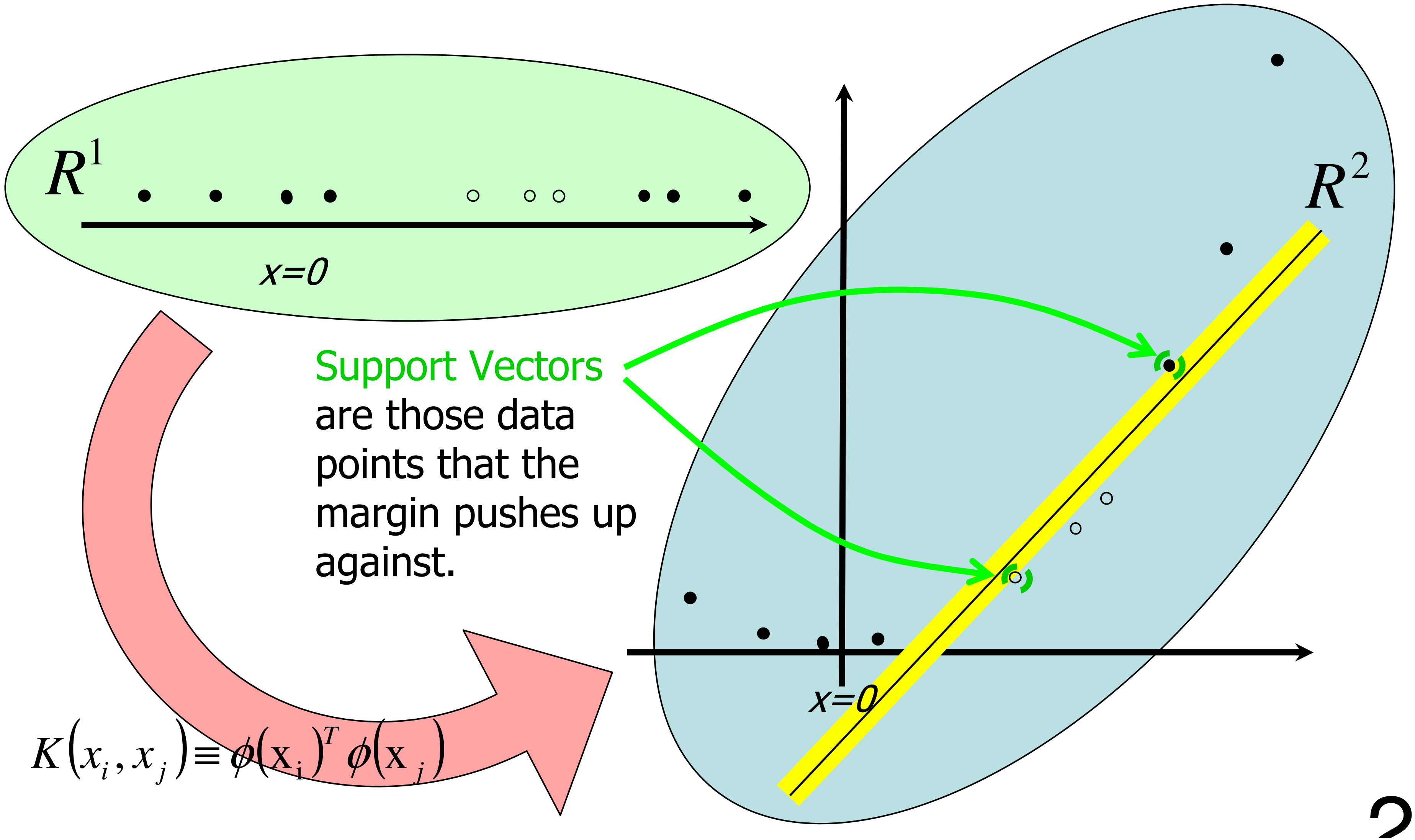
The basic idea is…

1. … to project the input data $x_i \in R^n$ via kernel $K(x_i, x_j)$ into a more expressive, high dimensional feature space…



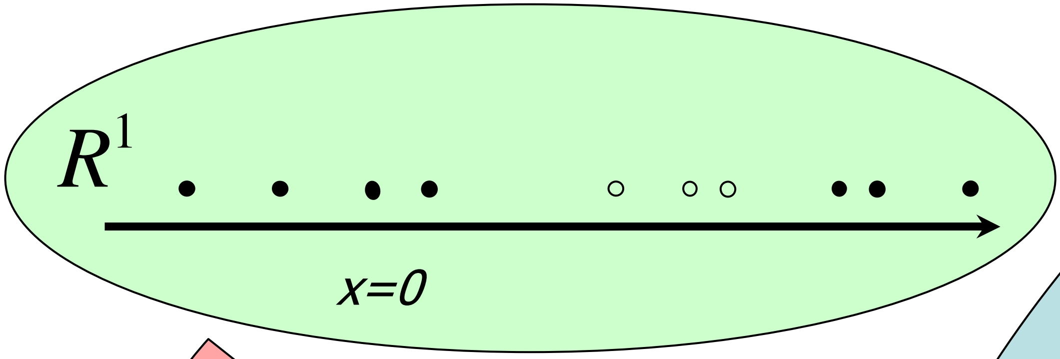
Support Vector Machines.
Basic Idea.

2. … where the SVM algorithm finds the decision plane that has **maximum distance** from the nearest training patterns.

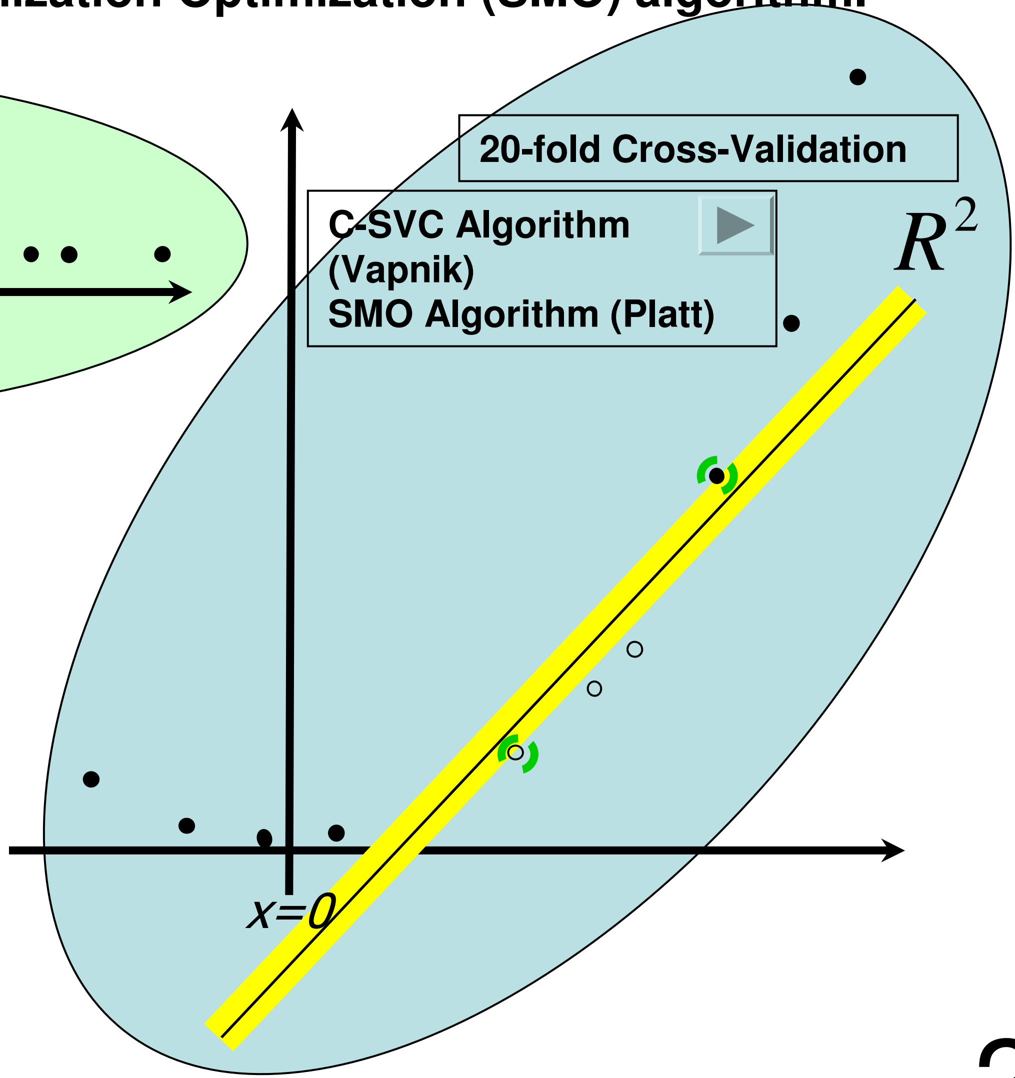


Support Vector Machine Model.
Training.

Per kernel, training the SVM requires the solution of a very large quadratic programming optimization problem (QP) which is solved by using the Sequential Minimization Optimization (SMO) algorithm.



Linear	$k(x,x') = \langle x,x' \rangle$
Polynomial	$k(x,x') = (scale \cdot \langle x,x' \rangle + \text{offset})^{\text{degree}}$
Laplace	$k(x,x') = \exp(-\sigma \lVert x - x' \rVert)$
Gaussian RBF	$k(x,x') = \exp\left(-\sigma \lVert x - x' \rVert^2\right)$
Hyperbolic	$k(x,x') = \tanh(scale \cdot \langle x,x' \rangle + \text{offset})$
Bessel	$k(x,x') = \dfrac{\text{Bessel}^{n}_{(v+1)}(\sigma \lVert x - x' \rVert)}{\left(\lVert x - x' \rVert^{-n(v+1)}\right)}$
P-Gaussian	$k(x_i,x_j) = \exp\left(-d(x_i,x)^p / \sigma^p\right)$

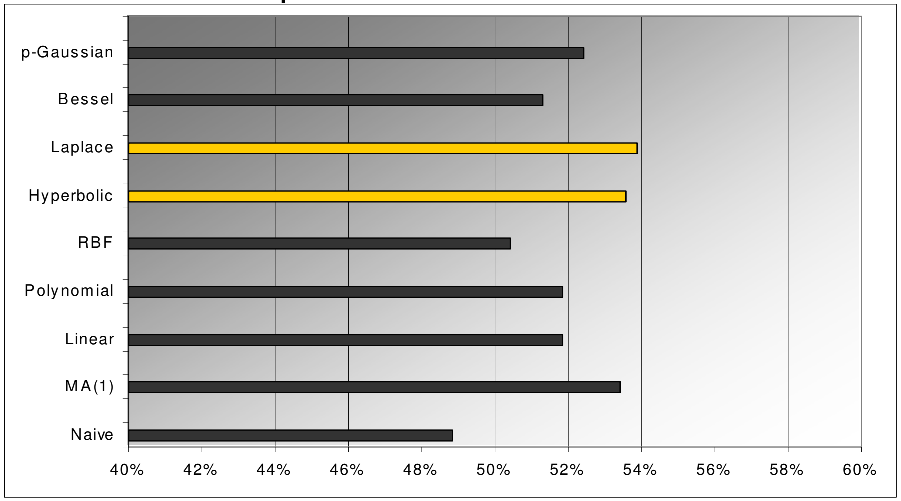


Out-of-sample Results.

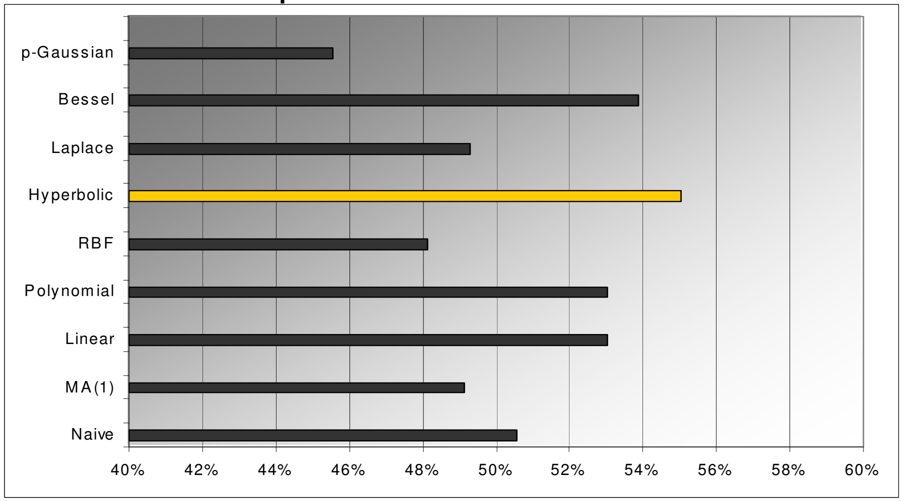
Classification Performance.

We focus on the task of predicting a rise ("+1") or fall ("-1") of daily EUR/GBP, EUR/JPY and EUR/USD exchange rate returns.

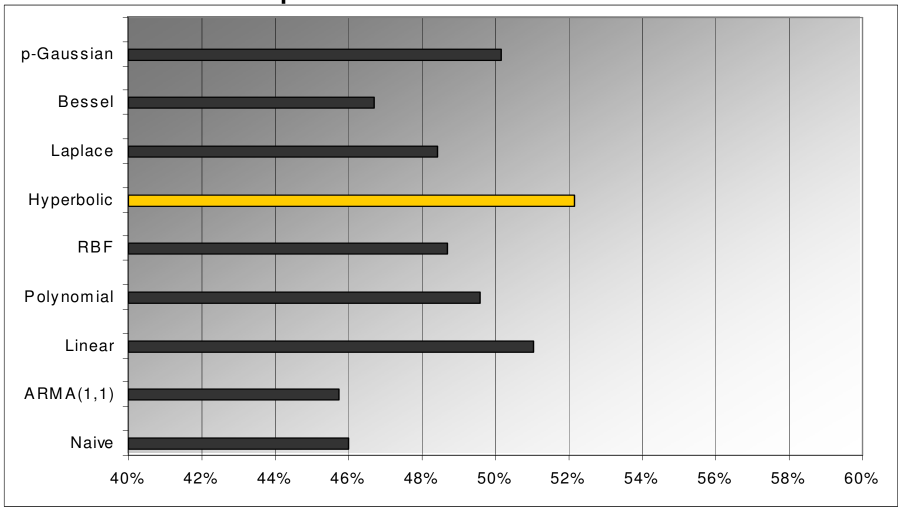
Classification performance EUR/GBP



Classification performance EUR/JPY



Classification performance EUR/USD



Out-of-sample Results.

Operational Performance.

If we set up a trading simulation: what is the influence on prominent performance metrics?

EUR/GBP	Naive	MA(1,3)	Linear	Polynomial	RBF	Hyperbolic	Laplace	Bessel	p-Gaussian
Cumulative P&L	-0,00750	-0,00953	-0,09360	-0,09360	-0,03896	**0,10360**	0,01546	-0,04114	0,05958
Sharpe ratio	-0,07966	-0,10112	-0,99367	-0,99367	-0,41354	**1,09938**	0,16407	-0,43671	0,63235
Maximum daily profit	0,01492	0,01492	**0,01684**	**0,01684**	**0,01684**	0,01492	**0,01684**	0,01385	0,01232
Maximum daily loss	-0,01684	-0,01684	-0,01492	-0,01492	**-0,01385**	-0,01684	**-0,01385**	-0,01684	-0,01684
Maximum drawdown	-0,03811	-0,03811	-0,03619	-0,03619	**-0,03496**	-0,03811	-0,03512	-0,03564	-0,03811
VaR (alpha = 0.05)	-0,00695	-0,00734	-0,00752	-0,00752	-0,00728	-0,00698	**-0,00691**	-0,00744	-0,00694
Net Cumulative P&L	-0,06120	-0,01013	-0,12750	-0,12750	-0,09026	**0,05590**	-0,01964	-0,09214	0,01428
Avg gain/loss ratio	**1,05178**	0,85038	0,80370	0,80370	0,91714	1,03981	0,89932	0,88235	1,01891
Trader's Advantage	0,00000	**1,00000**	0,53003	0,53003	0,48716	0,48144	0,58986	0,39350	0,43507

EUR/JPY	Naive	MA(1)	Linear	Polynomial	RBF	Hyperbolic	Laplace	Bessel	p-Gaussian
Cumulative P&L	**0,05441**	-0,11333	-0,09477	-0,09477	-0,21907	-0,13867	-0,28671	-0,31145	-0,24980
Sharpe ratio	**0,38680**	-0,80435	-0,67432	-0,67432	-1,55679	-0,98622	-2,03603	-2,21115	-1,77460
Maximum daily profit	**0,02187**	0,02187	0,02068	0,02068	0,02068	0,02174	0,02068	0,02068	0,02050
Maximum daily loss	**-0,02050**	-0,02174	-0,02187	-0,02187	-0,02187	-0,02187	-0,02187	-0,02187	-0,02187
Maximum drawdown	-0,08535	-0,08659	-0,06479	-0,06479	-0,08672	**-0,06197**	-0,08672	-0,06479	-0,08672
VaR (alpha = 0.05)	**-0,01003**	-0,01144	-0,01092	-0,01092	-0,01111	-0,01081	-0,01127	-0,01145	-0,01130
Net cumulative P&L	**0,00281**	-0,11363	-0,15267	-0,15267	-0,27607	-0,19837	-0,34461	-0,36185	-0,30260
Avg gain/loss ratio	**1,04111**	0,92829	0,89996	0,89996	0,88278	0,86458	0,83323	0,83752	0,82177
Trader's advantage	0,00000	0,00000	0,43005	0,43005	0,43247	**0,43647**	0,41154	0,40350	0,40139

EUR/USD	Naive	ARMA(1,1)	Linear	Polynomial	RBF	Hyperbolic	Laplace	Bessel	p-Gaussian
Cumulative P&L	-0,18070	-0,22255	-0,13259	-0,13259	-0,00927	0,04797	-0,10055	-0,16166	**0,10182**
Sharpe ratio	-1,23452	-1,52256	-0,90434	-0,90434	-0,06296	0,32520	-0,68505	-1,10372	**0,68905**
Maximum daily profit	0,01962	0,01962	0,01667	0,01667	0,01962	**0,01962**	0,01889	0,01869	0,01889
Maximum daily loss	-0,01889	-0,01889	-0,01962	-0,01962	**-0,01869**	-0,01889	-0,01962	-0,01962	-0,01962
Maximum drawdown	-0,04172	**-0,04112**	-0,04484	-0,04484	-0,04391	-0,04410	-0,04484	-0,04484	-0,04484
VaR (alpha = 0.05)	-0,01247	-0,01179	-0,01260	-0,01260	-0,01176	**-0,01085**	-0,01183	-0,01165	-0,01116
Net cumulative P&L	-0,23680	-0,22345	-0,17429	-0,17429	-0,05967	-0,00003	-0,14525	-0,21056	**0,05112**
Avg gain/loss ratio	0,94708	0,93486	0,88117	0,88117	1,03619	0,96269	0,94573	0,94569	**1,10874**
Trader's advantage	0,00000	0,31863	**0,62531**	**0,62531**	0,56826	0,55311	0,58379	0,42194	0,49915

Results.

Concluding Remarks.

The SVM approach is both justified and promising.

- Both the naïve and the linear model are beaten by SVM's with suitable choice of kernel.
- Hyperbolic kernels deliver superior performance for out-of sample prediction across all currency pairs.
- The Hyperbolic kernel provides the best notion of similarity between our data.
- P-Gaussian SVM's perform reasonably well in predicting EUR/GBP and EUR/USD return directions, but not EUR/JPY.
- Future research will focus on further improvements of SVM models, for instance:
  - Examination of other sophisticated kernels
  - Proper adjustment of kernel parameters
  - Development of data mining and optimization techniques for selecting the appropriate kernel
  - Do hyperbolic kernels play a dominant role in predicting other financial market returns?

Foreign Exchange Risk Management.
Objectives.

„It is not about predicting the future, but about being prepared for it.“

(Perikles, ~500 v. Chr.)

Thank you very much for your attention!

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Backup.

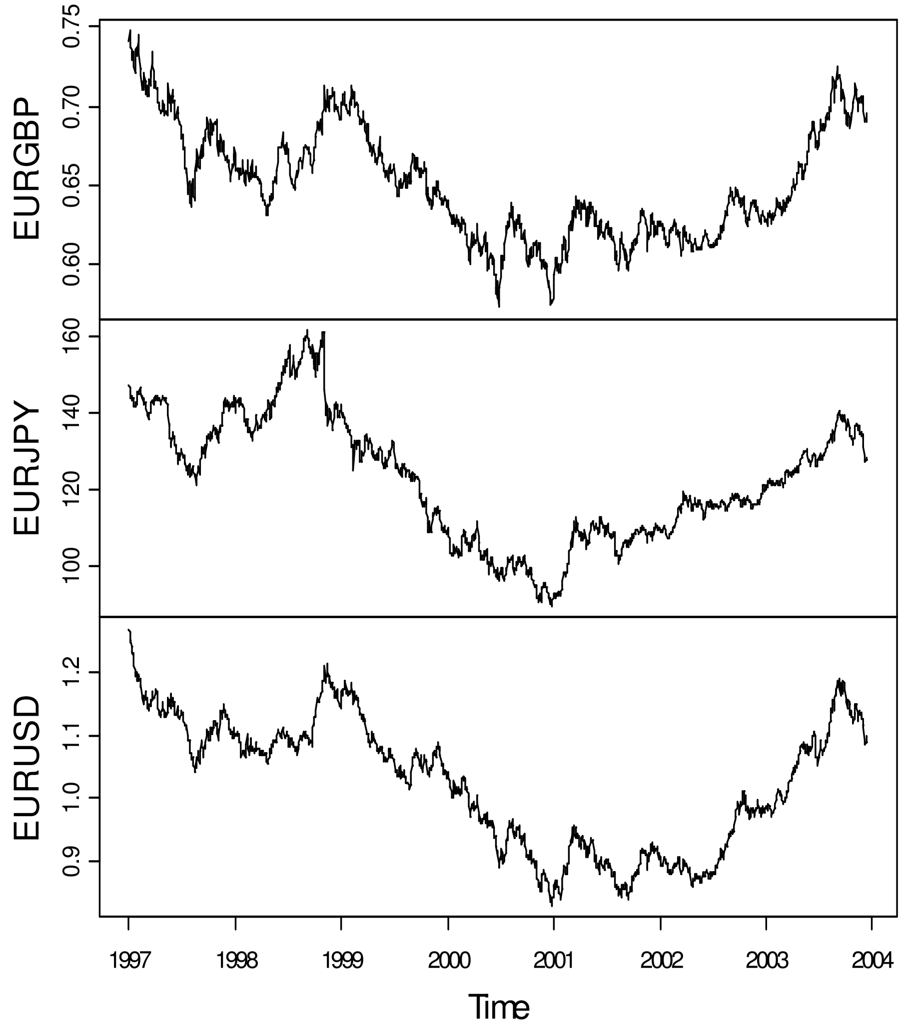
Time Series Analysis.

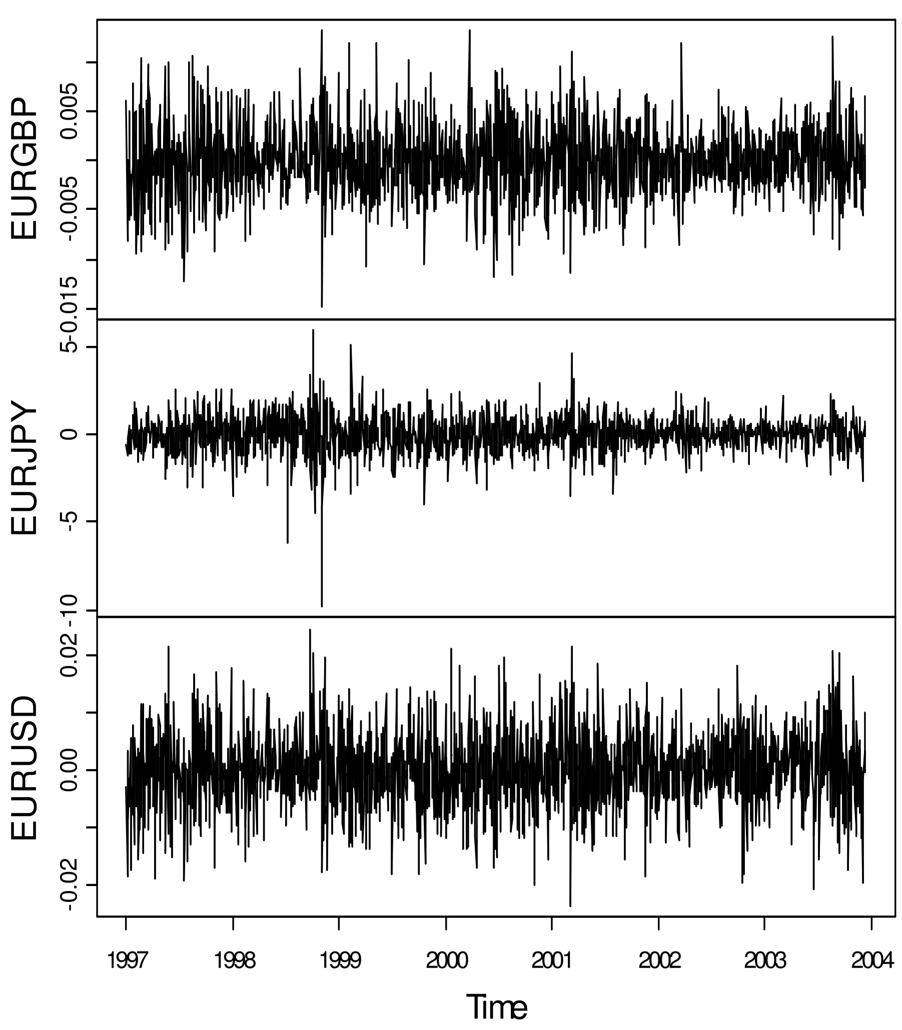
Exchange Rate Forecasting.
Overview.

Over the past several decades, researchers have used various forecasting methods to study time series events, the most important being:

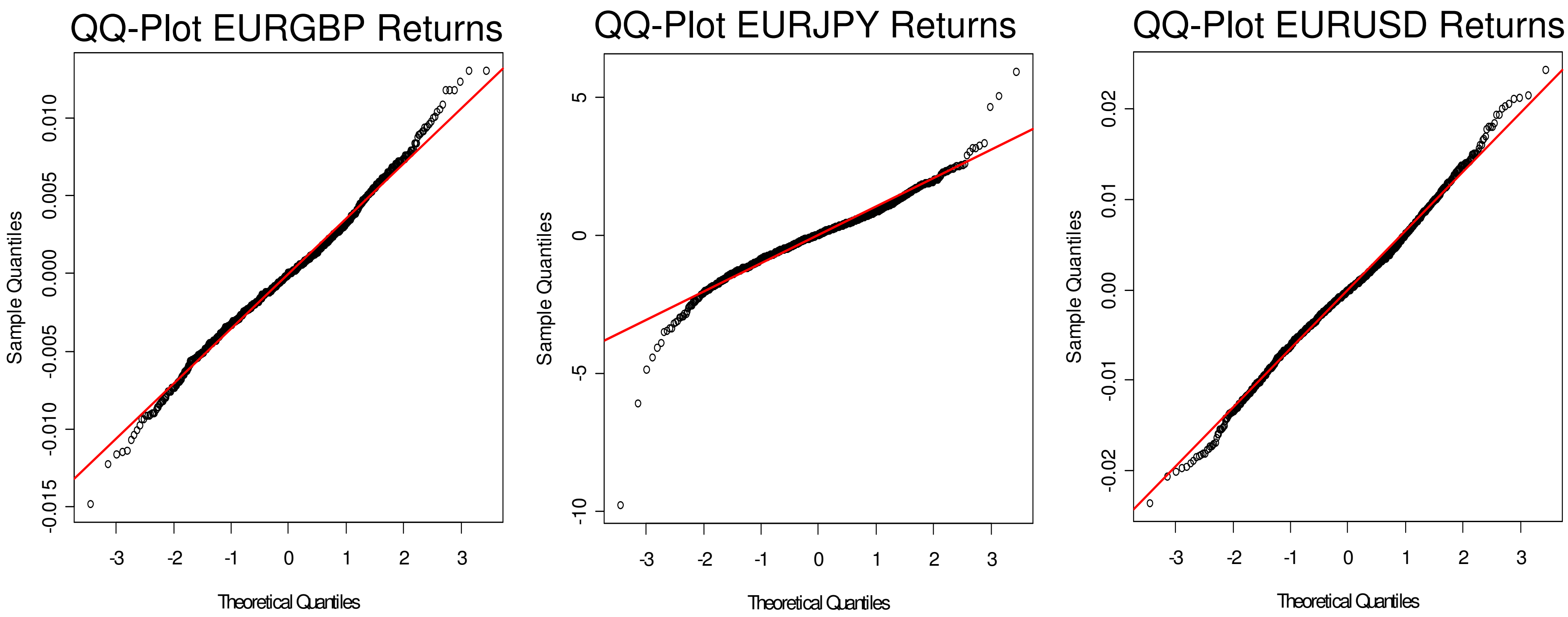
- Large macro-econometric models of the 1970s
- ARIMA models (Meese and Rogoff 1983)
- ARCH family models (Engle 1982)
- (Supervised) Machine Learning models
    - (K)-Nearest Neighbors (Steurer 1995)
    - Decision Trees (Peramunetilleke and Wong 2004)
    - Neural Nets (Bolland, Connor and Refenes 1998; Dunis and Wiliams 2002, etc.)

Time Series Analysis.
Stationarity.

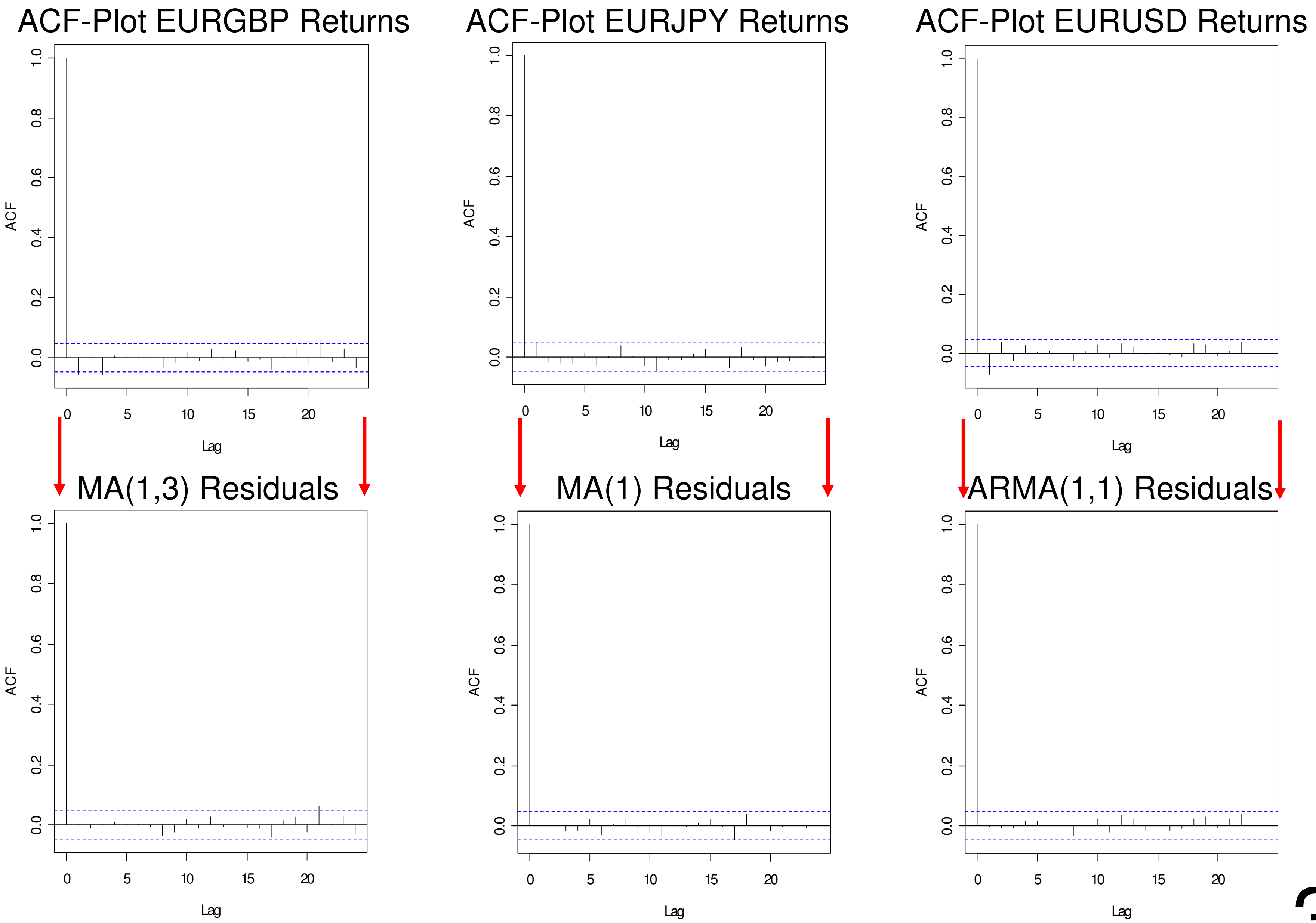




Time Series Analysis.
Normality.



Time Series Analysis.
Linear Dependencies.



Time Series Analysis.
Non-linear Dependencies.

Criterion	Null-Hypothesis	Testing Procedure	Time Series Input	Test Statistic Output		
				EURGBP	EURJPY	EURUSD
Heteroskedasticity	No Heteroskedasticity	Ljung-Box (LB)	(ARMA-Residuals)² of Δy_t	k=1: 21.82 k=2: 27.81 k=3: 55.01*** k=4: 58.05*** k=5: 75.90*** k=6: 86.44*** k=7: 104.63*** k=8: 107.02*** k=9: 111.53*** k=10: 119.70*** k=15: 140.35*** k=20: 164.70*** k=24: 180.57***	k=1: 103.59 k=2: 125.07*** k=3: 125.60*** k=4: 142.69*** k=5: 157.72*** k=6: 171.01*** k=7: 173.01*** k=8: 183.71*** k=9: 191.36*** k=10: 192.58*** k=15: 215.38*** k=20: 328.67*** k=24: 342.69***	k=1: 0.08 k=2: 0.27 k=3: 1.45 k=4: 1.63 k=5: 9.24** k=6: 13.25** k=7: 13.99** k=8: 14.57** k=9: 19.23*** k=10: 20.97*** k=15: 29.75*** k=20: 35.85*** k=24: 42.04***
		ARCH LM Test (F)	ARMA-Residuals of Δy_t	k=1: 22.06*** k=4: 12.48*** k=8: 9.85*** k=12: 7.26***	k=1: 109.77*** k=4: 33.65*** k=8: 18.70*** k=12: 13,04***	k=1: 0.0768 k=4: 0.3950 k=8: 1.7377* k=12: 1.6951*
Nonlinearity	Linearity	Ramsey-RESET-Test (F)	ARMA-Residuals of Δy_t	n=1: 3.73* n=2: 6.30*** n=3: 4.23*** n=4: 3.60***	n=1: 3.49* n=2: 8.93*** n=3: 5.95*** n=4: 4.69***	n=1: 0.3910 n=2: 0.8979 n=3: 0.3283 n=4: 2.3085*
		Brock-Dechert-Scheinkmann Test (BDS)	ARMA-Residuals of Δy_t	m=2: 0.0107*** m=3: 0.0186*** m=4: 0.0251*** m=5: 0.0287***	m=2: 0.0088*** m=3: 0.0195*** m=4: 0.0262*** m=5: 0.0298***	m=2: -0.0005 m=3: 0.0008 m=4: 0.0021 m=5: 0.0031
			GARCH(1,1)-Residuals of Δy_t	m=2: 0.0109*** m=3: 0.0188*** m=4: 0.0254*** m=5: 0.0289***	m=2: 0.0086*** m=3: 0.0192*** m=4: 0.0259*** m=5: 0.0294***	m=2: -0.0005 m=3: 0.0008 m=4: 0.0021 m=5: 0.0032

*, **, *** indicate signficance at the 10%-, 5%-, 1% significance level
k:= number of lags
n:= number of fitted terms included in test regression
m:= number of correlation dimension for which test statistic is calculated

Training the SVM.
C-SVC.

The C-SVC algorithm solves the following convex optimization problem.

Given training vectors $x_i \in R^n$, $i = 1,\ldots,l$, in two classes, and a vector $y \in R^l$ such that $y_i \in \{+1,-1\}$, C-SVC solves the following problem:

$$\min_{w,b,\xi} \quad \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \qquad (1)$$

$$y_i \left(w^T \phi(x_i) + b \right) \geq 1 - \xi_i$$
$$\xi_i \geq 0, i = 1,\ldots,l.$$

Its dual representation is

$$\min_{\alpha} \quad \frac{1}{2} \alpha^T Q \alpha - e^T \alpha \qquad (2)$$

$$0 \leq \alpha_i \leq C, i = 1,\ldots,l,$$
$$y^T \alpha = 0$$

where e is the vector of all ones, C is the upper bound, Q is an lxl positive semidefinite matrix, $Q_{ij} \equiv y_i y_j K(x_i, x_j)$, and $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ is the kernel

Training the SVM.

SMO.

The SMO algorithm solves the convex optimization problem more efficiently.

- Do we really need to solve the dual? Maybe not. Sometimes the data is too large to do so.
  - The convex optimization problem that is solved by C-SVC implies a *l x l* Kernel matrix *Q* that is fully dense.
  - This makes finding a fast solution computationally difficult.
- One solution is to approximate either from primal or dual side.
- Another solution consists in selecting a working set using second order information. Sub problem in each iteration:

$$\min_{\boldsymbol{\alpha}_B} \quad \frac{1}{2}\begin{bmatrix}\boldsymbol{\alpha}_B^T & (\boldsymbol{\alpha}_N^k)^T\end{bmatrix}\begin{bmatrix}Q_{BB} & Q_{BN} \\ Q_{NB} & Q_{NN}\end{bmatrix}\begin{bmatrix}\boldsymbol{\alpha}_B \\ \boldsymbol{\alpha}_N^k\end{bmatrix} - \begin{bmatrix}\mathbf{e}_B^T & (\mathbf{e}_N^k)^T\end{bmatrix}\begin{bmatrix}\boldsymbol{\alpha}_B \\ \boldsymbol{\alpha}_N^k\end{bmatrix}$$

subject to $0 \leq (\boldsymbol{\alpha}_B)_t \leq C, t = 1, \ldots, q, \ \mathbf{y}_B^T \boldsymbol{\alpha}_B = -\mathbf{y}_N^T \boldsymbol{\alpha}_N^k$

- Sub problem can be analytically solved.

Why computational complexity matters?

There are some provable results on computational complexity of markets in general and decision problems in Economics.

- experiments with Zero-Intelligence Traders [Gode, Sunder 1993]
- Computable Economics [Velupillai 1999]
- there exist games whose equilibrium strategies are not effectively computable [Rabin 1975]
- to determine a best response to any fixed strategy of an opponent in an infinitely repeated two player game is not effectively computable [Nachbar 1993]
- many economic concepts are not effectively computable (Walrasian general equilibria, Stackelberg equilibria, Hurwiczian resource allocation problems) [Lewis 1985,86,92]

Why computational complexity matters?

There are some provable results on computational complexity of markets in general and decision problems in Economics.

There are complexity bounds for

- curse of dimensionality [Traub, Wasilkowski, Wózniakowski 1988]
  i.e. lower bounds on time/space costs needed to implement the solution algorithms for ϵ-approximations of d-dimensional problems of the form $(1/\epsilon)^d$ for some integration and optimization problems apply to utility maximization, Walrasian equilibria, Nash equilibria
- dynamic programming [Chow, Tsitsiklis 1989]
- social planning [Friedman, Oren 1995]
- Walrasian equilibrium [Papadimitriou 1995]

Why computational complexity matters?

There are some provable results on computational complexity of markets in general and decision problems in Economics.

There are complexity bounds for special models of artificial stock markets:

- **If there are a large number of traders but they employ a relatively small number of strategies, then there is a polynomial-time algorithm for predicting future price movements with high accuracy**

  [Aspnes et al 2001].

- **If the number of trading strategies is large, market prediction becomes computationally very hard.**

  [Aspnes et al 2001]

Foreign Exchange Market Efficiency.

A perspective from computational complexity theory.

The speed at which an arbitrage opportunity can be located and be taken advantage of may give an important indication on how efficient foreign exchange markets are.

- The minimum requirement a foreign exchange market must satisfy if it is said to be efficient is that no arbitrage opportunities must exist.
- Three interesting questions (Cai and Deng 2005):
  - Could it be that it is too complex for investors to identify arbitrage opportunities?
  - Are the arbitrage opportunities, which are hard to compute, significant or insignificant?
  - Under which conditions are arbitrage opportunities computable?

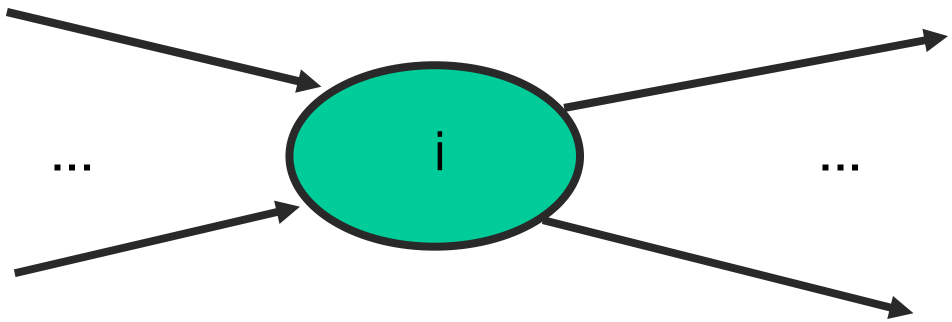
A simple model of an exchange market, which is provably complex:

N = {1,2,...,n}   n foreign currencies

r_{ij} exchange rate from i to j

(one unit of currency i is changed to r_{ij} units of currency j)

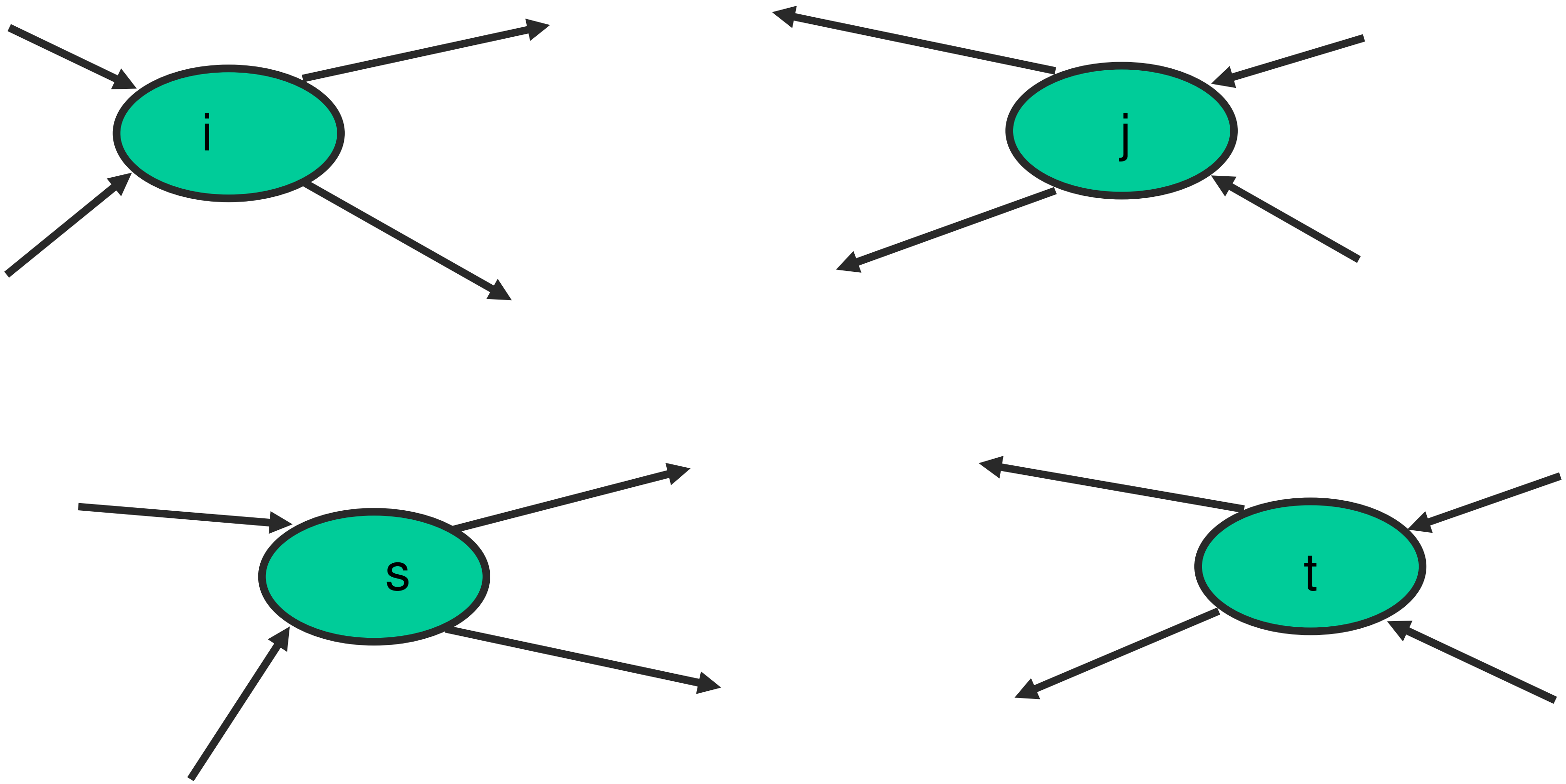
arbitrage opportunity: set of exchanges between pairs of currencies such that the net balance for each involved currency is non-negative and there is at least one currency for which the net balance is positive



ideal market: the exchange rate holds for any amount that is exchanged

A simple model of an exchange market, which is provably complex:

- Under **ideal market conditions**, there is no arbitrage if and only if there is no arbitrage among any three currencies [Mavrides 1992].



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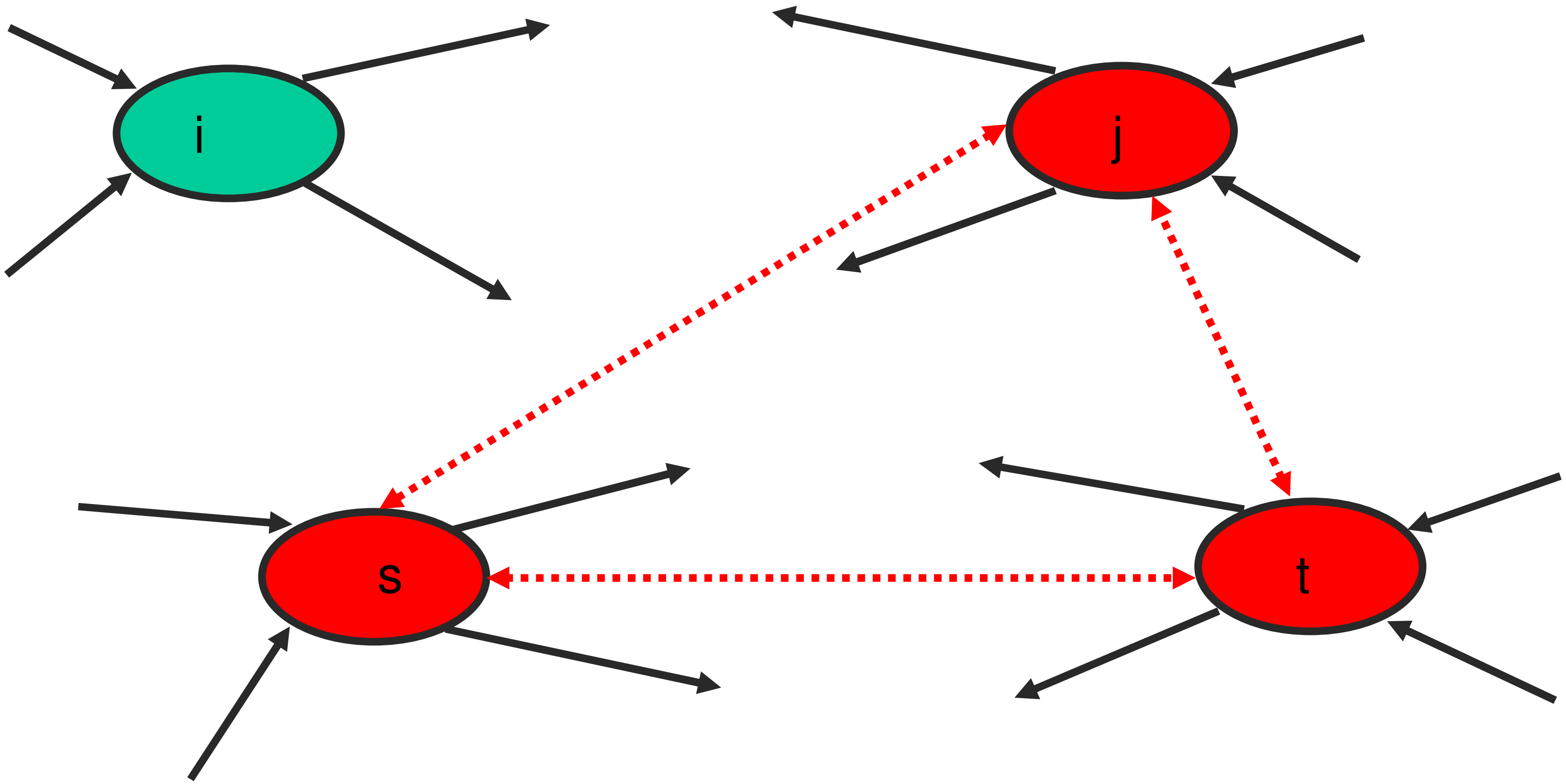


A simple model of an exchange market, which is provably complex:

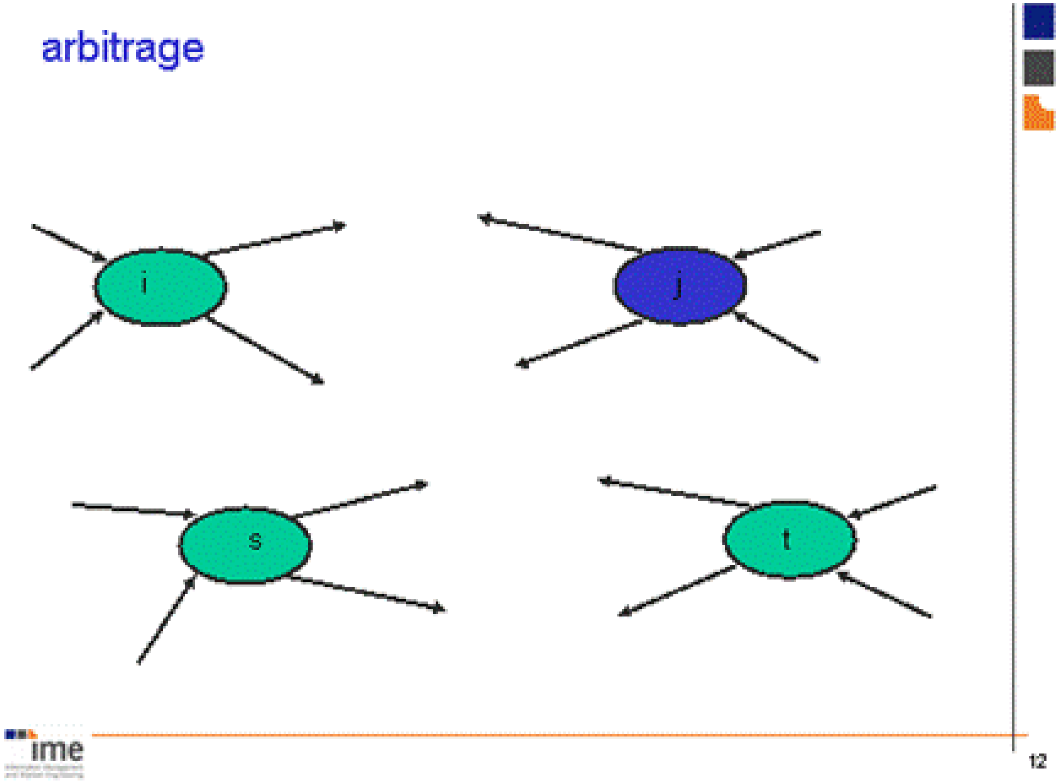
In reality frictions exist:

- bid-offer spread for i and j: $r_{ij}\, r_{ji} < 1$

- traded amount is required to be in multiples of a fixed integer amount

- different traders may bid or offer at different rates, and each for a limited amount

A simple model of an exchange market, which is provably complex:



General model:

for pairs $i \neq j \in N$,

l_{ij} different rates r_{ij}^k of exchanges from currency i to j up to b_{ij}^k units of currency i,

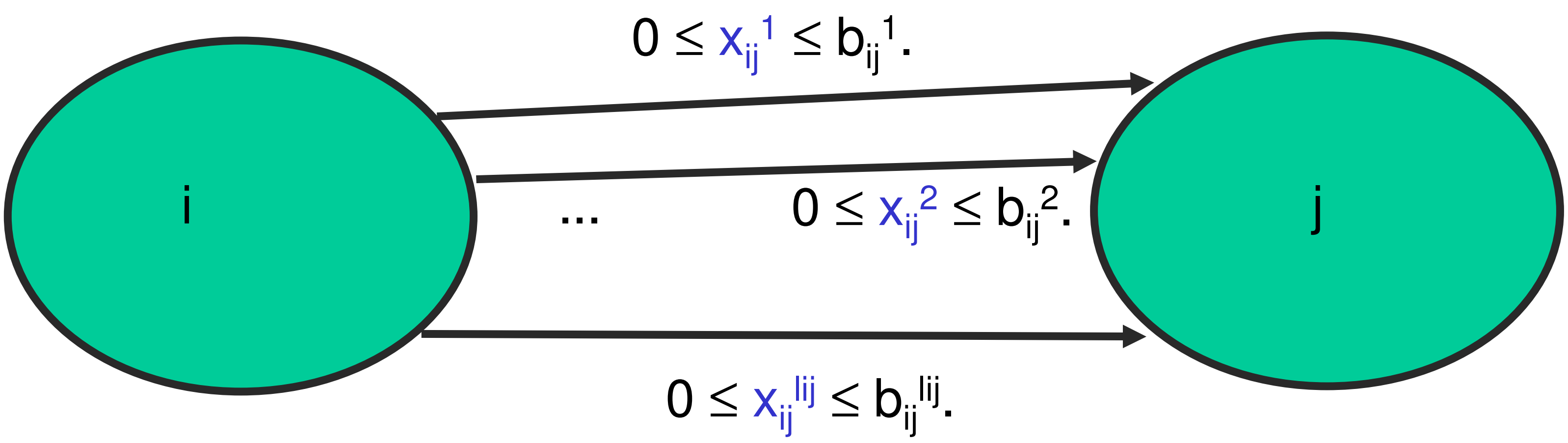
$k = 1,\ldots,l_{ij}$, where l_{ij} is the number of different exchange rates from currency i to j.

A simple model of an exchange market, which is provably complex:

General model:

Let $x = (x_{ij}^k)$ be a currency exchange vector such that

(1) $$0 \leq x_{ij}^k \leq b_{ij}^k.$$

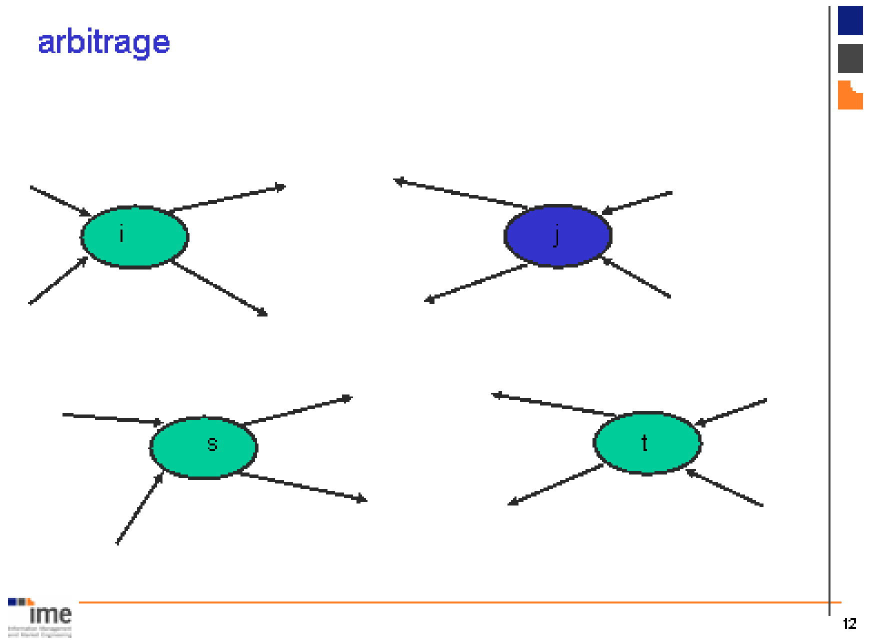


A simple model of an exchange market, which is provably complex:

There exists **arbitrage** in the market if there is a currency exchange vector $x = (x_{ij}^k)$ satisfying the following inequalities with at least one strict inequality

(2) $$\sum_{j \neq i} \sum_{k=1}^{l_{ji}} \left\lfloor r_{ji}^k x_{ji}^k \right\rfloor - \sum_{j \neq i} \sum_{k=1}^{l_{ij}} x_{ij}^k \geq 0$$ $i = 1, \ldots, n$

(3) x_{ij}^k is integer, $1 \leq k \leq l_{ij}$, $1 \leq i, j \leq n$, $i \neq j$.



A simple model of an exchange market, which is provably complex:

Theorem 1 [Mao-cheng Cai, Xiaotie Deng, 2005]:

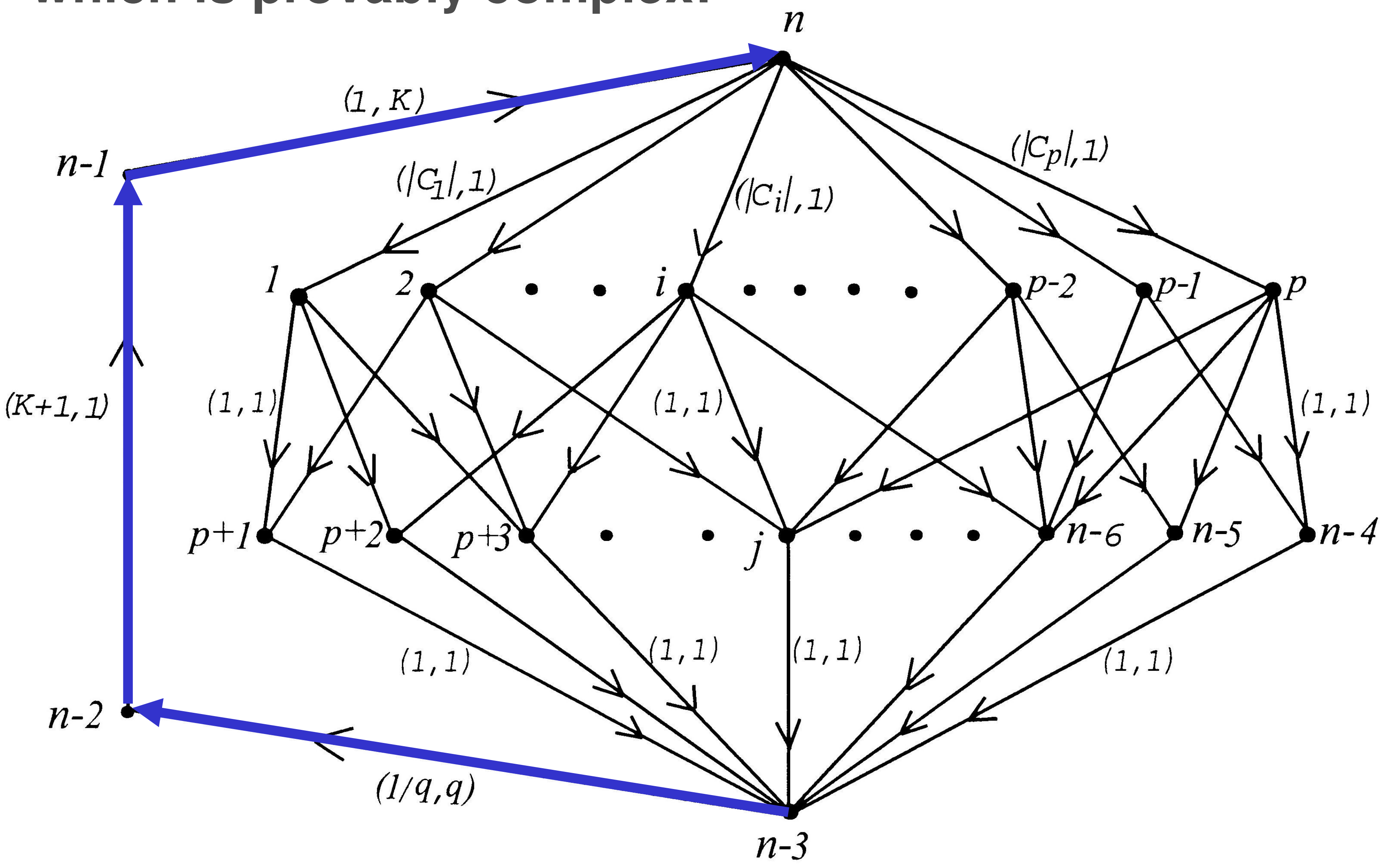
It is **NP**-complete to determine whether there exists arbitrage in a frictional foreign exchange market with bid-ask spreads, bound and integrality constraints.

Theorem 2 [Mao-cheng Cai, Xiaotie Deng, 2005]: There exists a fixed $\varepsilon>0$ such that a corresponding approximation problem within a factor of n^{ε} is **NP**-hard.

The proof is done by reduction of the MAX-SET-PACKING problem which is **NP**-hard for some fixed $\varepsilon>0$ (Zuckerman, 1993).

Given a collection $C = \{C_1, C_2, \ldots, C_p\}$ of subsets $S = \{e_1, e_2, \ldots, e_q\}$, find a subcollection of disjoint subsets $C' \subseteq C$ such that $|C'|$ is maximized.

A simple model of an exchange market, which is provably complex:



G_1

Exchange Rate Modelling.
To do.

Exchange rate modelling involves the examination of three phenomena.

Taylor (2004, p.15) recommends:

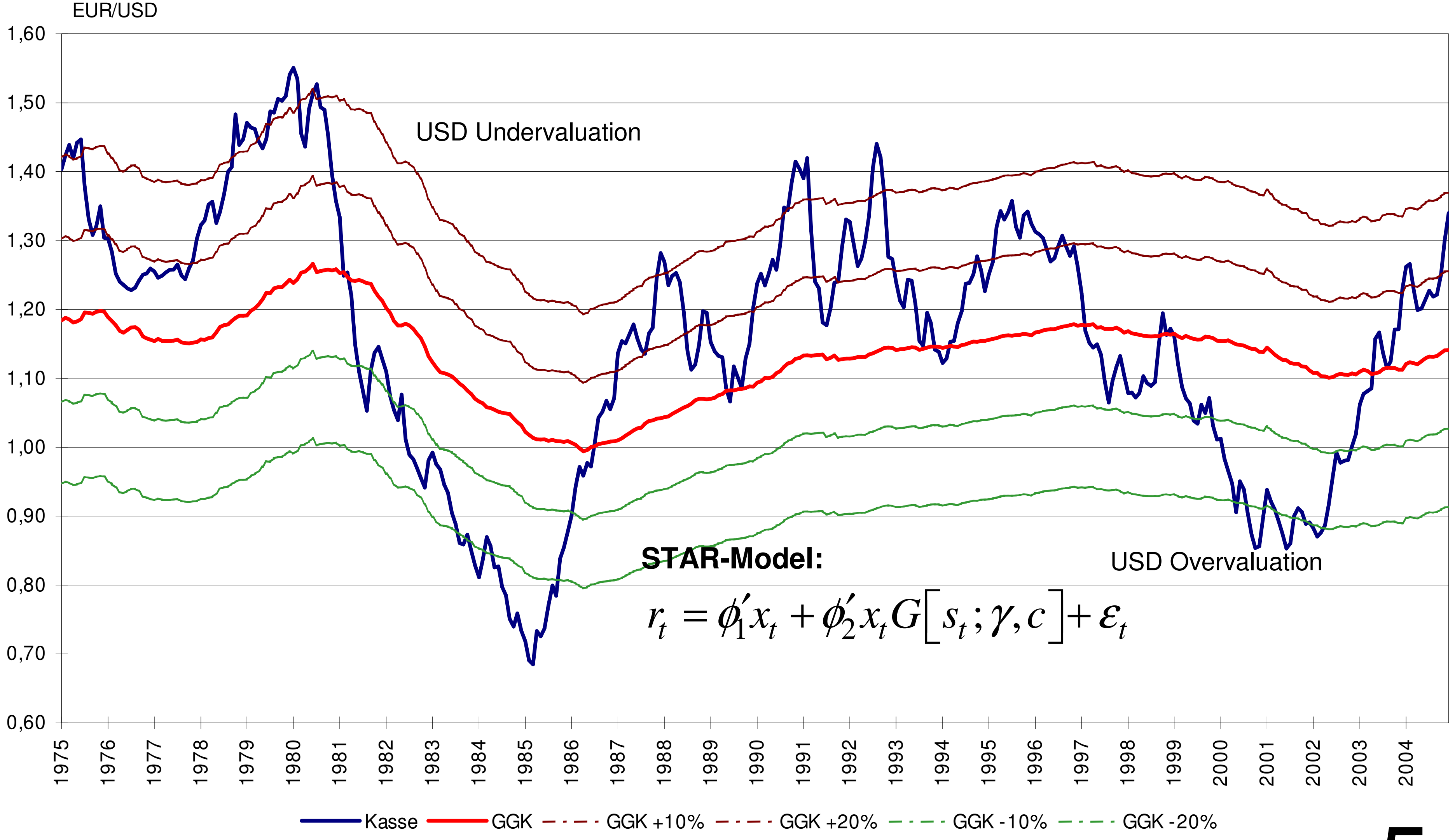
“Empirical work that focuses on the path of the real exchange rates must grapple with three key factors:

- **the reversion speed [medium run]**
- **the volatility of the disturbance term [short run], and**
- **equilibrium level [long run]**

of the real exchange rate.”

Exchange Rate Modelling.
Equilibrium and Mean Reversion.

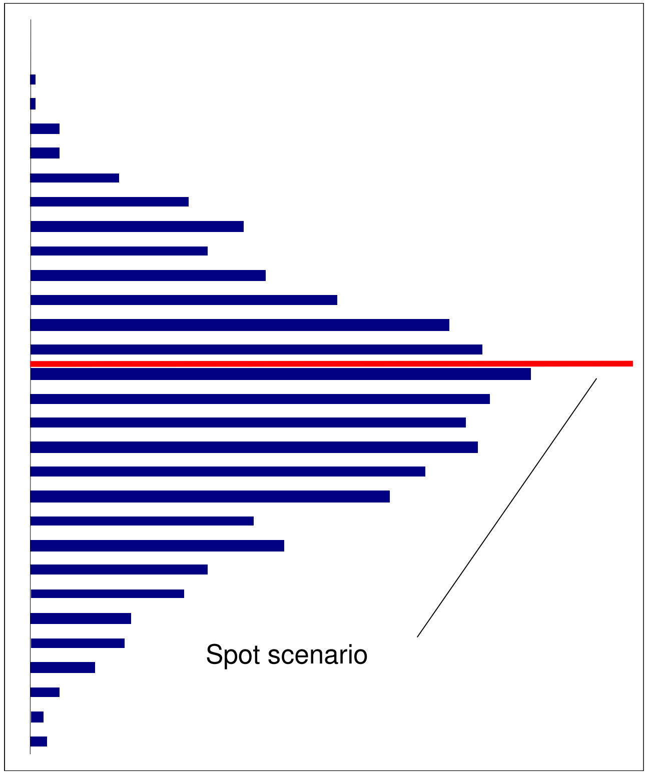
According to economic theory, relative price indices are a determinant for the exchange rate in the long run.



Risk and Return.

Scenario Generation and Cashflow Distribution.

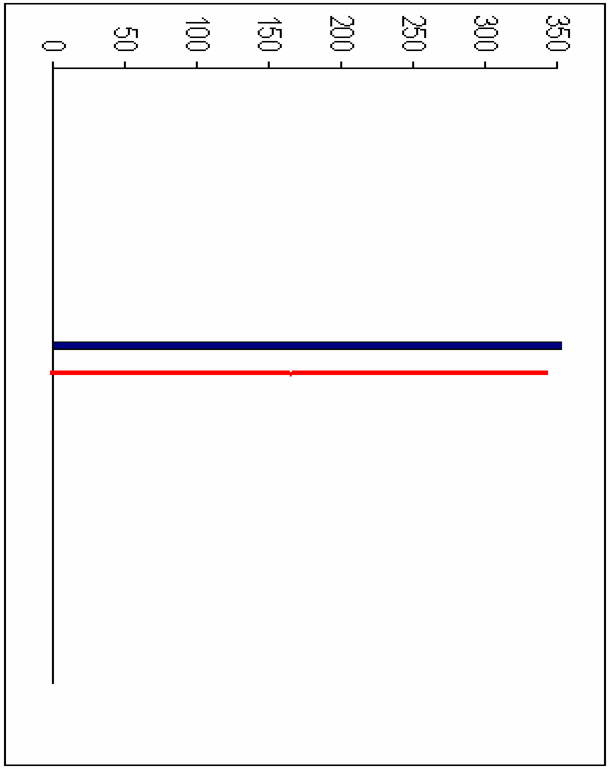
Once precise exchange rate model is determined, exchange rate scenarios can be determined via Monte Carlo method.



→ Open exposure leads to relatively large bandwidth of possible reults.

Risk and Return.
Forward Hedge.

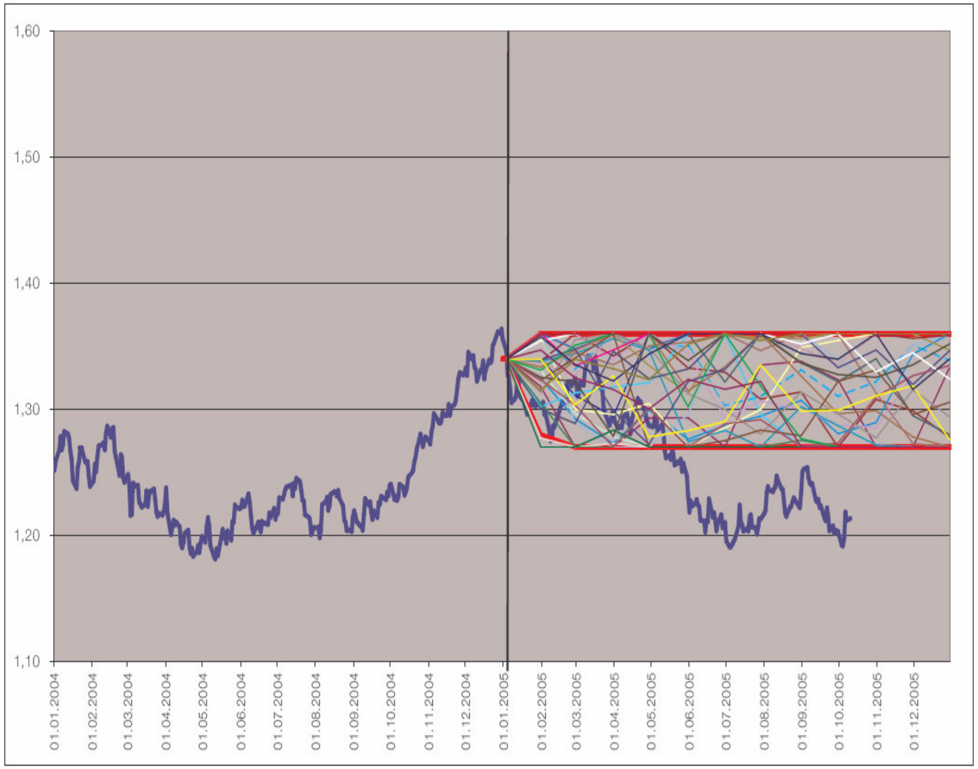
Once the exchange rate model is determined, the effect of hedging instruments on the open exposure can be determined.

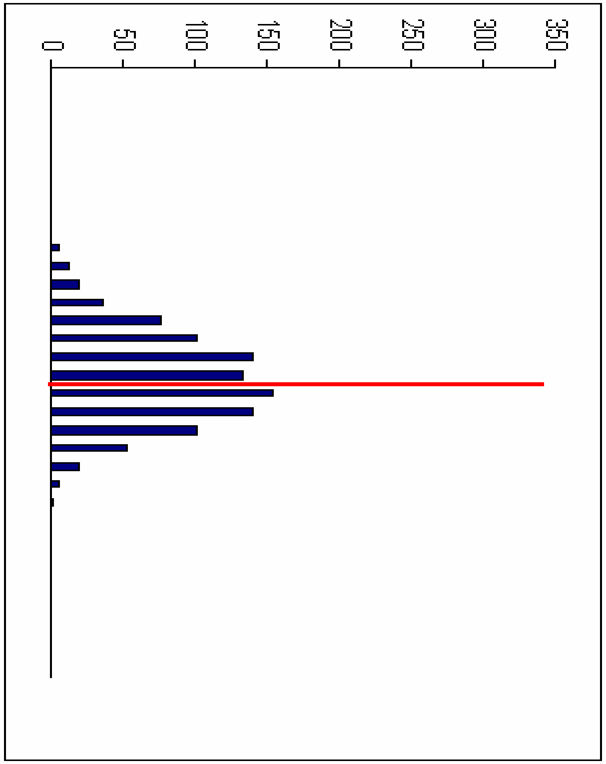


→ Forward Hedge locks in the current forward rate
(no risks, no opportunities)

Risk and Return.
Range Option.

Once the exchange rate model is determined, the effect of hedging instruments on the open exposure can be determined.

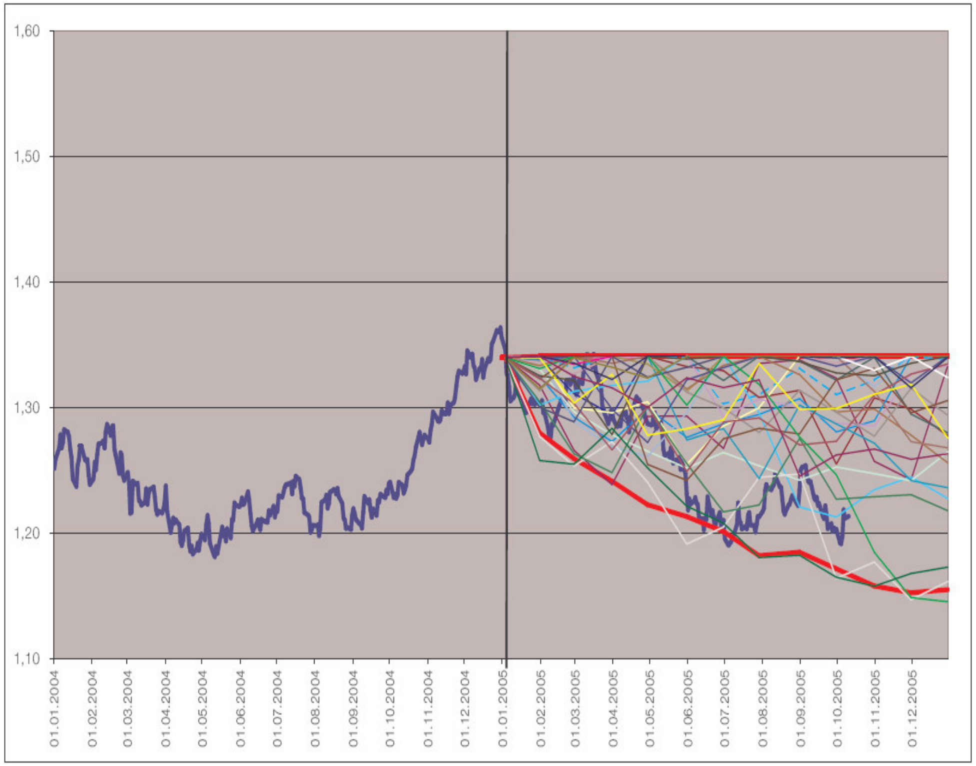


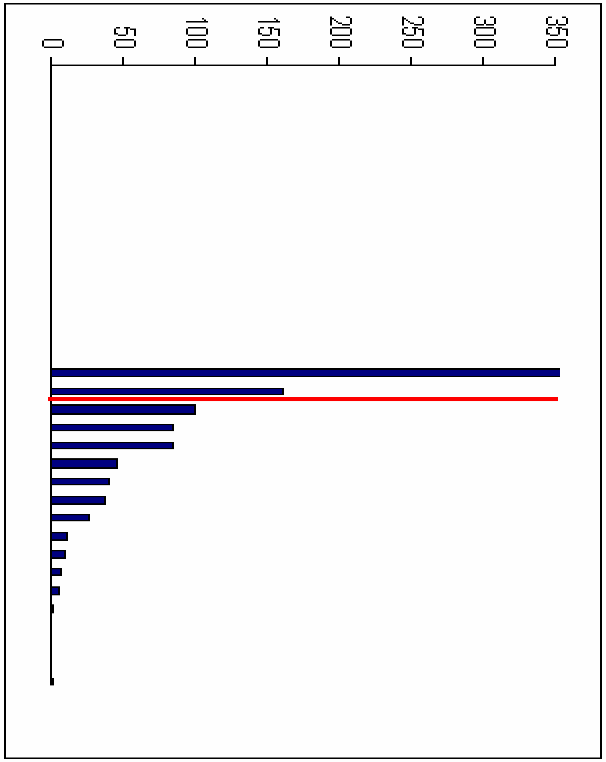


→ Hedging with range options lowers the bandwidth of possible results (less risks, less opportunities) with the expected result remaining constant.

Risk and Return.
Vanilla Call Option.

Once the exchange rate model is determined, the effect of hedging instruments on the open exposure can be determined.

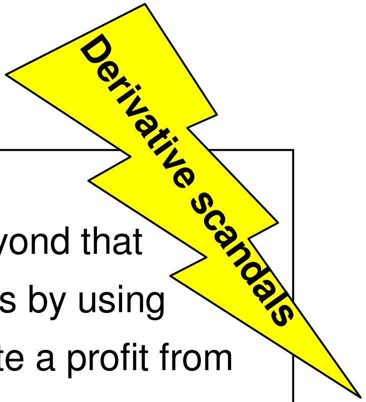


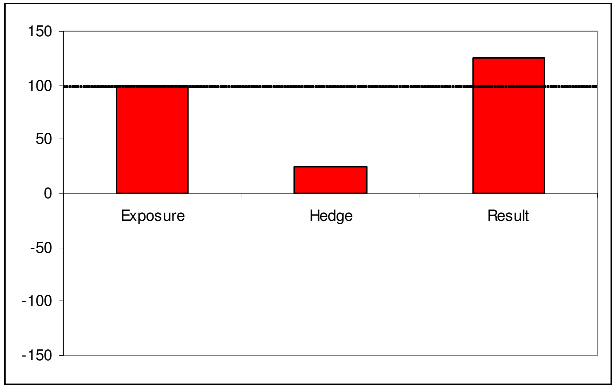


→ Hedging with vanilla call lowers the realized result as well as the expected value in terms of the option premium (decrease risks, keep opportunities)

Foreign Exchange Risk.

Strategies.





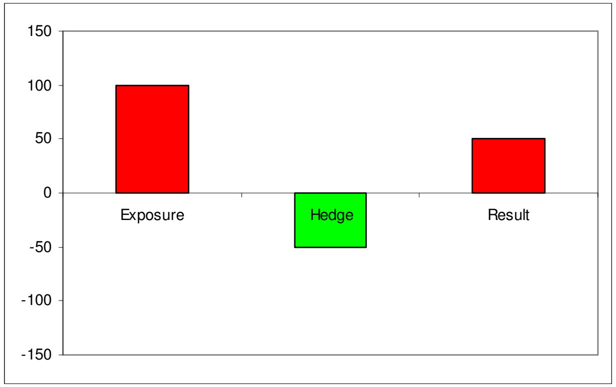
Speculation:

Permit to create exposure beyond that arising from business activities by using derivatives in order to generate a profit from exchange rate movements.

+ high profit potential

- no protection

No hedging



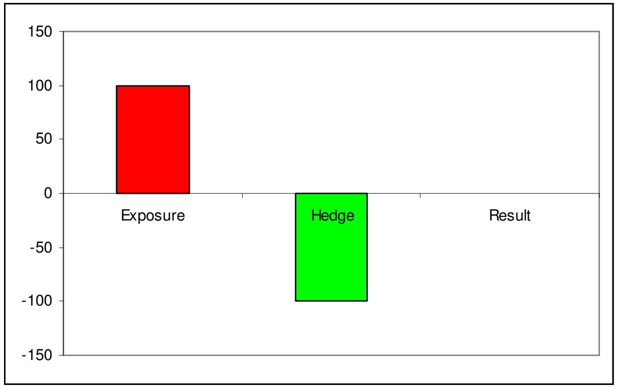
Selective Hedging:

Mitigate risk by choosing hedge ratio and instrument based on forecast of (bandwidth of) future exchange rate changes or risk/return considerations.

+ profit potential, risk avoidance, flexibility

- decision-support?

Fixed rule partial hedging



Hedging:

eliminate risk by setting up contrary position

+ planning safety

- no profit potential from favourable exchange rate movements

Risk Management.
Legal requirements and best practice standards.

National Developments

- Gesetz zur Kontrolle und Transparenz im Unternehmensbereich (KonTraG; 1998)
- Kapitalaufnahmeerleichterungsgesetz (KapAEG; 1998)
- Transparenz- und Publizitätsgesetz (TransPubG; 2002)
- Deutscher Corporate Governance Kodex (DCGK; 2002 – annual examination)

Sector Regulations

- MaRisk (2005) – Mindestanforderungen an das Risikomanagement (replaces MaH and Mak)
- Basel II (likely 2006)
- Solvency II (likely 2006)

International Developments

- USA: Sarbanes-Oxley Act (2002)
- EU, inter alia:
  - Fair Value-Code (2001)
  - IAS-Order (2002)
  - Marginal Value-Code(2003)
  - Insider Codes (2003)
  - 8. EU-Code (2004)
  - Transparency Code (2004)

International Risk Management-Standards

- FERMA (2002) – Federation of European Risk Management Associations „The Risk Management-Standard“
- COSO II (2004) – The Committee of Sponsoring Organization of the Treadway Commission „Enterprise Risk Management – Integrated Framework“

Exchange Rate Forecasting.
Overview.

Over the past several decades, researchers have used various forecasting methods to study time series events, the most important being:

- Large macro-econometric models of the 1970s
- ARIMA models (Meese and Rogoff 1983)
- ARCH family models (Engle 1982)
- (Supervised) Machine Learning models

  - (K)-Nearest Neighbors (Steurer 1995)
  - Decision Trees (Peramunetilleke and Wong 2004)
  - Neural Nets (Bolland, Connor and Refenes 1998; Dunis and Wiliams 2002, etc.)