Der Leitzins und die Zinsen auf dem Girokonto

Konversatorium "Berufsbild Mathematik (Finanzmathematik in der Praxis)"

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Wien, am 06. Juni 2018

Definitions

Account types

» A **savings account** is a deposit account held at a retail bank that pays interest but cannot be used directly as money in the narrow sense of a medium of exchange. A **time deposit** is a bank deposit account that has a **specified** date of **maturity** and usually earns a fixed interest. Money cannot be withdrawn before the maturity date (unless a penalty is paid). When the time deposit expires, it can be withdrawn or it can be renewed for another term (subject to new interest rates).

» The opposite, sometimes known as a **sight deposit** or "on call" deposit, can be withdrawn at any time, without any notice or penalty, e.g. a **current account** held at a bank. In economic terms, the funds held in a sight deposit are regarded as liquid funds and in accounting terms they are **considered** as **cash.**

Liquidity

» Market **liquidity** is a market's feature whereby an individual or firm can quickly purchase or sell an asset without causing a drastic change in the asset's price. Money, or cash, is the most liquid asset, because it can be "sold" for goods and services instantly with no loss of value.

» In the case of sight deposits the bank faces **funding liquidity risk,** the risk that liabilities cannot be met when they fall due, i.e. when the customer wants to withdraw their funds.

» As sight deposits do not have a contractual maturity, the bank needs to dispose of a clear understanding of their **duration** level within the banking books.

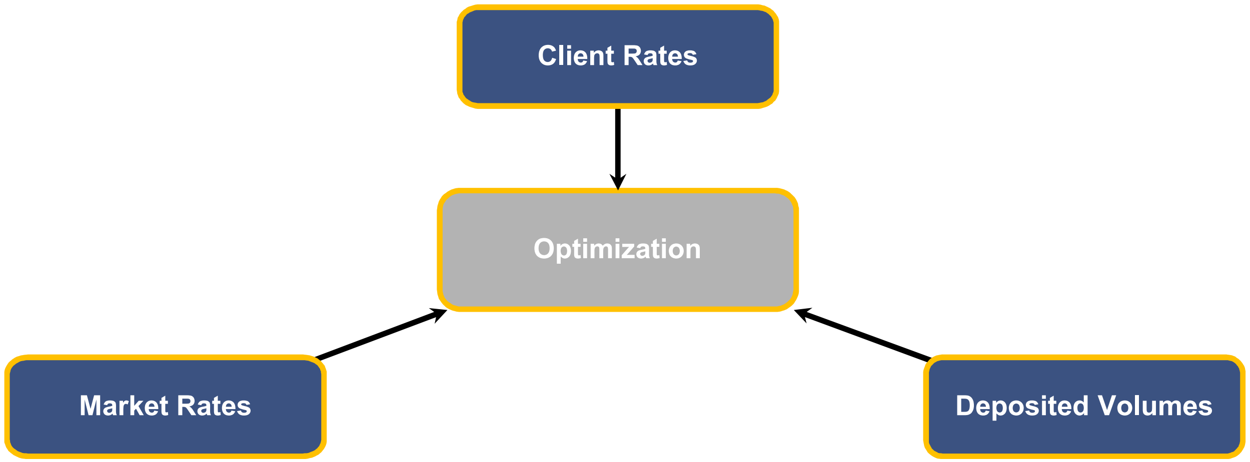
Replication

» In such models one attempts to find the **optimal portfolio** of investments (replication portfolio), which, if being refinanced by a particular product to be analyzed, best fits a set of well defined interest rate risk and/or liquidity risk criteria.

Source of Definitions: Wikipedia

Function of Interest Rate Replication Models

- Bank pays **Client Rate** for **deposits of undetermined maturity** (current and savings accounts)
- Bank **invests the deposits** into **maturity buckets** between 3M and 10Y with **fixed bucket weights in monthly time steps**
- IR replication model optimizes the **investment weights** of the buckets aiming to
  1. generate **stable margins** between **investment rate** and **client rate**
  2. provide **sufficient liquidity** for buffering volume changes **by means of maturing investments**
     Note: Liquidation of non-maturing investments would create IR risk



IR replication models mitigate IR and liquidity risk by optimization of the investment portfolio

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Function of the Interest Rate Replication Model

- The IR replication model determines **optimal** rolling **investment portfolios** for **deposits with undetermined maturity** such as current and savings accounts
- The optimization **output** are **investment weights** for a set of **maturity buckets** between 3 months and 10 years
- Weights are determined separately for the **savings, commercial,** and **current accounts**
- The optimization aims to selects investment weights that
  1. generate **stable margins** between investment and client rate
  2. provide **sufficient liquidity** to buffer volume changes **by means of maturing investments**
- Technically, the optimization
  - **minimizes the variance** of the mean **margin** on a 10 year forward looking horizon over a set of **10,000 hypothetical scenarios**
  - Imposes **constraints** on the maturing volume **to provide liquidity for coverage of volume changes**
- The model does ***not* optimize** the **expected margin**

The IR replication model mitigates IR and liquidity risk by optimization of the investment portfolio

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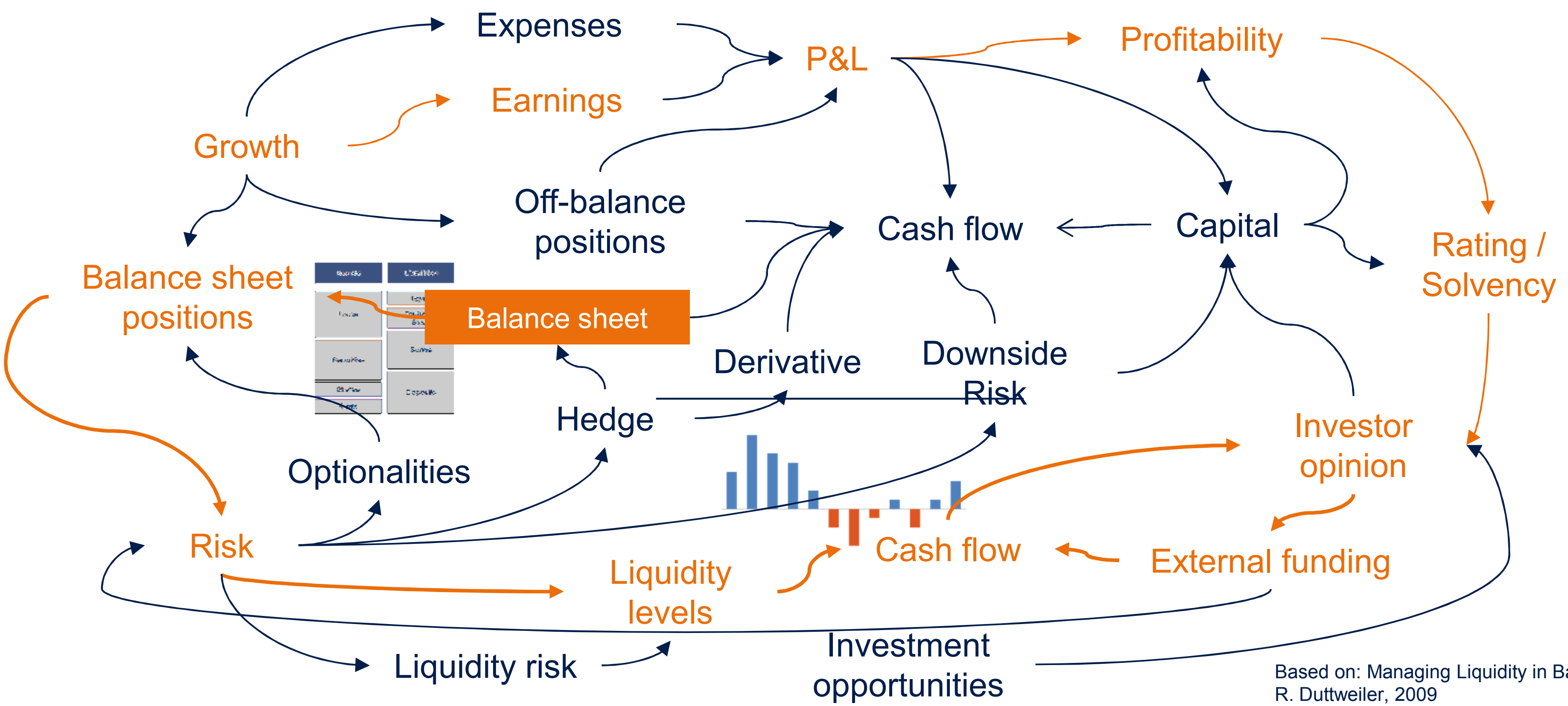
Challenge: Complex network of dependencies have to be understood and managed comprehensively

Sample (sub-)path for the effect from interest rate replication model on the balance sheet composition:



Based on: Managing Liquidity in Banks,
R. Duttweiler, 2009

Analysis paths is key → Systems and processes to analyze new pathways in a short time frame

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The development of a scenario model should be focussed on the essential value drivers initially neglecting driver interactions

A Products / Positions

B Market parameters

C Model parameters

- » Assumptions
- » Correlations
- » Sensitivities

D Time dependence

Time dep. parameters
New business assumptions, etc.

"flow" of information

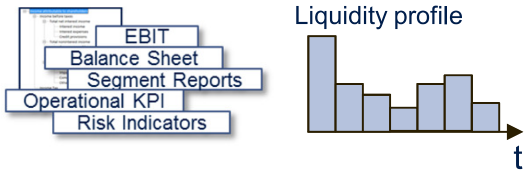
"The Model"

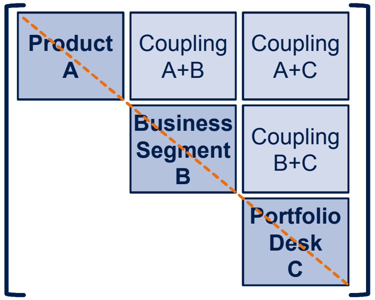
- FTP
- Tax effects
- Accounting Rules
- Products
- Pricing Engine
- Cash Flows

Plan / Forecast

Analysis of effect of input factor variations on resulting (time dependent) figures

- » Single deals
- » Market environment
- » Modell assumptions





The development of a scenario model should consider materiality:

- » Focus on primary and direct effects (*diagonal*)
- » Secondary effects and interactions/correlations of value drivers should be considered subsequently (*secondary diagonals)*

In its core, simple scenario driven model mechanics, however handling of complex correlations between model parameters needed

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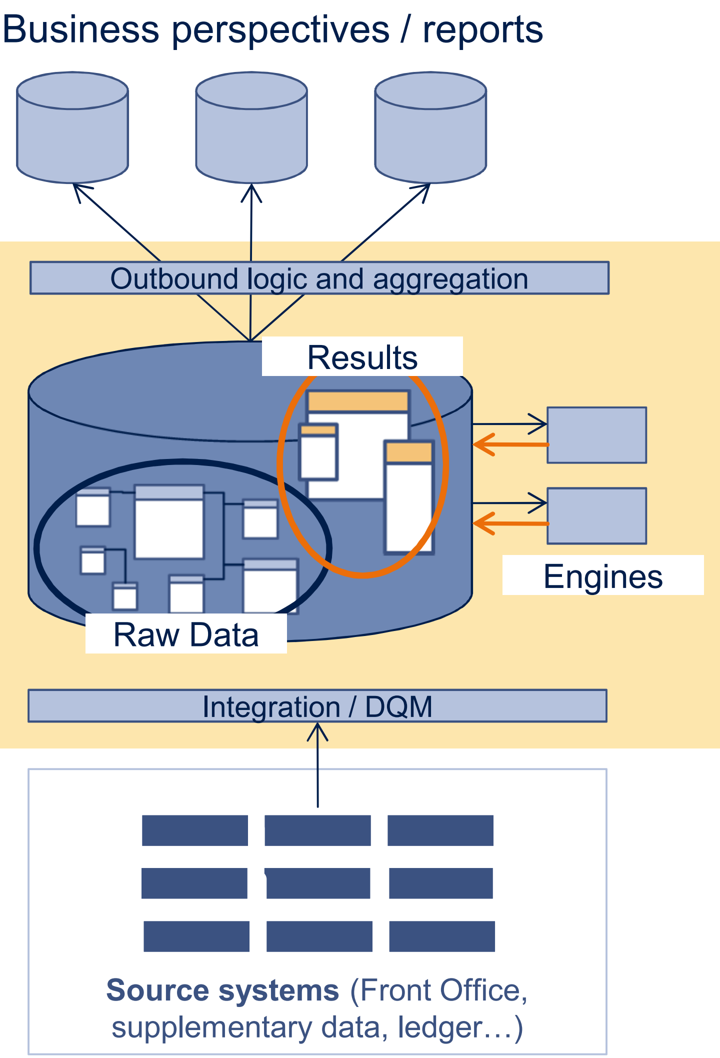
Implementation: comprehensive bank management by a central data hub including raw data, calculation engines and result data aggregation

Internal reporting, regulatory reporting, accounting, financial controlling

Goal:

Business data hub in a sustainable and **source system independent** structure in order to provide **common consistent** calculation and reporting logic for all business users

System landscape, products, processes, group structure



Vision

» Deliver all data and functions (risk types, accounting, reg. reporting etc.) out of one harmonized source

» Provide different perspectives on the same data

» Establish common taxonomies in order to achieve consistent reporting across risk types

» Enable integrated (stress) scenario evaluation across risk types

» Avoid individual data sourcing and source system dependent business logic across the departments

» Create transparency through central function architecture

First Step: Linear Regression

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Linear Regression to forecast Client Rates

Approach

Fitting of a linear **regression model**
Dependent variable: TS of CRs
Explanatory variables: TS of IRs

Application of fitted linear model to **simulated market IR** scenarios

Forecasted Client Rate per market IR scenario

Model

Market IR of bucket j (e.g. Euribor 6M) in scenario i at time t

Market IR with time lag

Client Rate in scenario i at time t

$$c_{t,i} = \alpha_0 + \sum_{j=1}^{J} \alpha_j r_{t,i}^{j} + \sum_{j=1}^{J} \alpha_j^{lag1} r_{t-1,i}^{J} + \sum_{j=1}^{J} \alpha_j^{lag2} r_{t-2,i}^{j} + \varepsilon_{t,i}$$

Noise

Assumptions

» $\{\varepsilon_{t,i}\}$ independent with $\mathrm{Var}(\varepsilon_{t,i}) < \infty \Rightarrow$ LSE for $\{\alpha_j\}$ unbiased and consistent

» $\{\varepsilon_{t,i}\}$ homoskedastic (same variance) $\Rightarrow$ LSE has minimum variance

» $\{\varepsilon_{t,i}\}$ independent and normally distr. $\Rightarrow$ Validity of standard statistical tests for the significance of the linear relationship (F-Test) and single explanatory variables α_j (t-Test).

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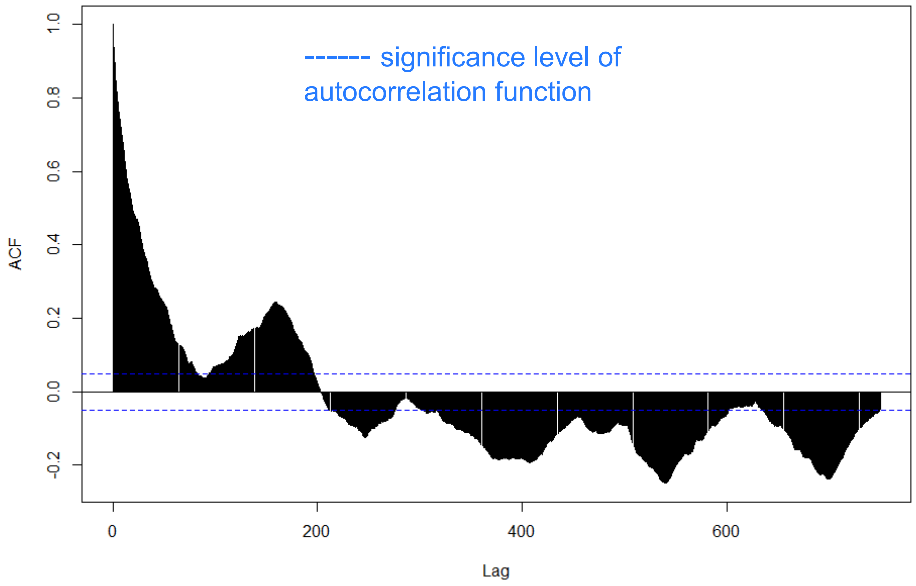
Analysis of Linear Regression Approach

» Very high **autocorrelation of the regression residuals** indicates **spurious regression**, i.e. the model may assume a **functional relationship without economic validity**

Autocorrelation



» Consequence: standard **significance tests** for a good model-fit are **not valid**

» This is also true for the regression constants

» A high significance of the t-tests has therefore no value

The model for Client Rates should hence be based on uncorrelated data

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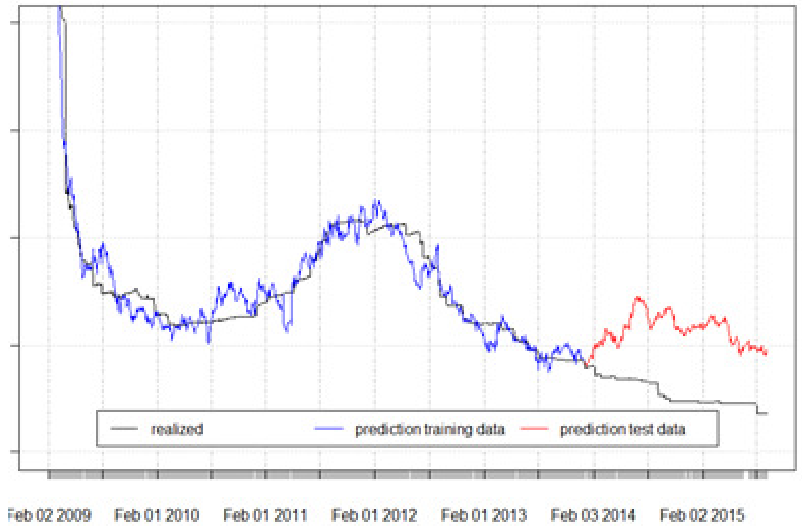
Spurious Regression and Consequences for Prediction Quality

» **Does the model work for prediction** anyway?
  › **No!**
  › Too many explanatory autocorrelated market IR time series cause **overfitting** since they act like a **set of basis functions.**

» **Consequences of overfitting**:
  › Almost **perfect fit for training data**
  › Risk of a drastic **loss in prediction quality after structural disruptions** of the market
  › Example: **Shift from normal to low IR regime**



modeling goals: reduce overfitting and increase robustness of predictions under structural market changes

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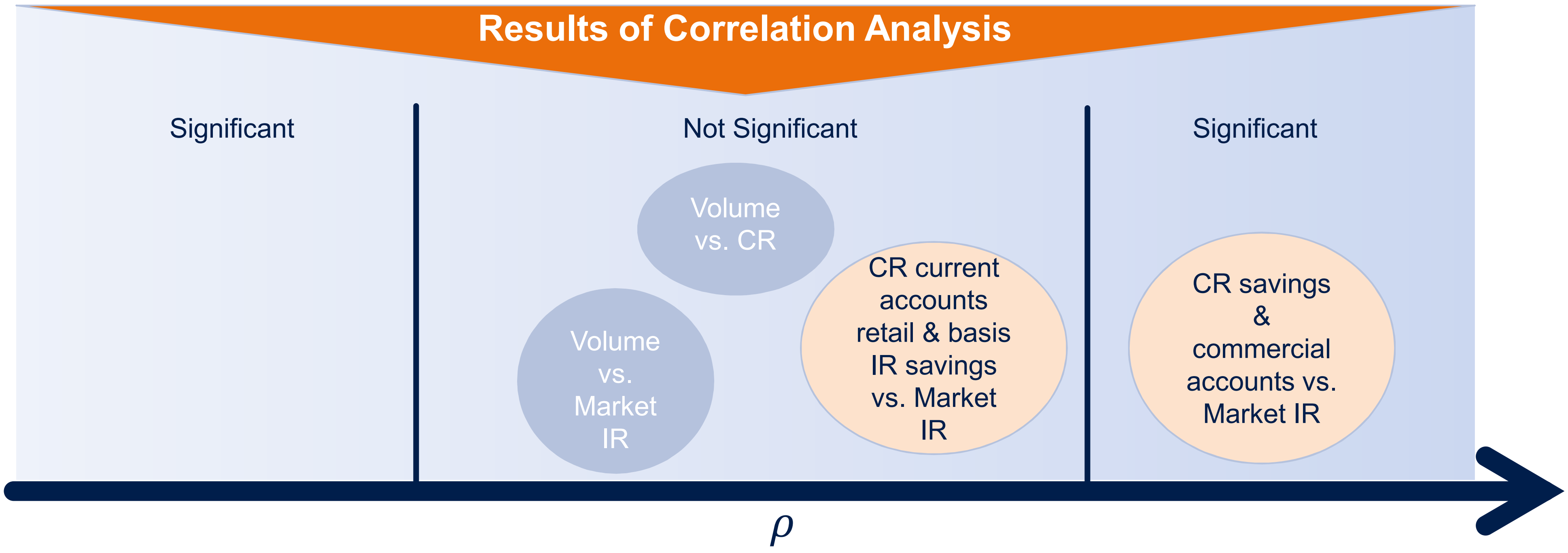
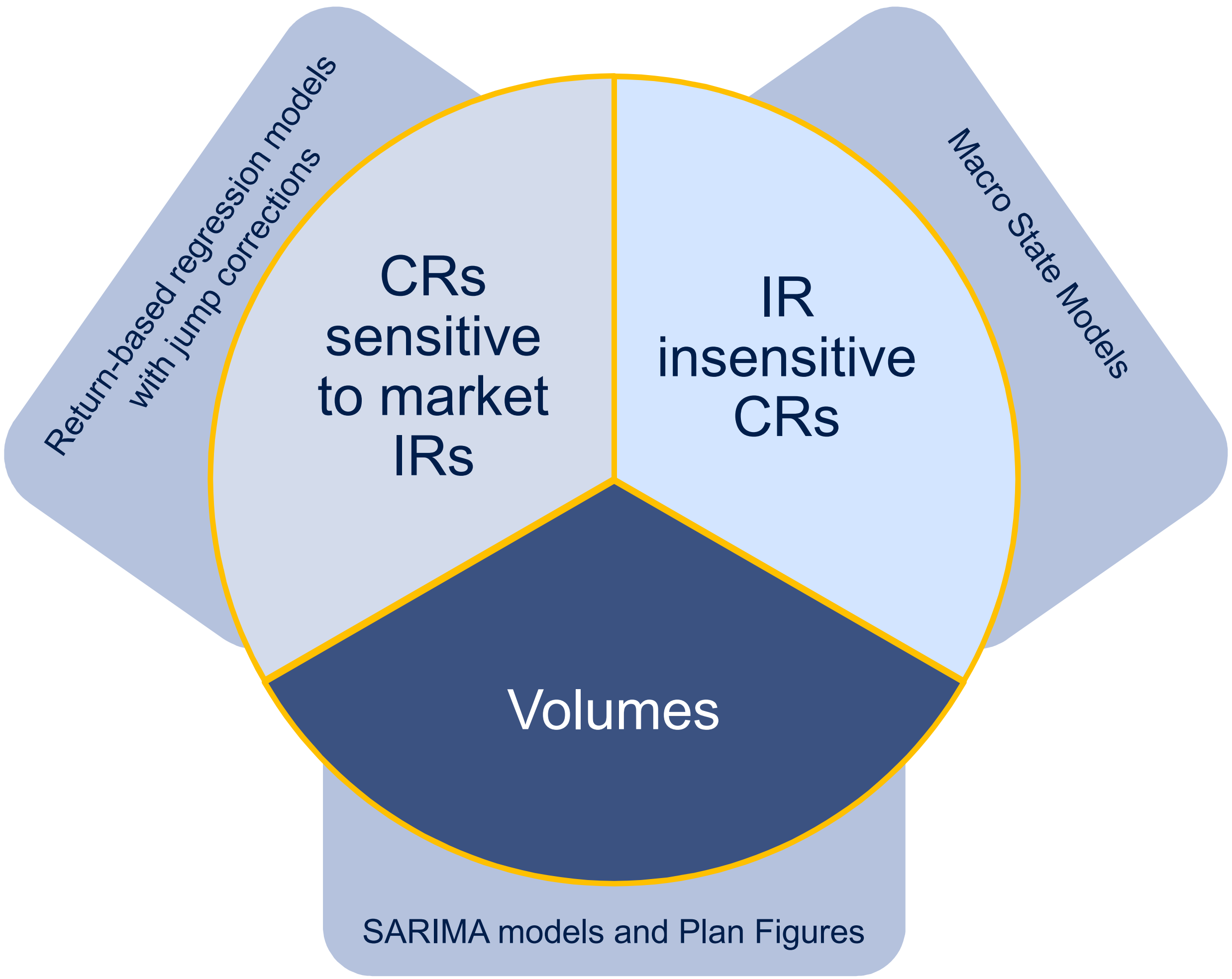
Fixing the Regression: Analyzing Returns

Correlation Analysis of Returns

- **Autocorrelation of returns** found to be **very small** for **Client Rates, Volumes** as well as **Market IRs**
- **Return-based regression models** are therefore **not prone to spurious regression**
- **Statistical tests** can therefore be used to **assess model validity**
- **Variable Selection**
  1. **Correlation analysis** of returns **identifies products** where return-based **regression models may succeed** in forecasting Client Rates and/or Volumes based on market IRs
  2. **Backward elimination** identifies a „parsimonious Model“ to **avoid overfitting**



Grouping of Modeling Approaches for Forecasting



Forecasts are based on three basic model types

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Return-based regression model

» Linear model for **returns**

$$\Delta c_{t,i} = c_{t,i} - c_{t-1,i} = \alpha_0 + \sum_{j=1}^{J} \alpha_j \left(r^{j}_{t-lag(j),i} - r^{j}_{t-lag(j)1,i}\right) + \varepsilon_{t,i}$$

» This yields the **estimators**

$$\Delta\hat{c}_{t,i} = \hat{\alpha}_0 + \sum_{j=1}^{J} \alpha_j \left(\hat{r}^{j}_{t-lag(j),i} - \hat{r}^{j}_{t-lag(j)1,i}\right),$$

where $\hat{r}^{j}_{t,i}$ denotes the simulated market IR of maturity bucket j at time t in the i-th scenario.

» **Forecast:**

$\hat{c}_{t,i} = \max\{c_{floor}, \hat{c}_{t,i-1} + \Delta\hat{c}_{t,i}\}$, t>0

$\hat{c}_{0,i} \coloneqq c_0$ (real observed starting Client Rate)

» **Floor-Parameter** c_{floor} applies to all retail products, set by **management decision** within legal bounds

Drawbacks

» **Misprediction of single returns** may lead to sustainable **bias in CR** levels with very slow decay

» Model does not account for the **market** tending to keep the **spread between CR and market IRs at historically observed levels**

» Introduction of a **jump component** was able to **reduce** these **shortcomings**

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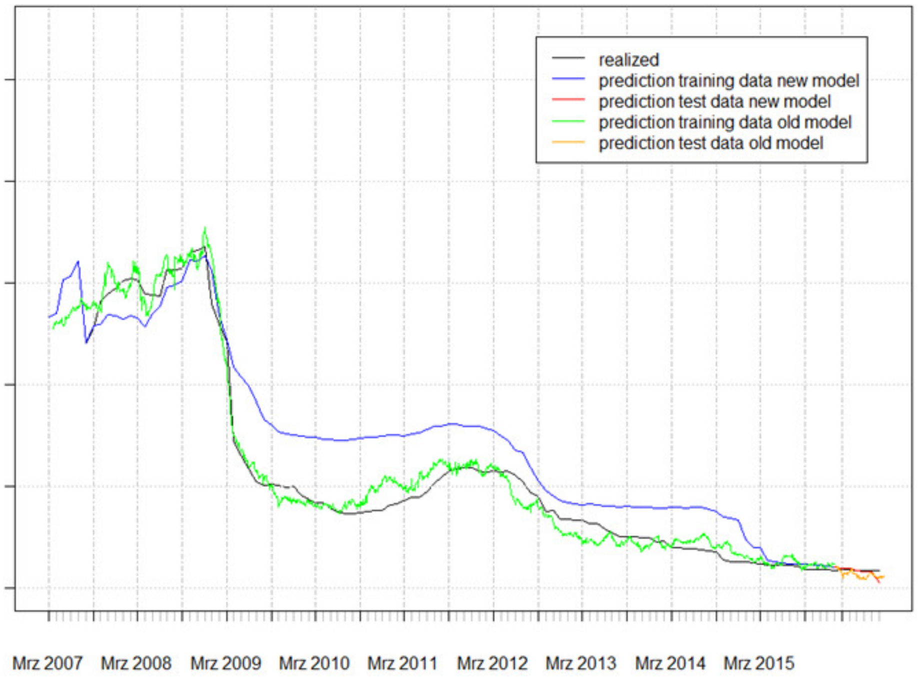
Fitting Results for Pure Return-Based Regression Models



Drawbacks

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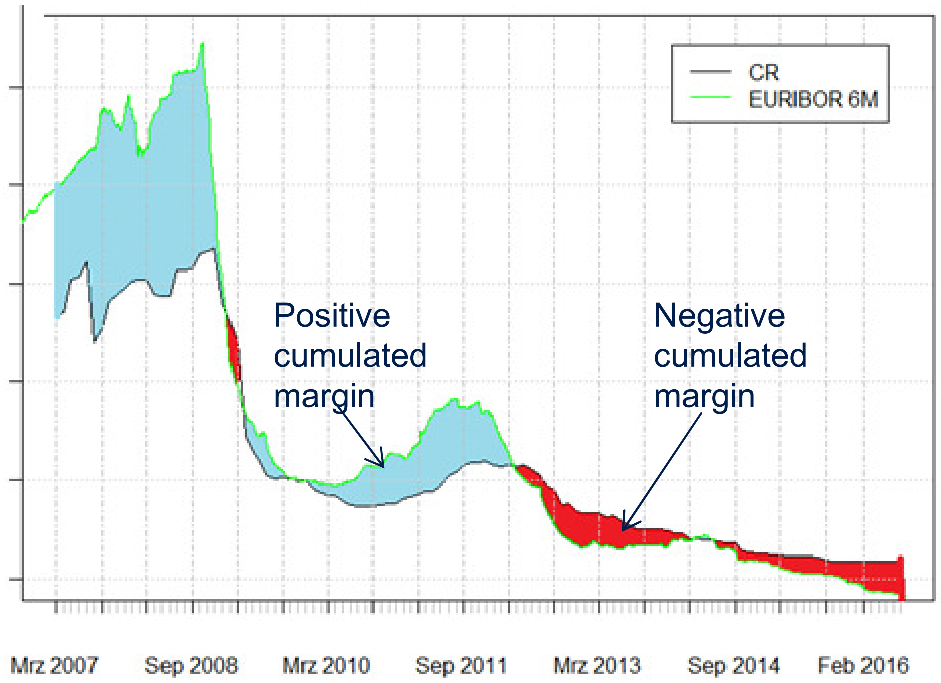
Return-Based Regression Models: Design of the Jump Component

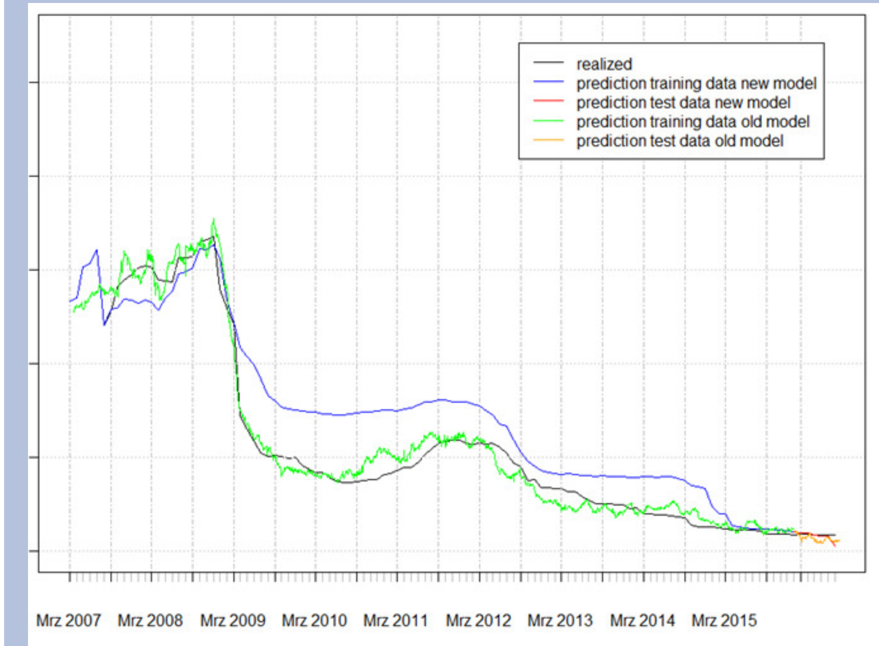
- Compute cumulated margin between intersections of CR and a historical reference CR after shift by mean margin
- Determine max and min cumulated margins $S_{max} > 0$ (for IR>CR) und $S_{min} < 0$ (for IR<CR)
- Suggest CR increment by regression model
- Compute cumulated margin $S_i(t)$ since last curve crossing
- If CR>IR, a downshift occurs with probability $p^d(t,i) = d \cdot S_i(t)/S_{min}$ and size $p^d\left(\hat{r}_{t,i}(t) - \hat{c}_{t,i}\right) < 0$
- If CR<IR, an upshift occurs with probability $p^u(t,i) = u \cdot S_i(t)/S_{max}$ and size $p^u\left(\hat{r}_{t,i}(t) - \hat{c}_{t,i}\right) > 0$



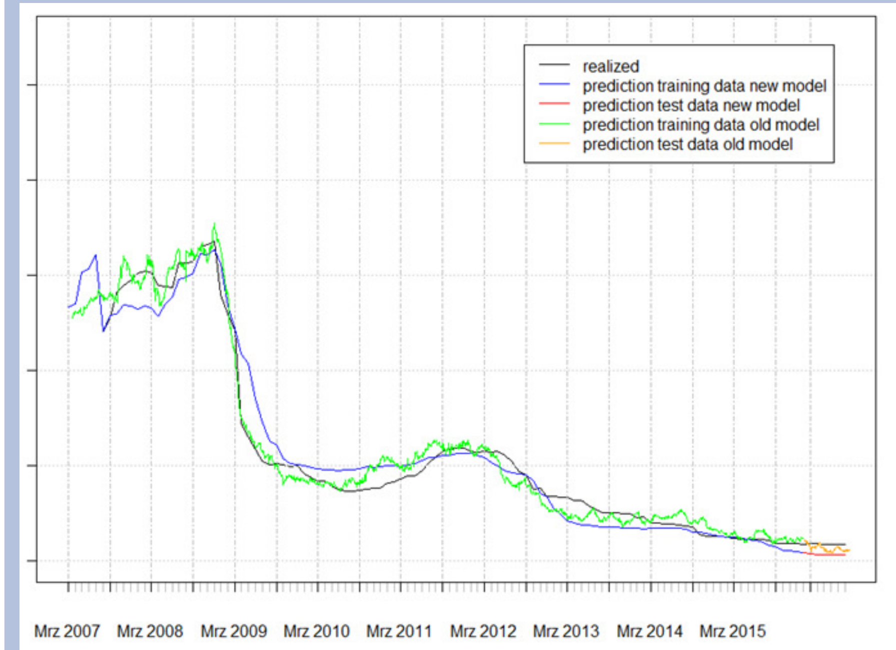
Model parameters u and $d \in$ 0,1 controlling jump-behavior are calibrated via Least-Squares-Minimization

Fitting Results: CR Forecast by Return-Based Regression with Jumps

Without Jump Correction



With Jump Correction



Jump Component keeps margin at historically observed levels and corrects forecasts for level errors

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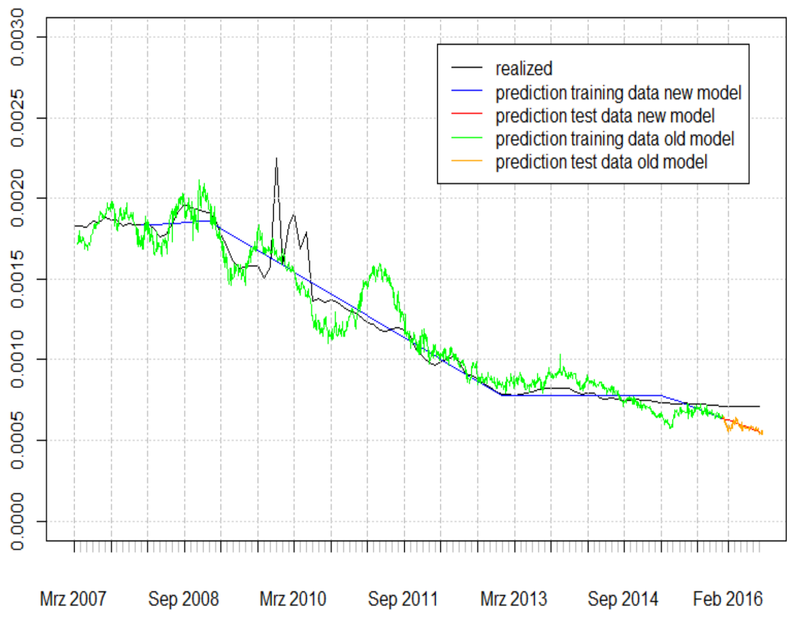
Macro State Model

» Modeling Client Rates with infrequent adjustments:

- › CRs for **new accounts** are set by the bank to few **fixed levels** (called macro states)
- › CR **changes** only affect new accounts and and **propagate slowly**

Macro-State Model



Two modeling approaches capture diverse product-specific behavior of CRs

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The Model for Client Rates

Direct Regression Model

Basic assumption

» CR is a linear combination of market IR curves

» Statistical validity of regression approach relies on uncorrelated input data
(This is severely violated by the data)

Model parameters

» (time lagged) market IR time series

Calibration

» Least Squares

Scenario generation

» Apply regression model to simulated market IRs

Model Evolution

Return-Based Regression Models and Macro State Model

Basic assumptions

» IR-sensitive CRs:

› CR *returns* are a linear combination of market IR *returns*

› the bank tries to adjust spreads between CR and market IR to the historically observed levels

» CRs with infrequent adjustments:

› CRs for new accounts are set by the bank to few fixed levels (called macro states)

› CR changes only affect new accounts and propagate slowly

Calibration

» Least Squares Calibration

Scenario generation

» Apply model to simulated returns of market IRs

For CRs with significant correlations to IR returns, return-based regression models avoid the pitfalls of spurious regression. Alternative modeling approaches cover products without significant correlations.

Modeling Deposit Volumes

Deposit Volume Modeling

Basic observations

» Deposit volumes show a significant trend component (can usually be steered by the bank)

» Deposit volumes show an inter-month seasonal pattern, e.g. pre-holiday season gain, new year drop, …

» Current accounts also have a distinct intra-month pattern, i.e. pay-day and consecutive draw-downs

Observations from calculating correlations

» No correlation to Client Rates discernible, i.e. clients seem to be insensitive to rate changes (this clearly just holds within bounds and in the current interest rate environment)

» No correlation to market rates discernible, i.e. clients do not change their saving behavior based on the interest rate environment
(this should also be taken with a large grain of salt)

Calibration and scenario generation

» Detrend the historical time series

» Fit a SARIMA time series model to the detrended data

» Take trend from plan figures (constant extrapolation beyond planning horizon)

» Simulate seasonal component via time series model

» Add residuals by bootstrapping from the historical data

Volume forecasts can be based on SARIMA model, but assumptions should be re-evaluated carefully from time to time!

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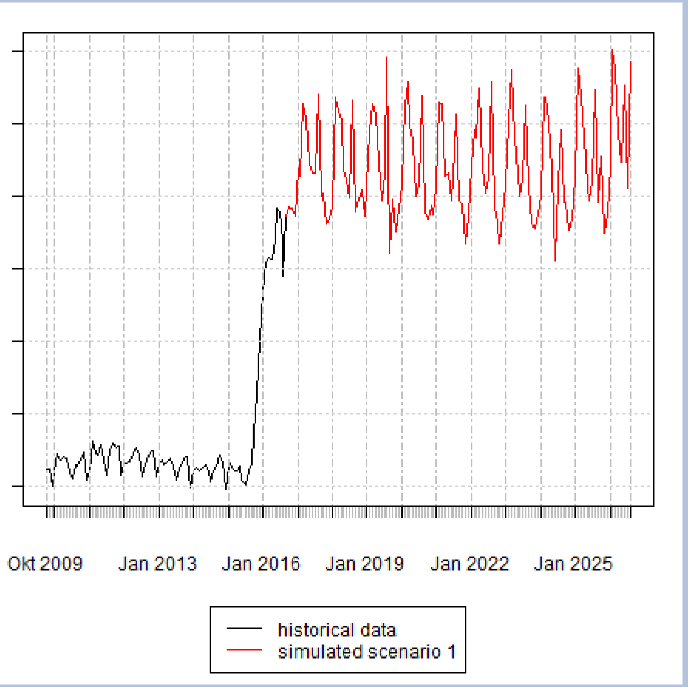
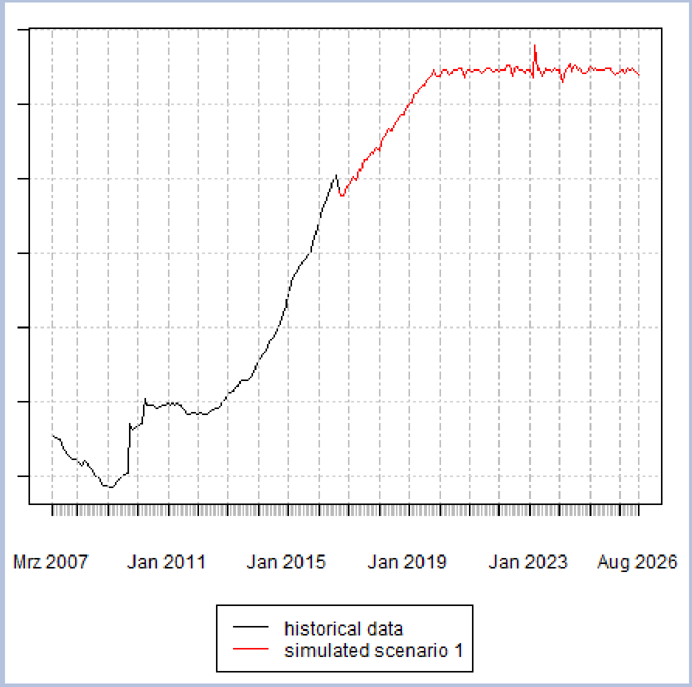
Deposit Volume Forecast

Model for constant plan figures



Model for increasing plan figures with constant extrapolation beyond the planning horizon



Single model type captures diverse landscape of volume trajectories.

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Volume Prediction: Combining Plan Figures with Time Series Modeling

Direct Regression Model

Basic assumption

- Volume is a linear combination of market IR curves and CR
(This assumption is not supported by the data)
- Statistical validity of regression approach relies on uncorrelated input data.
(This assumption is severely violated by the data)

Model parameters

- (time lagged) market IR time series
- CR

Calibration

- Least squares calibration on historical data

Scenario generation

- Apply regression model to simulated market IRs and CR prediction

Model Evolution

Seasonal Time Series Model with Plan Figures for Trend

Basic assumptions

- Volume trends develop according to plan figures
- Inter-Month fluctuations can be captured by a seasonal time series model
- Future fluctuations are similar to historically observed client behavior

Calibration

- Detrend the historical time series
- Fit a SARIMA time series model to the detrended data

Scenario generation

- Take trend from plan figures (constant extrapolation beyond planning horizon)
- Simulate seasonal component via time series model
- Add residuals by bootstrapping from the historical data

Liquidity risk due to volume drops can be captured by classical time series models. Replacing the trend component by plan figures yields replication portfolios that are consistent with the plan.

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Interest Rate Scenario Generation

The Hull-White 2 Factor Model

- The Hull-White 2 factor model is a so called short-rate model. This model class models only the very front end of the yield curve
- It uses two stochastic processes $x(t)$ and $y(t)$ to model the short rate

$$r(t) = x(t) + y(t) + \phi(t), \qquad r(0) = r_0$$

- $\phi(t)$ assures that the initial term structure of the yield curve is matched
- The dynamics of the two stochastic processes $x(t)$ and $y(t)$ are described by the following stochastic differential equations (SDEs)

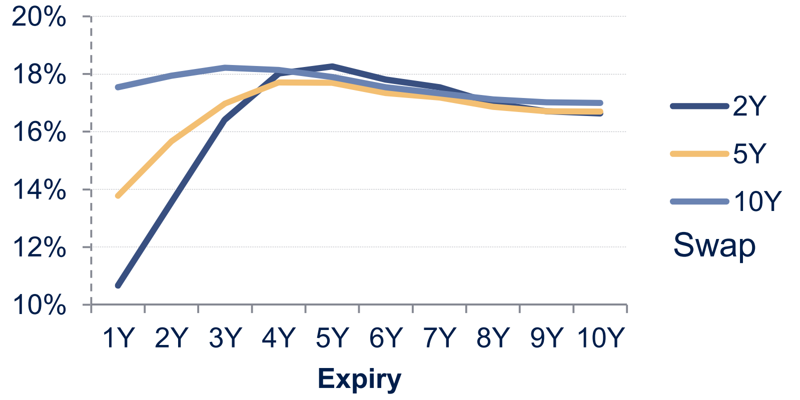
$$\begin{aligned} dx(t) &= -a \cdot x(t)dt + \sigma dW_1(t), \qquad & x(0) = 0 \\ dy(t) &= -b \cdot y(t)dt + \eta dW_2(t), \qquad & y(0) = 0 \\ dW_1(t)\, dW_2(t) &= \rho dt & \end{aligned}$$

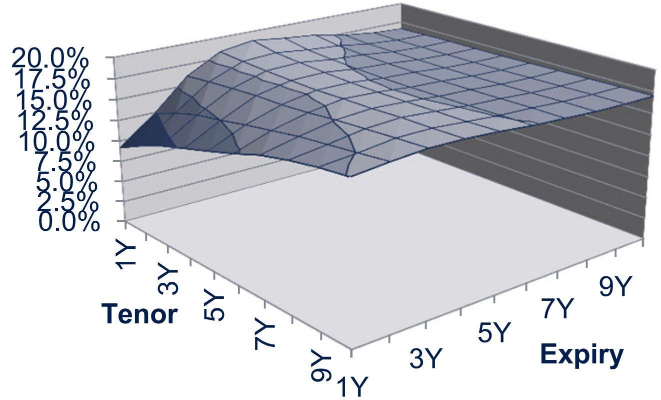
- Hence, the level and shape of the yield curve at any future date is completely determined by two stochastic quantities

Calibration of the Hull-White 2 Factor Model

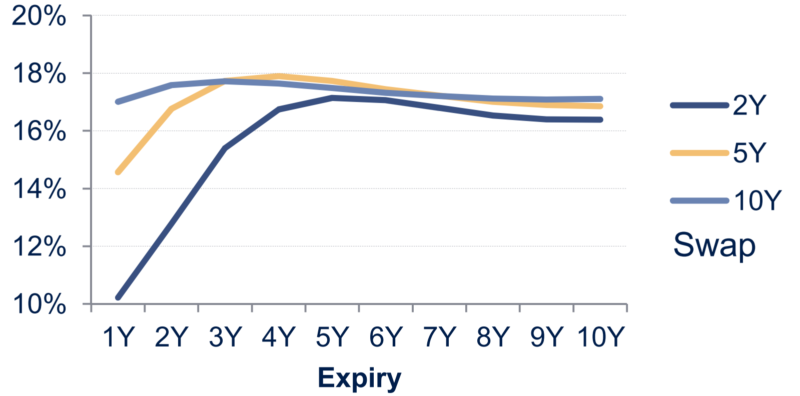
- » The five free parameters a, b, σ, η, ρ are set by fitting the model to ATM swaption volatilities
- » Set of benchmark instruments: [1Y,2Y, 3Y…10Y] x [1Y,2Y, 3Y…10Y] swaptions
- » Use of vega-weighting improves stability and puts focus on long end of yield curve

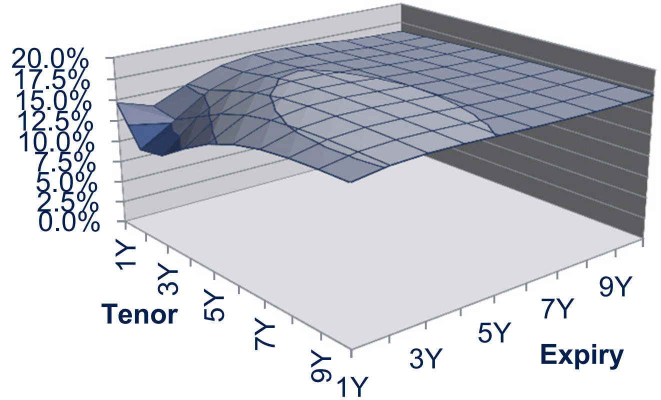
Market implied volatilities





Model implied volatilities





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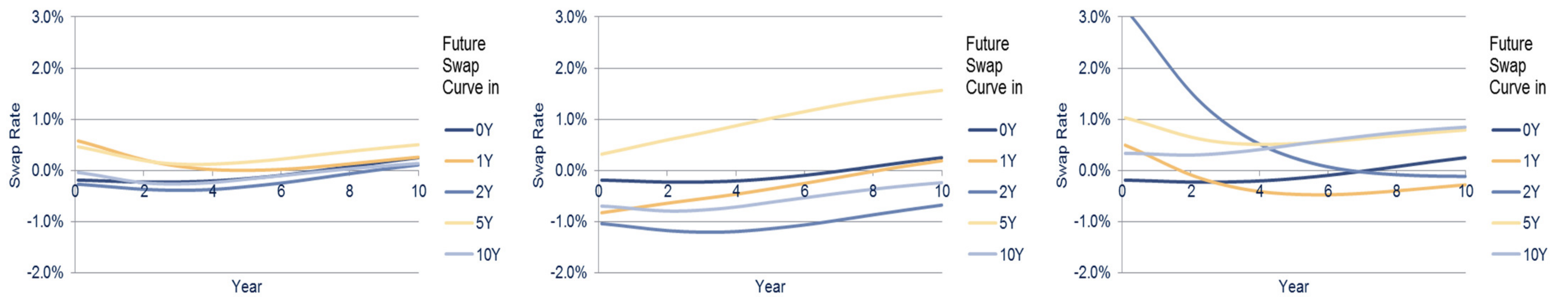
Yield curve scenario generation using the Hull-White 2 factor model

Steps required

Generation of random numbers → Transformation into correlated, normally distributed numbers for $dW_1(t)$ and $dW_2(t)$ → Calculation of $x(t)$ and $y(t)$ by applying Euler's method to SDEs → Calculation of discount factors using HW2F model → Calculation of yield curves (zero and swap rates for future spot dates)

Exemplary scenarios



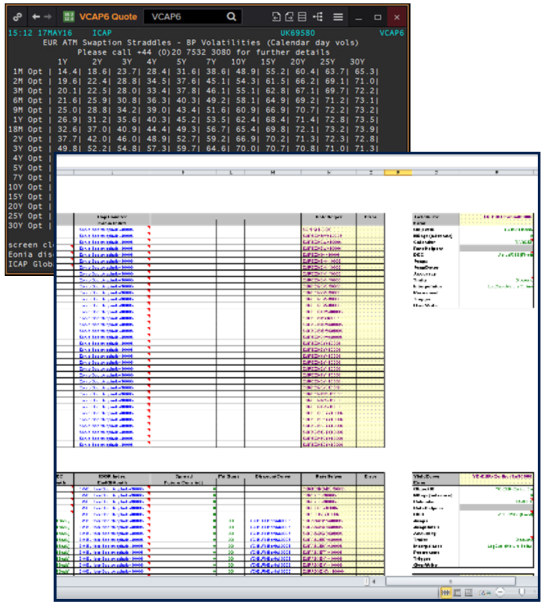
Simulation covers a variety of normally distributed scenarios

New process and model yields robust calibration and scenario generation

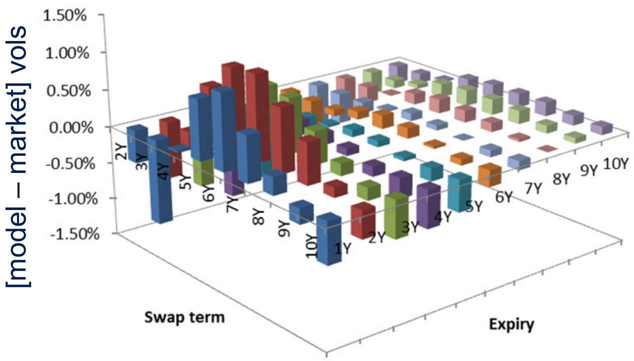
Market data input from Reuters to Excel/QuantLib

2-Factor Hull White model calibration in Excel/QuantLib/VBA

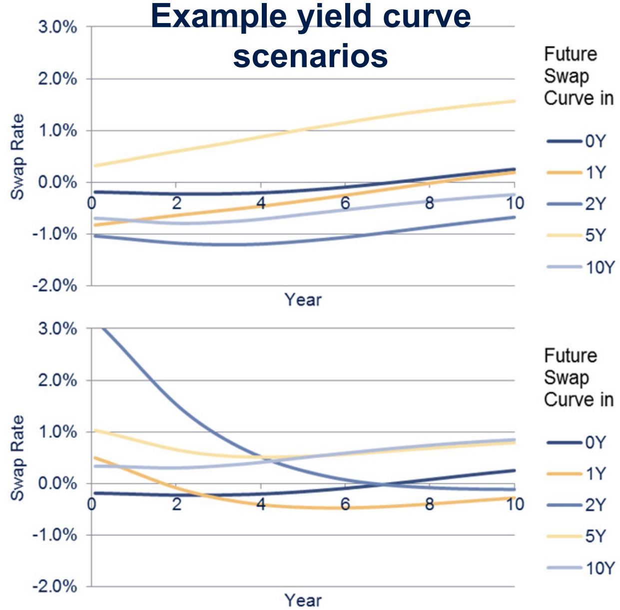
Scenario generation in Excel/VBA and output to CSV files



Example calibration results show variances between market and model-implied volatilities(1)



Example yield curve scenarios



Though there are variances between market and model-implied volatilities (e.g. for short expiries/swap terms) the overall model fit is fairly good and fit for purpose

(1) Variances expressed in terms of shifted log-normal volatilities with 3% shift size

Optimization Problem

Optimization Problem

» Consider **time-averaged margin** over the next 10 years and **minimize its variance**

» **Liquidity Constraints**: maturing volume fraction > historical quantile of volume drops

» Theoretical **Target Function**

$$f(w_1, \dots, w_n) = \mathrm{Var}\left(\frac{1}{T}\sum_{j=1}^{J} w_j \sum_{t=1}^{T} m_j(t)\right) = w'\mathbf{\Sigma}\mathrm{w} \longrightarrow \min$$

deposited volumes (for volume weighting)
Market Rates
Client Rates

» **Covariance matrix $\mathbf{\Sigma} = < \mathrm{Cov}(\overline{m}_i, \overline{m}_j) >$** of the time-averaged margins $\overline{m}_j = \frac{1}{T}\sum_{t=1}^{T} m_j(t)$ **to be estimated**

Monte-Carlo-Simulation

Market IRs

» **10,000 trajectories of market swap par rates** over the next 10 years (2-Factor Hull White Model)

- Normal distribution allows for modeling of negative IRs
- Five Parameters (for volatilities, mean reversion and correlation) fitted to ATM swaption

Client Rates

» **Prediction of Client Rates** that are consistent with market rates (correct correlation)

Volumes

» **Prediction of Deposited Volumes** reflecting historically observed client behavior

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Details on the Optimization Problem

Target Function to be minimized

Minimize variance of the average margin over the next 120 months

- Dependent on margins $m_j(t)$ in the investmet buckets 3M, 6M, 1Y, 3Y, 5Y, 10Y and their covariances

$$f(w_1, \ldots, w_n) = \mathrm{Var}\left(\frac{1}{T}\sum_{j=1}^{J} w_j \sum_{t=1}^{T} m_j(t)\right) = w'\Sigma_{(\overline{m}_1,\ldots,\overline{m}_J)} w \longrightarrow \min,$$

where $\Sigma_{(\overline{m}_1,\ldots,\overline{m}_J)}$ denotes the covariance matrix of the time averaged bucket margins

$$\overline{m}_j = \frac{1}{T}\sum_{t=1}^{T} m_j(t), \quad j \in \{1, \ldots, J\}$$

- The **margin of the ON bucket is neglected**, since the **ON weight is determined by external calibration** and not part of the optimization

Variance is estimated by Monte-Carlo simulation

- There is no analytical expression for the covariance in the target function due to the complex interaction of market rates, CRs and volumes
- Hence, the theoretical covariance $\Sigma_{(\overline{m}_1,\ldots,\overline{m}_J)}$ is replaced by its empirical counterpart $\widehat{\Sigma}_{(\overline{m}_1,\ldots,\overline{m}_J)}$ which yields the target function

$$w'\widehat{\Sigma}_{(\overline{m}_1,\ldots,\overline{m}_J)} w \longrightarrow \min$$

Constraints

Consistency and prohibition of short selling

$$\sum_{j=1}^{J} w_j = 1 - w_{ON}, \qquad w_j \geq 0 \quad \forall j \in \{1, \ldots, J\}$$

Liquidity constraint on maturing volume

- The overnight weight $w_{ON} \in [0,1]$ is calibrated as a historical quantile of the maximum monthly ON volume drop relative to the mean volume in the preceding month
- A rolling investment of € 1with maturity of $M(j)$ months leads to monthly maturing volume of € $\frac{1}{M(j)}$
- If the mean monthly volume drops, it needs to be ensured that the overall maturing volume and the part of the ON bucket no longer needed suffice to cover the drop without having to liquidate non-maturing parts of the portfolio. The latter would lead to additional IR risk. Hence it is required that

$$\sum_{j=1}^{J} \frac{w_j}{M(j)} \geq (1 - w_{ON}) Q_{\gamma_{Liqui}}$$

where $Q_{\gamma_{Liqui}}$ denotes the quantile at level γ_{Liqui} of the relative month to month changes of the mean deposited volume.

IRRBB constraints

Optimal solution needs to respect the IRRBB constraints

- on declaration of core deposits and
- on average duration of core deposits

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Time Series Forecasts with Automated Modell Selection

Application of an Automated Time Series Forecast Procedure

- Forecasts can be used to model a realistic expected behaviour of a time series firmly based in well understood mathematics, for example:
  - **Customer deposits**
  - **Volume of new business**
  - Operating expenditures (non-project related)
- Often the setup is highly manual and done very infrequently, but in principle the process can be automated

Pros and Cons of an automated time series forecast compared to a manual setup

Pro	Contra
» Can expand a consistent forecast procedure to many products and different departments » Can perform the forecast frequently and can steer accordingly » Higher granularity possible » Higher accuracy of the forecast	» Initial setup has to be performed » Maintenance of the running system required » Higher requirements for data quality » Results may need more interpretation

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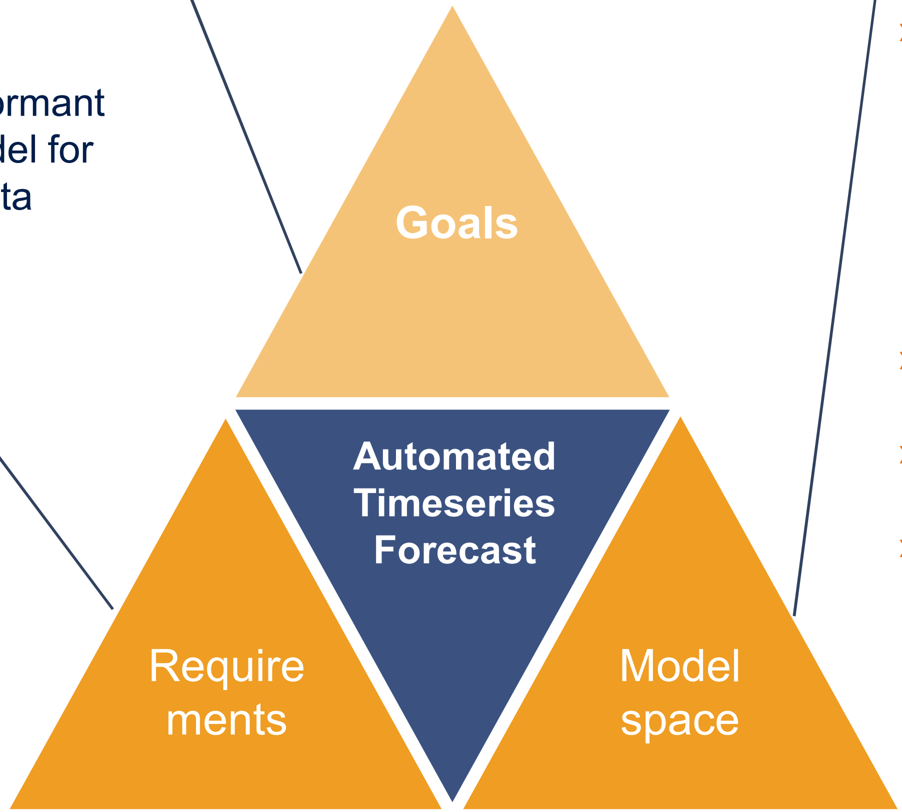
Basic Goals and Requirements of an Automated Time Series Forecast

Goals

- » Highly automated
- » Ideally no manual steps
- » Scalable and highly performant
- » Selection of the best model for the currently available data

Requirements

- » Time series with a sufficiently long history
- » No outliers in the time series due to bad data quality



Model Space

- » ARIMA models
  $p \leq 4, d \leq 2, q \leq 4$
  (Non-Seasonal parameters)
  $P \leq 2, D \leq 1, Q \leq 2$
  (Seasonal parameters)
  where $p + q \leq 4$ and $d + D \leq 2$.
- » Range of seasonality $(1 \leq f \leq 12)$
- » Yeo and Johnson parameter
- » Parameters for ETS
  - › error term
  - › trend term
  - › seasonality term
  - › damping term

Want to achieve a highly automated model selection over a large model space with minimal manual input

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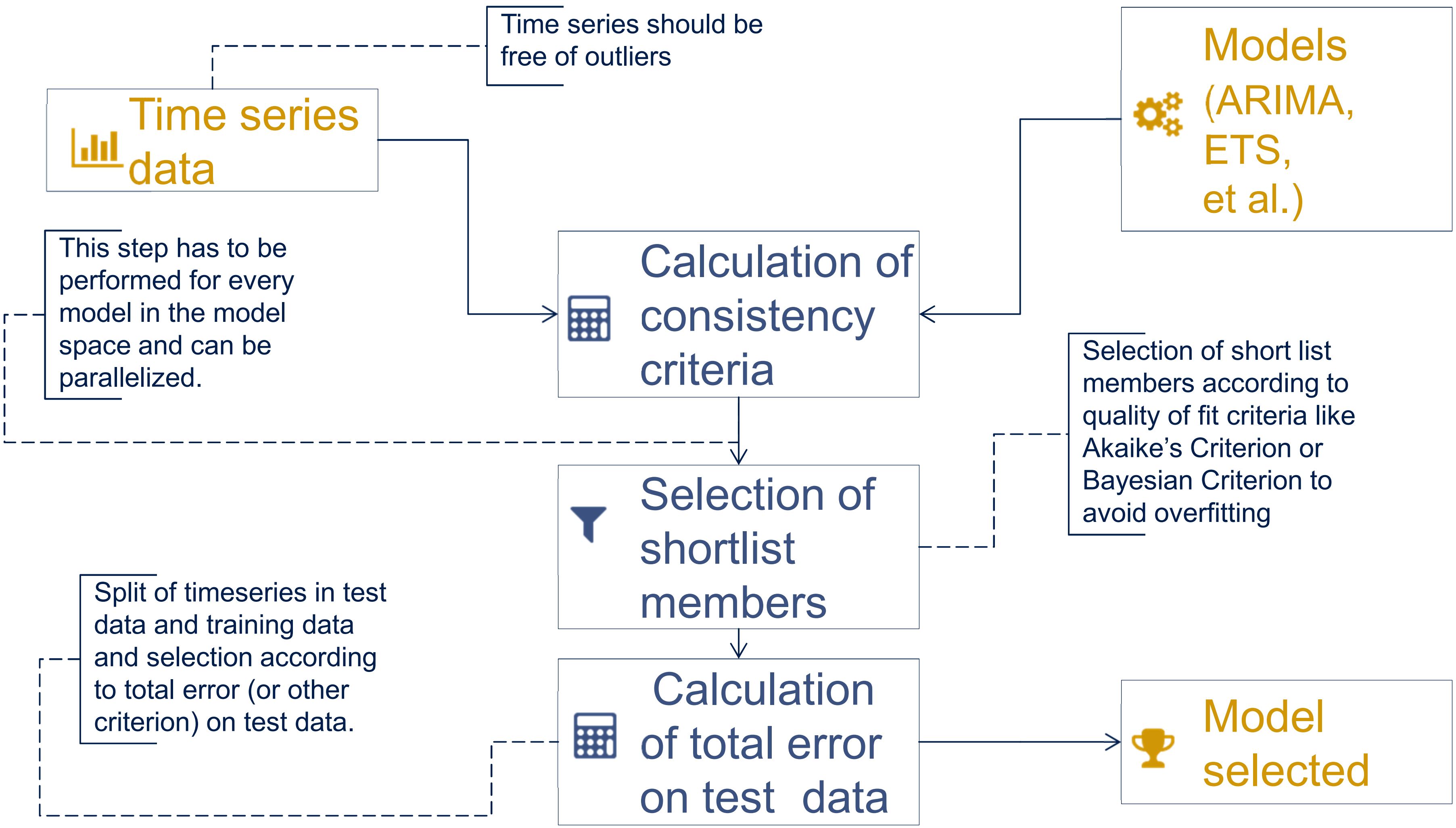
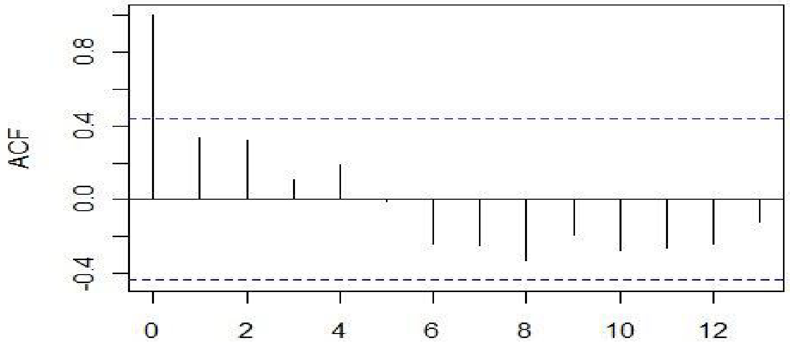
Schematic Depiction of the Forecast Procedure



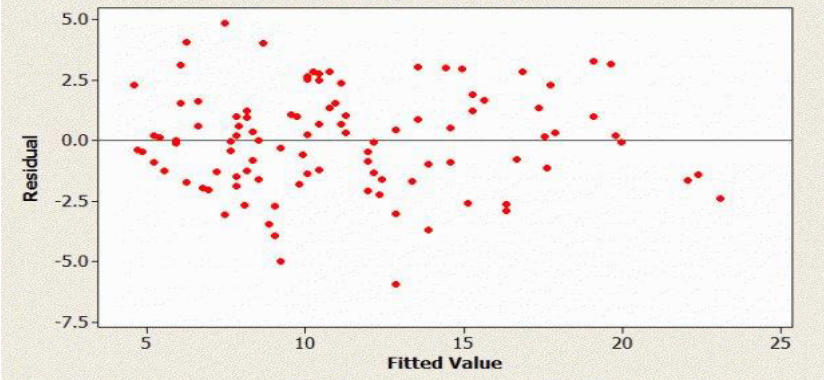
From Models to Shortlist – Calculation of Consistency Criteria

» Only models that pass the following criteria are accepted for the shortlist:

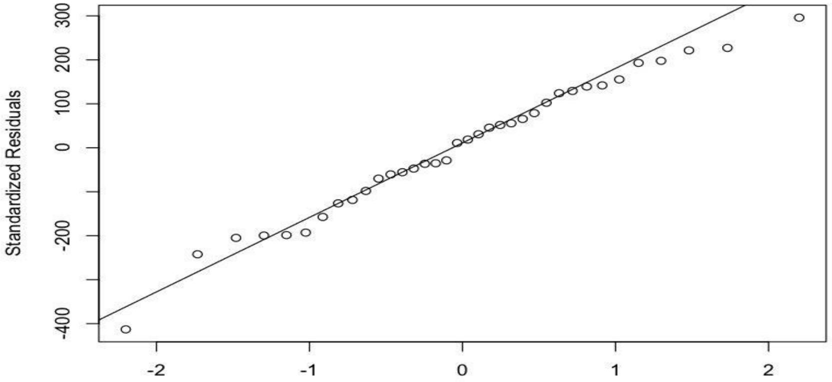
Small autocorrelation of residuals



Variance of residuals constant



Residuals follow a normal distribution



Only models that pass basic consistency criteria are considered for the shortlist

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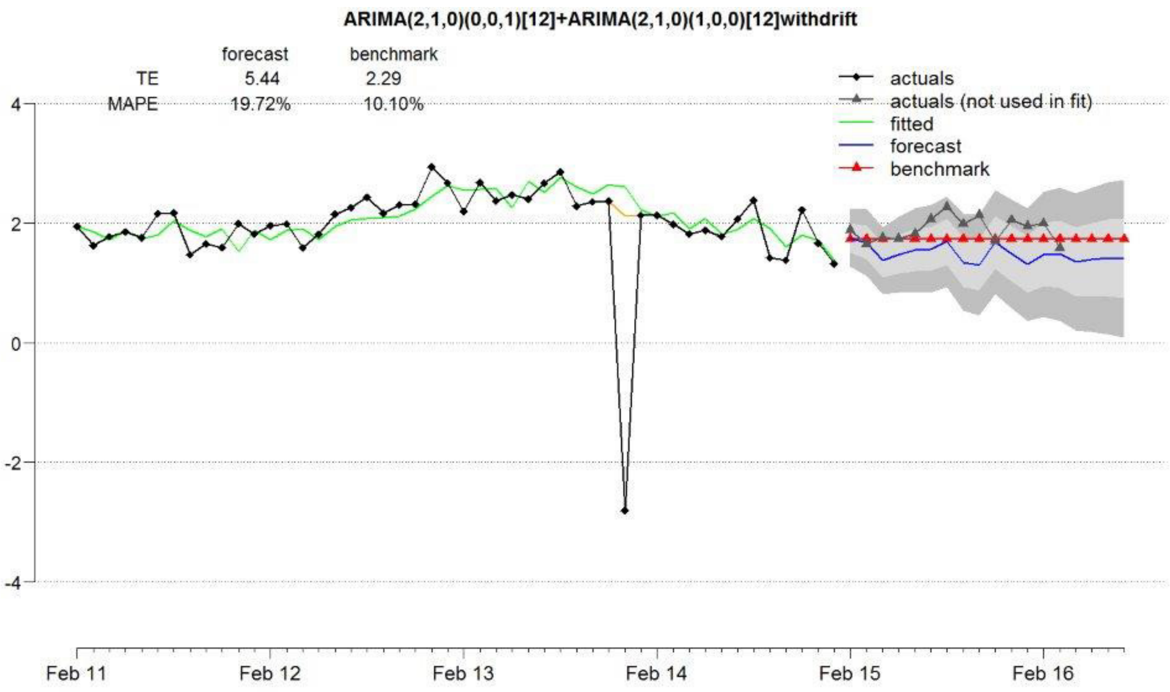
From Shortlist to Model Selection

» **Select from the shortlist the top 10 models according to:**
  - Sample corrected Akaike's Information Criterion AIC_c (preferred)
  - Akaike's Information Criterion AIC
  - Bayesian Information Criterion BIC

» **Selection of the model:**
  - Divide data in training set and test set
  - Calculate expectation for models on the shortlist and combination of these models (i.e. sums of two models)
  - Compute forecast errors on the test data and select model according to:
    - Mean absolute error (MAE) (preferred)
    - Mean error (ME)
    - Mean absolute scaled error (MASE)



The model that describes the test data set in the best way based on the training data is automatically selected

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