Modeling and forecasting the yield curve

DOFIN MSc Student: Anca JELEA
Motivation

- The yield curve is a good predictor of economic cycles
  An usual term structure would be positive, but if it tends to flatten and have downslopes could be a sign of recession
- The yield curve can be used as a benchmark for prices of other securities*
- Could be seen as an indicator of investors’ expectations about future developments of interest rates

* involving a particular risk (for example)
Objectives

- (I) General aspects on T-securities, data used
- (II) Dynamics of yield curve in Romania
- (III) Specific algorithms to determine the principal elements of the yield curve
- (IV) What drives the yield curve (or specific elements of yield curve more exactly)?
  - (IV.1) global, regional or local factors?
  - (IV.2) correlation with macroeconomic indicators
(I) Overview of yields computation

- Current yield
- **Yield to maturity** quoted on the market
- Yield to redemption
- **Zero Coupon Bond Yield** not directly quoted, should be computed

*Data used in this study: zero coupon yields - Anderson method (cubic spline)*
maturities: 6M, 9M, 1Y, 2Y, 3Y, 4Y, 5Y, 6Y, 7Y, 8Y, 9Y, 10Y
source: Thomson - Reuters

Sources of bond yield returns can be classified as:
- Periodic coupons payments
- Reinvesting principal
- Revenues from reinvesting coupons
(II) RO Yield curve (1)

Structure of maturities
- short-term (<= 1 year)
- medium term (1-3 years)
- long-term (>= 5 years)

38 outstanding RON ISINs (25-June-2015)

Rebalancing of debt structure

Maturity profile of outstanding RON government securities (% of total)

- Maturity up to 1 year
- Maturity > 1 year and up to 3 years
- Maturity > 3 years
RO Yield curve(2)

- Inclusion of Romanian T-bonds in international indices such as Barclays MLCGI (Nov'12) and JPM GBI-EM (Jan'13) ➔ ++ non-residents

![Graph showing holdings of non-residents (RON bn) from sep 10 to oct 15](chart)

- Structure of outstanding RON government securities by holders (% of total)
  - Local banks, 53.2
  - Local non-bank investors, 28.3
  - Non-residents, 18.2
  - Central Depository, 0.3

Data as of end-February 2015

Source Ministry of Finance, own computations
Dynamics of RO T-securities yields
(Sep.2011 - Mar.2015, daily data)
Drivers:
- NBR’s monetary policy decisions
- Uncertainty on the political scene (the breakup of the governing alliance)
- Russia-Ukraine conflict
- Greek bailout program
Literature review

- Svensson (1994) → four factors
- Diebold & Li (2008), Mehl (2009), Hoffmaister (2010) → interactions between yield curves in a global market
- Carriero (2010), Laurini & Hotta (2010) → focus on Bayesian estimation methods
(III) How to determine the three characteristics (level, slope, curvature) of the RO yield curve?

(a) Classical approach

does NOT take into account yields for ALL maturities

\[
\begin{align*}
\text{level} & = y_l \\
\text{slope} & = y_l - y_s \\
\text{curvature} & = 2y_m - (y_s + y_l)
\end{align*}
\]
(b) Principal component analysis

<table>
<thead>
<tr>
<th>Eigenvalues of the Correlation Matrix</th>
<th>Eigenvalue</th>
<th>Difference</th>
<th>Proportion</th>
<th>Cumulative</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11.7137216</td>
<td>11.4430774</td>
<td>0.9761</td>
<td>0.9761</td>
</tr>
<tr>
<td>2</td>
<td>0.2706441</td>
<td>0.2565159</td>
<td>0.0226</td>
<td>0.9987</td>
</tr>
<tr>
<td>3</td>
<td>0.0141283</td>
<td>0.0128564</td>
<td>0.0012</td>
<td>0.9999</td>
</tr>
<tr>
<td>4</td>
<td>0.0012687</td>
<td>0.0010564</td>
<td>0.0001</td>
<td>1.0000</td>
</tr>
<tr>
<td>5</td>
<td>0.0002123</td>
<td></td>
<td>0.0000</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

Correlation between PC and RO yields for different maturities
(c) Adjusted Nelson-Siegel approach

- Nelson & Siegel (1987) — Yield curve: \( y_t(\tau) = b_{1t} + \frac{b_{2t}(1 - e^{-\lambda_t \tau})}{\lambda_t \tau} - b_{3t} e^{-\lambda_t \tau} \)

- Diebold & Li (2006) propose an adjustment of Nelson-Siegel model:

\[
\begin{align*}
    y_t(\tau) &= l_t \times 1 + s_t \times \frac{(1 - e^{-\lambda_t \tau})}{\lambda_t \tau} + c_t \times \left( \frac{(1 - e^{-\lambda_t \tau})}{\lambda_t \tau} - e^{-\lambda_t \tau} \right) \\
    l_t &= b_{1t} ;
    s_t &= b_{2t} - b_{3t} ;
    c_t &= b_{3t}
\end{align*}
\]
(c) Adjusted Nelson-Siegel approach
Model estimation(1)

- Yields for various maturities $\tau_1, \tau_2, \ldots, \tau_M$

\[
\begin{pmatrix}
y_t(\tau_1) \\
y_t(\tau_2) \\
\vdots \\
y_t(\tau_M)
\end{pmatrix} =
\begin{pmatrix}
1 & \frac{1-e^{-\lambda_t \tau_1}}{\lambda_t \tau_1} & \frac{1-e^{-\lambda_t \tau_1}}{\lambda_t \tau_1} - e^{-\lambda_t \tau_1} \\
1 & \frac{1-e^{-\lambda_t \tau_2}}{\lambda_t \tau_2} & \frac{1-e^{-\lambda_t \tau_2}}{\lambda_t \tau_2} - e^{-\lambda_t \tau_2} \\
1 & \frac{1-e^{-\lambda_t \tau_M}}{\lambda_t \tau_M} & \frac{1-e^{-\lambda_t \tau_M}}{\lambda_t \tau_M} - e^{-\lambda_t \tau_M}
\end{pmatrix}
\begin{pmatrix}
l_t \\
s_t \\
c_t
\end{pmatrix}
\]

\[y_t = X_{\lambda_t} \beta_t\]

\[
\min_{\lambda_t, l_t, s_t, c_t} \sum_{i=1}^{M} (l_t + s_t \frac{1 - e^{-\lambda_t \tau_i}}{\lambda_t \tau_i} + c_t \left( \frac{1 - e^{-\lambda_t \tau_i}}{\lambda_t \tau_i} - e^{-\lambda_t \tau_i} \right) - y_t(\tau_i))^2
\]

\[= \min_{\lambda_t, \beta_t} (X_{\lambda_t} \beta_t - y_t)^T (X_{\lambda_t} \beta_t - y_t)\]
(c) Adjusted Nelson-Siegel approach
Model estimation(2)

- $\lambda_t = \text{constant} \Rightarrow OLS$
  
  (++tractability & --additional restrictions)

- The parameter $\lambda$ is the level at which the medium term component takes a maximum value

  $\lambda = 0.0609$ (30 months)
(c) Adjusted Nelson-Siegel approach
Results of estimation

! Adjusted Nelson-Siegel model tracks the negative of yield curve slope (in classical approach)
(IV) Dynamics of yield curves in RO, HU, PL, GE, US, JP

Sep.2011-Mar.2015

Maturities: 6M to 10Y
Additional hints for the existence of unobservable “global factors”

Preliminary analysis (1)

<table>
<thead>
<tr>
<th>Level factors: RO,HU,PL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigenvalue</td>
</tr>
<tr>
<td>4,81</td>
</tr>
<tr>
<td>Variance prop(%)</td>
</tr>
<tr>
<td>Cumulative prop(%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Level factors: RO,HU,PL,US,GE,JP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigenvalue</td>
</tr>
<tr>
<td>5,22</td>
</tr>
<tr>
<td>Variance prop(%)</td>
</tr>
<tr>
<td>Cumulative prop(%)</td>
</tr>
</tbody>
</table>
Additional hints for the existence of unobservable “global factors”

Preliminary analysis (2)

Slope factors: RO, HU, PL

<table>
<thead>
<tr>
<th></th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigenvalue</td>
<td>2.78</td>
<td>0.43</td>
<td>0.23</td>
</tr>
<tr>
<td>Variance prop(%)</td>
<td>80.9</td>
<td>12.4</td>
<td>6.7</td>
</tr>
<tr>
<td>Cumulative prop(%)</td>
<td>80.9</td>
<td>93.3</td>
<td>100.0</td>
</tr>
</tbody>
</table>

Slope factors: RO, HU, PL, US, GE, JP

<table>
<thead>
<tr>
<th></th>
<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
<th>PC4</th>
<th>PC5</th>
<th>PC6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Eigenvalue</td>
<td>3.29</td>
<td>0.57</td>
<td>0.40</td>
<td>0.07</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>Variance prop(%)</td>
<td>75.3</td>
<td>13.1</td>
<td>9.2</td>
<td>1.5</td>
<td>0.8</td>
<td>0.2</td>
</tr>
<tr>
<td>Cumulative prop(%)</td>
<td>75.3</td>
<td>88.4</td>
<td>97.6</td>
<td>99.1</td>
<td>99.8</td>
<td>100.0</td>
</tr>
</tbody>
</table>
Additional hints for the existence of unobservable “global factors”

Preliminary analysis (3)
Moving to N-country framework…

How to estimate the global (unobservable) factors?

**Global model construction and assumptions (1)**

- \[ y_{it}(\tau) = l_{it} + s_{it} \left( \frac{1-e^{-\lambda_{it}\tau}}{\lambda_{it}\tau} \right) + c_{it} \left( \frac{1-e^{-\lambda_{it}\tau}}{\lambda_{it}\tau} - e^{-\lambda_{it}\tau} \right) + v_{it}(\tau) \]

- 6 countries included in the analysis: RO, HU, PL, GE, JP, US

Define a **global yield curve** - Diebold&Li (2008):

\[ Y_{gt}(\tau) = l_{gt} + s_{gt} \left( \frac{1-e^{-\lambda_{t}\tau}}{\lambda_{t}\tau} \right) + c_{gt} \left( \frac{1-e^{-\lambda_{t}\tau}}{\lambda_{t}\tau} - e^{-\lambda_{t}\tau} \right) + v_{gt}(\tau) \]

\[
\begin{pmatrix}
  l_{gt} \\
  s_{gt} \\
  c_{gt}
\end{pmatrix} =
\begin{pmatrix}
  \Phi_{11} & \Phi_{12} & \Phi_{13} \\
  \Phi_{21} & \Phi_{22} & \Phi_{23} \\
  \Phi_{31} & \Phi_{32} & \Phi_{33}
\end{pmatrix}
\begin{pmatrix}
  l_{gt-1} \\
  s_{gt-1} \\
  c_{gt-1}
\end{pmatrix} +
\begin{pmatrix}
  U_{gt}^l \\
  U_{gt}^s \\
  U_{gt}^c
\end{pmatrix}
\]

\[ H1 \]

\[ U_{gt}^F \text{ errors} \begin{cases} 
  EU_{gt}^F U_{gt}^{F'} = (\sigma_g)^2 \text{ if } t = t' \text{ and } F = F' \\
  0, \text{ otherwise}
\end{cases} \]

\[ H2 \]
Global model construction and assumptions (2)

- \( l_{it} = \alpha^l_i + \beta^l_i l_{gt} + \varepsilon^l_{it} \)
- \( s_{it} = \alpha^s_i + \beta^s_i s_{gt} + \varepsilon^s_{it} \)
- \( c_{it} = \alpha^c_i + \beta^c_i c_{gt} + \varepsilon^c_{it} \)

Assume \( \sigma^F_g = 1 \) as the magnitude of global factors and factors loadings are not separately identified.

Where \( \varepsilon^F_{it} \) are local factors and follow:

\[
\begin{pmatrix}
\varepsilon^l_{it} \\
\varepsilon^s_{it} \\
\varepsilon^c_{it}
\end{pmatrix} =
\begin{pmatrix}
\psi_{11} & \psi_{12} & \psi_{13} \\
\psi_{21} & \psi_{22} & \psi_{23} \\
\psi_{31} & \psi_{32} & \psi_{33}
\end{pmatrix}
\begin{pmatrix}
\varepsilon^l_{it-1} \\
\varepsilon^s_{it-1} \\
\varepsilon^c_{it-1}
\end{pmatrix} +
\begin{pmatrix}
\psi_{11} & \psi_{12} & \psi_{13} \\
\psi_{21} & \psi_{22} & \psi_{23} \\
\psi_{31} & \psi_{32} & \psi_{33}
\end{pmatrix}
\begin{pmatrix}
\varepsilon^l_{it-1} \\
\varepsilon^s_{it-1} \\
\varepsilon^c_{it-1}
\end{pmatrix} +
\begin{pmatrix}
\varepsilon^l_{it-1} \\
\varepsilon^s_{it-1} \\
\varepsilon^c_{it-1}
\end{pmatrix}
\]

\( u^F_{it} \) errors

\[
Eu^F_{it}u^F_{it'} = \left( \sigma^F_i \right)^2 \text{ if } i = i', t = t' \text{ si } F = F' , F = l, s, c
\]

\[ 0 \text{, otherwise} \]
Global model construction and assumptions (3)

In the current global framework, yield curve might be described as follows:

\[
\begin{bmatrix}
  y_{1t}(\tau_1) \\
  y_{1t}(\tau_2) \\
  \vdots \\
  y_{Nt}(\tau_{J-1}) \\
  y_{Nt}(\tau_J)
\end{bmatrix}
= A
\begin{bmatrix}
  \alpha^l_i \\
  \alpha^s_i \\
  \vdots \\
  \alpha^s_N \\
  \alpha^c_N
\end{bmatrix}
+ B
\begin{bmatrix}
  l_{gt} \\
  s_{gt} \\
  \vdots \\
  c_{gt}
\end{bmatrix}
+ A
\begin{bmatrix}
  v_{1t}(\tau_1) \\
  v_{1t}(\tau_2) \\
  \vdots \\
  v_{Nt}(\tau_{J-1}) \\
  v_{Nt}(\tau_J)
\end{bmatrix}
+ A
\begin{bmatrix}
  \varepsilon^l_{1,t} \\
  \varepsilon^s_{1,t} \\
  \vdots \\
  \varepsilon^s_{N,t} \\
  \varepsilon^c_{N,t}
\end{bmatrix}
\]

- \( A = \begin{pmatrix}
  1 & \frac{1-e^{-\tau_1\lambda}}{\tau_1\lambda} & 0 & \ldots & 0 & 0 \\
  1 & \frac{1-e^{-\tau_2\lambda}}{\tau_2\lambda} & 0 & \ldots & 0 & 0 \\
  \vdots & \vdots & \ddots & \ddots & \vdots & \vdots \\
  0 & 0 & \ldots & 1 & \frac{1-e^{-\tau_{J-1}\lambda}}{\tau_{J-1}\lambda} \\
  0 & 0 & \ldots & 1 & \frac{1-e^{-\tau_J\lambda}}{\tau_J\lambda}
\end{pmatrix} \)

- \( B = \begin{pmatrix}
  \beta^l_1 & \beta^s_1(\frac{1-e^{-\tau_1\lambda}}{\tau_1\lambda}) & \beta^c_1(\frac{1-e^{-\tau_1\lambda}}{\tau_1\lambda} - e^{-\tau_1\lambda}) \\
  \beta^l_1 & \beta^s_1(\frac{1-e^{-\tau_2\lambda}}{\tau_2\lambda}) & \beta^c_1(\frac{1-e^{-\tau_2\lambda}}{\tau_2\lambda} - e^{-\tau_2\lambda}) \\
  \vdots & \vdots & \vdots \\
  \beta^l_N & \beta^s_N(\frac{1-e^{-\tau_J\lambda}}{\tau_J\lambda}) & \beta^c_N(\frac{1-e^{-\tau_J\lambda}}{\tau_J\lambda} - e^{-\tau_J\lambda})
\end{pmatrix} \)

\( N \) is the number of countries, \( J \) is the number of tenors.
Global model estimation (1)

Multi step approach, more convenient

(1) Estimate the model for each country

\[ y_{it}(\tau) = l_{it} + s_{it} \left( \frac{1-e^{-\lambda_it\tau}}{\lambda_it\tau} \right) + c_{it} \left( \frac{1-e^{-\lambda_it\tau}}{\lambda_it\tau} - e^{-\lambda_it\tau} \right) + v_{it}(\tau) \]

and obtain series of level, slope and curvature factors

(2) Estimate a dynamic factor model composed of:

\[
\begin{pmatrix}
    l_{gt} \\
    s_{gt} \\
    c_{gt}
\end{pmatrix} =
\begin{pmatrix}
    \Phi_{11} & 0 & 0 \\
    0 & \Phi_{22} & 0 \\
    0 & 0 & \Phi_{33}
\end{pmatrix}
\begin{pmatrix}
    l_{gt-1} \\
    s_{gt-1} \\
    c_{gt-1}
\end{pmatrix} +
\begin{pmatrix}
    U^l_{gt} \\
    U^s_{gt} \\
    U^c_{gt}
\end{pmatrix} \tag{1}
\]

- \( l_{it} = \alpha^l_i + \beta^l_i l_{gt} + \epsilon^l_{it} \)
- \( s_{it} = \alpha^s_i + \beta^s_i s_{gt} + \epsilon^s_{it} \)
- \( c_{it} = \alpha^c_i + \beta^c_i c_{gt} + \epsilon^c_{it} \)

\[
\begin{pmatrix}
    \epsilon^l_{it-1} \\
    \epsilon^s_{it-1} \\
    \epsilon^c_{it-1}
\end{pmatrix} =
\begin{pmatrix}
    \psi_{1,i} & 0 & 0 \\
    0 & \psi_{2,i} & 0 \\
    0 & 0 & \psi_{3,i}
\end{pmatrix}
\begin{pmatrix}
    \epsilon^l_{it} \\
    \epsilon^s_{it} \\
    \epsilon^c_{it}
\end{pmatrix} +
\begin{pmatrix}
    U^l_{it} \\
    U^s_{it} \\
    U^c_{it}
\end{pmatrix} \tag{2}
\]

-as there is little cross-factor dynamic interaction, we assume the matrices of coefficients in (1) and (2) are diagonal
Global model estimation (2)

We can estimate the model factor by factor

- For each of the three state-space models there would be 25 parameters to estimate.
- Maximum likelihood is difficult to implement in multi-country framework because of the large number of parameters to be estimated; the Bayesian approach using Markov Chain Monte Carlo methods is more suitable.
- If $\Phi = (\alpha_i, \beta_i, \psi_{1,i}, \sigma_i, \Phi_{11})$, $F =$ global factors (latent) and $Z$ are estimated levels at previous step we want to simulate from a posteriori distribution $P(\Phi, F | Z)$.
- Using Gibbs algorithm this would be equivalent with simulating from conditional distributions: $P(\Phi | F, Z)$ and $P(F | \Phi, Z)$.
Global Level - estimation summary

j=1; repeat {

- **Step 1:** simulate from $P(\Phi | F, Z)$
  - $l_{it} = \alpha_i^l + \beta_i^l l_{gt} + \varepsilon_{it}^l$
  - $\varepsilon_{it}^l = \psi_{1,i} \varepsilon_{it-1}^l + u_{it}^l$
  - $l_{gt} = \Phi_{11} l_{gt-1} + U_{gt}^l$

- **Step 2:** simulate from $P(F | \Phi, Z)$
  - $l_{it} = \alpha_i^l + \beta_i^l l_{gt} + \varepsilon_{it}^l$
  - $\varepsilon_{it}^l = \psi_{1,i} \varepsilon_{it-1}^l + u_{it}^l$
  - $l_{gt} = \Phi_{11} l_{gt-1} + U_{gt}^l$

Regression with AR(1) errors

Model in “state-space” form

Observation equation:

$$
\begin{bmatrix}
  l_{1t}^* \\
  \vdots \\
  l_{6t}^*
\end{bmatrix} = \begin{bmatrix}
  \alpha_1 (1 - \varphi_{1,11}) \\
  \vdots \\
  \alpha_6 (1 - \varphi_{6,11})
\end{bmatrix} + \begin{bmatrix}
  \beta_1 \\
  \vdots \\
  \beta_6
\end{bmatrix} \begin{bmatrix}
  \varphi_{1,11} \\
  \vdots \\
  \varphi_{6,11}
\end{bmatrix} \begin{bmatrix}
  L_t \\
  L_{t-1}
\end{bmatrix} + \begin{bmatrix}
  u_{1t} \\
  \vdots \\
  u_{6t}
\end{bmatrix}
$$

Transition equation:

$$
\begin{bmatrix}
  L_t \\
  L_{t-1}
\end{bmatrix} = \begin{bmatrix}
  \theta_{11} & 0 \\
  1 & 0
\end{bmatrix} \begin{bmatrix}
  L_{t-1} \\
  L_{t-2}
\end{bmatrix} + \begin{bmatrix}
  U_t \\
  0
\end{bmatrix}
$$

if $j \leq 200000$ then discard simulation; $j++$ until $j=1000000$;
Global model - Results of estimation (1)

- Even if there are hints that two latent factors could explain the evolution of level factors (for example), in the case of the countries analyzed in this paper the second factor proved to be statistically insignificant re-estimate the model to include only a global factor

“global ” LEVEL
Global model - Results of estimation (2)

- “global” SLOPE

- “global” CURVATURE
Global model - Results of estimation (3)

Weight of global factors -> Variance decomposition

- As global and local factors estimated by Kalman filter prove to be quite correlated ($\rho=0,35$), we will orthogonalise them by regressing the local country factors on the extracted global factors.

\[ var(l_{it}) = (\beta_i^l)^2 var(l_{gt}) + var(\varepsilon_{it}^l) \]

- Also fitting the yield curve using the estimated factors highlight the fact that “global yield” explains a lower proportion (60%) for very short maturities => this segment is correlated with money market conditions.
(IV.2) What drives the global factors?

(a) Global Level

Strongly correlated ($\rho$) with EA inflation rate

(monthly data, yoy)
What drives the global factors?

(b) Global Slope

- correlated with real sector activity

Aggregating global slope data to quarterly frequency

High correlation with real GDP growth (yoy) in Eurozone

\( \rho = 0.7 \), \( \rho = 0.85 \), \( \rho = 0.4 \)
What drives the global factors?

(c) Global Curvature

- No macroeconomic factors found to have a significant linear correlation with global curvature dynamics.

- The question that arises is if there could be a nonlinear connection between macroeconomic indicators and the global curvature?

  neural networks might answer to this question.

- However, due to a limited set of data, the over-fitting /overlearning problem has a very high likelihood.
What drives the global factors?

(c) Global Curvature
Modeling with Neural networks (1)

- VIX index, NASDAQ index, S&P index, PMI Eurozone taken as inputs for global curvature

- Network architecture: a hidden layers of 10 units, including 2 delays
What drives the global factors?
(c) Global Curvature Modeling with Neural networks (2)

!!! Over-fitting problem is conspicuous
What drives the local factors in RO?

(a) Local Level (1)

- Correlated with core inflation, yoy ($\rho=0.65$)

- Correlation with headline inflation rate (yoy) much weaker (0.35)
What drives the local factors in RO?

(a) Local Level (2)

- Also correlated with RO CDS (5 years, USD) and ROBOR 6M-key rate

\[ \rho = 0.6 \]

\[ \rho = 0.5 \]
What drives the local factors in RO?

(b) Local Slope

- Correlation with retail sales ($\rho=0.4$), proxy for private consumption
What drives the local factors in RO?

(c) Local Curvature

- No significant linear correlation with macroeconomic indicators
- Most likely, there are not macro fundamentals to explain the dynamics of (local) curvature
- Local curvature might be linked with:
  - impossible to exactly quantify factors
  - (e.g. investors’ sentiment / risk aversion)
Conclusion & further research (1)

- **Global factors exist** and explain more than 90% of yields variation (< impact for <=1Y tenors)
- Regional factor -> **not** significant at monthly frequency
- **Level** <-> inflation, **slope** <-> real sector
- **Curvature** -> no linkage with macro factors
- Obtained results are very useful for banks (that hold T-bonds portfolios) when conducting **stress-test scenarios**
Conclusion & further research (2)

- Having in mind the macro-fundamentals that drive the Romanian yield curve, next step would be to develop a daily frequency model which would be useful for T-bond traders.

- Another interesting subject would be to assess to what extent the divergent monetary policies of US Fed (when starting to hike interest rate, most likely in Q4 2015) and ECB (will continue with QE until 2016) will affect Romanian T-bond yields dynamics.
Bibliography (selection)


Thank you for your attention!