ACADEMY OF ECONOMIC STUDIES DOCTORAL SCHOOL OF FINANCE AND BANKING - DOFIN

DISSERTATION PAPER

ON THE ROMANIAN YIELD CURVE: THE EXPECTATIONS HYPOTHESIS AND CONNECTIONS TO THE REAL ECONOMY

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Abstract

This paper discusses the construction of the yield curve in Romania using the prices on the primary and secondary bond markets, and studies its relationship with other macroeconomic variables. Although the data are scarce and volatile, especially those on the secondary market, several conclusions can be drawn: (a) Up to 1 year, BUBOR is a good approximation of T-bill yields, suggesting that BUBOR is followed closely when bidding for T-bills; (b) On the primary market yields are higher than on the secondary market, which indicates a winner's curse in the bidding phase; (c) The expectation hypothesis does not hold; the market still anticipates the direction, but not the degree of change in the interest rates; (d) A large part of yield curve movements is due to factors that affect all maturities equally (level factors); (e) The Taylor rule is verified in its backwards-looking form, but not in the original, no-lag, form (f) The connections between the yields and the real economy are difficult to assess because of the scarcity and volatility of data; however, from the two models used, the one that incorporates the price of a commodity (oil) is better for predicting short term yields, and the one without the commodity price is better for predicting medium-term yields.

Introduction

The existence of the yield curve in an economy is important for several reasons, both at the macroeconomic level and at the level of private financial entities. It represents a benchmark in the economy, which is also important for private issuing of bonds (at present they are tied to BUBOR and BUBID); insurance companies and the newly launched pension funds have restrictions for investment and need to find fixed-income securities; banks and other financial institutions use the yield curve to match the duration of their assets and liabilities; at macroeconomic level, the yield curve has a predictive power for the state of economy (for example, in the US an inverted yield curve anticipates a recession after two years). In Romania, a yield curve is difficult to construct because the issuing on the primary market is very irregular (for example, there was no new bond issuing in 2005 and 2006), and the secondary market is very volatile. However, with the available data I try to draw some conclusions on the shape of the yield curve and its relations to the real economy. The computations and the models will have to be adjusted once higher quality data become available.

The paper uses the available data (1999-present) on the primary and secondary market for yields and tries to sketch a yield curve for short, medium and long maturities. First, I explore within a panel data the differences between BUBOR and yields with maturities up to 1 year, and I find that they move together, with BUBOR usually higher. Then, I look at the differences in yields on the primary and secondary market. Auction theory states that the yields should be higher on the primary market. The evidence is slightly in favor, as there are very few data points.

Further, I test the expectations hypothesis on the Romanian market by regressing computed forward rates on the realized yields. The expectation hypothesis claims that current forward rates (which are constructed based on the current yield curve) equal on average the future spot interest rates. Besides finding out if the market correctly anticipates future spot rates, this would allow filling in missing data in the yields table (with the computed forward rate). The expectations of the market differ from the realization of the yields, so I do not add any more data to the table.

In order to analyze the yield curve, I use a cubic spline interpolation to generate a continuous line which passes through the realized yields. To display the method, I choose three examples where more maturities are available.

After discussing the shape of the yield curve at a given moment in time, I analyze the movements in the yield curve. I run a principal component analysis to identify the risk factors

that drive these movements. Consistent with the fixed income literature, I identify that the main risk factors are: level, slope and curvature. The largest risk factor is the level factor (representing parallel shifts in the yield curve), which explains 68.22% of the yield curve movements. In order to assess the connections with the real economy, I use (a) inflation, described either by the consumer price index (CPI) or by a principal component of: CPI, producer price index (PPI) and the price of a commodity; and (b) real activity (industrial production - IP). First, I test the Taylor rule, original and backwards looking, using 3-month yields as rate, CPI as measure for inflation and IP as measure for real activity (output). I find that the original Taylor rule (no lags) does not perform well (adjusted R² is 4.72%), but the backwards looking Taylor rule is a good model (adjusted R^2 is 67.41%). Second, I estimate two VARs, to see how the short term yields and the medium term yields respond to changes in the measure of inflation and the measure of real activity. Although the models do not perform well because of the scarcity and volatility of data, the one that incorporates the price of commodity (oil) is better for predicting short term yields, and the one without the price of commodity is better for predicting medium-term yields. This may indicate that people care more about the price of oil and inflation on the short term than on the medium term. For longer maturities, I do not have enough data to draw a conclusion.

Literature Review

There exists a large literature of yield curves, the expectation hypothesis and the relation to the real economy.

Regarding the expectation hypothesis, Fama and Bliss (1987) find that for the US there is little evidence that forward rates can forecast near-term changes in interest rates, but once the horizon extended the forecast power improves.

Regarding the yield curve, Evans and Marshall (1998) present a model to evaluate the impact of real economy on the different maturities of the yield curve. For each separate observation they make a quadratic approximation by regressing yields on a constant, maturity and maturity squared. The coefficients (which are time-varying because of regressing of each observation) represent the level, slope and curvature factors. To see how the shape of the yield curve changes in response to a shock, they estimate VARs in which the yield is replaced by one of these coefficients. If, for example, the curvature - which is usually negative - has a positive response, it means the yield curve flattens.

For the connections of the yield curve to the real economy, Ang and Piazzesi (2003) present a model where they estimate a VAR to which they impose a no-arbitrage condition. They estimate the impact of different types of factors to the yield curve - macroeconomic factors and latent factors. They find that the macroeconomic factors account for 85% of the modifications in the yield curve, for the US.

A short list of the literature in the field also includes: Litterman and Scheinkman (1991), Longstaff and Schwartz (1992), Chen and Scott (1993), Duffie and Kan (1996), Dai and Singleton (2000), etc.

The relationship between LIBOR and UK Yield Curve

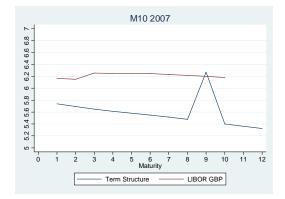
In order to gain insight into the relationship between the inter-bank interest rates and government bond yields, I perform some tests in a foreign market, where longer time series are available. For this, I choose the GBP LIBOR and the UK Yield Curve. There are several tests I was interested in:

1. First, I wanted to see what the relation is between GBP LIBOR¹ and the UK T-bills yield curve. I made a panel regression and looked for α and β . To see if they are constant over the years, I repeated the regression for each particular year in the period 1997-2006. Then I looked for cointegration and Granger-causality relationships between monthly yields for 3-month GBP LIBOR and UK T-bills.

2. Second, I wanted to check how the introduction of the credit spread (the difference in yield between corporate bonds and treasury bonds) further explains LIBOR.

1. I plotted the GBP LIBOR and term structure for UK T-bills. The panel variable (Maturity) covers the 1-12m maturities, without 9m - for this maturity, the results were completely different from both 8m and 10m so I left it out. This means analyzing the short end (1m-3m) and the medium part (3m-12m) of the curve. The graph is done for the M10 2007 moment. The plot seems to indicate that there is no apparent "moving together" of the two series.

Fig. 1 - The UK T-bills term structure and GBP LIBOR in October 2007



¹ LIBOR is owned by the British Bankers' Association and calculated by Reuters. The contributors, which are known as opposed to other indexes, are 16 banks which operate in London and trade reasonable amounts in GBP. The index is fixed each day at 11:00 a.m. (UK time). The value is an arithmetic average, after trimming out the extreme values.

However, I go on to do a panel data regression to see if there is a relation between the two series over the entire period analyzed (M1 1997-M10 2007). I performed the tests in STATA. I performed a panel data regression, where I analyzed the dependence between LIBOR and UK T-bills. I did a regression with fixed effects and a regression with random effects². Then I performed a Hausman Test to choose the better model.

Fixed-effects (within) re Group variable: Maturity	gression		ofobs groups =	= 1257 10
R-sq: within = 0.9917 between = 0.7043 overall = 0.9891		Obs per g	roup: min = avg = max =	98 125. 7 130
corr(u_i, Xb) = 0.0150		F(1 , 1246) Prob > F	= 1 =	48689. 10 0. 0000
LIBOR Coef.	Std. Err. t	P> t	[95% Conf.	Interval]
Yi el ds 1. 087196 _cons 1007898	. 0028195 385. 60 . 0146163 -6. 90	0. 000 0. 000		1. 092728 0721145
sigma_u . 06444394 sigma_e . 10610913 rho . 26946381	(fraction of vari	ance due to	u_i)	
F test that all u_i=0:	F Q , 1246) = 44 .	11	Prob > F	= 0.0000

Table 1 - LIBOR-Term Structure regression w/ fixed effects

² In the model $y_{it} = x_{it}\beta + c_i + u_{it}$, t = 1, 2, ..., T, if i indexes individuals, c_i is called *individual effect*, or *individual heterogeneity*. The u_{it} are called the *idiosyncratic errors* or *idiosyncratic disturbances* because these change across t as well as across i. In a random effects model, we assume strict exogeneity ($E(u_{it}|x_i, c_i) = 0, t = 1, ..., T$) in addition to orthogonality between c_i and x_{it} ($E(c_i|x_i) = E(c_i) = 0$). In a fixed effects model, we maintain strict exogeneity of x_{it} but we allow for c_i and x_i to be correlated. The random effects estimator is assumed to be more efficient than the fixed effects one (but it may not be consistent). In order to choose between the models, the Hausman test is used. In a linear model y = bX + e, we have two estimators: b_0 and b_1 . Under the null hypothesis, both the estimators are consistent, but b_1 is more efficient. Under the alternative hypothesis, one or both of the estimators is inconsistent. The statistic is: $H = T(b_0 - b_1)'Var(b_0 - b_1)^{-1}(b_0 - b_1)$, where T is the number of observations. This statistic has a chi-square distribution with k (length of b) degrees of freedom.

Table 2 - LIBOR-Term	Structure regression	w/ random effects

Random-effect Group variabl		si on			r of obs of groups	
. betwee	= 0. 9917 n = 0. 7043 l = 0. 9891			Obs per	group: min avg max	= 125.7
Random effect corr(u_i, X)				Wald ch Prob >		= 148099.08 = 0.0000
L I BOR	Coef.	Std. Err.	Z	P> z	[95% Co	onf. Interval]
Yi el ds _cons	1. 08723 0988186	. 0028252 . 0217056	384.84 -4.55		1. 081693 1413609	
sigma_u sigma_e rho	. 05053555 . 10610913 . 18488701	(fraction	of varia	ance due	to u_i)	

Table 3 - Hausman Test

	Coeffic (b)	cients—— (B) re	(b-B) Difference	sqrt(diag(V_b-V S.E.	_B))
Yi el ds	1. 087196	1.08723	000034	. 0000138	
	= inconsistent	: under Ha, ef	t under Ho and Ha; fficient under Ho; ts not systematic		
Test. no		(b-B)'[(V_b-V_ 6.08	_B)^(-1)](b-B)		

The null hypothesis tested is that the coefficients of the more efficient model (RE) are not systematically different from the coefficients of the consistent model $(FE)^3$. The first time I ran the test, the value was negative, which is puzzling! However, this can happen in finite samples, unless the same estimate of the error variance is used throughout the H statistic. To avoid this, one can use the *sigmamore* or the *sigmaless* commands (base both (co)variance matrices on disturbance estimate from efficient/consistent estimator).

³ An unbiased estimator A is more **efficient** than an unbiased estimator B if the sampling variance of A is less than that of B. An estimator A of a parameter a is a **consistent** estimator if and only if plim A = a.

The computed W (=6.08) exceeds the critical value in the table for a 0.05 probability level (=3.84). Therefore, the null hypothesis is rejected and the **fixed effects model** is used.

The fixed effects model has significant coefficients for the constant (individual effects) and the UK T-bills term structure. The implied equation is:

LIBOR = -0.101% + 1.087 x Term_Struct

The R-squared is 0.99, which means that the regressors explain 99% of LIBOR! One can notice that β is very close to 1, so basically LIBOR differs by a constant from the UK T-bills yields. If I run the same, fixed effects, regression for each year separately, I obtain the following α 's and β 's. β is significant and approximately constant (equal to 1) over the studied years.

Year	β	α (%)	\mathbf{R}^2
1997	1.099	-0.224	0.98
	(74.71)	(-2.29)	
1998	0.952	0.840	0.97
	(76.02)	(9.71)	
1999	1.068	0.130	0.95
	(45.48)	(1.07)	
2000	0.898	0.997	0.97
	(66.43)	(12.52)	
2001	1.054	0.199	0.97
	(179.90)	(0.71)	
2002	0.924	0.538	0.98
	(75.2)	(11.16)	
2003	1.032	0.958	0.99
	(103.39)	(2.69)	
2004	1.0469	0.691	0.99
	(114.28)	(1.69)	
2005	1.174	-0.559	0.89
	(28.96)	(-3.04)	
2006	1.051	0.022	0.97
	(54.84)	(0.25)	
1997-2007	1.087	-0.101	0.99
	(385.60)	(-6.9)	

Table 4 - α 's and β 's for individual years (t-stats in brackets); α 's in percents

The purpose of the following tests is to show that LIBOR and UK T-bills are cointegrated. The spread between LIBOR and UK T-bills affects long-term financing costs for a growing number of financial instruments, so it is important to determine the dynamics of the relation between the two series - for example, derivative contracts based on floating rates use either LIBOR or UK Tbills rates as benchmark. I wanted to determine whether historic spreads between LIBOR and UK T-bills yields are a good estimate for future spreads between the two floating rates. Furthermore, cointegration of the two series would suggest a long-run equilibrium spread, with only temporary deviations.

I find unit roots for both 3-month LIBOR and UK T-bills yields. However, first differences are stationary. A stationary variable has a tendency for mean-reversion after one-time shocks, but non-stationary variables have permanent adjustments. 3-month LIBOR and UK T-bills yields could both have unit roots and still have a long-run equilibrium spread relationship (cointegration) if the disturbances which cause non-stationarity in one yield also cause nonstationarity in the other yield.

Dickey-Full	er test for unit	root	Number of ob	s = 127
		Inter	polated Dickey-Ful	l er
	Test	1% Critical	5% Critical	
	Statistic	Val ue	Value	Value
Z(t)	-0. 882	-3. 501	-2.888	-2. 578

Table 5 Unit reat test for 3 month UK T bills yields

MacKinnon approximate p-value for Z(t) **€0.7939**

Table 6 - Unit root tests for 3-month LIBOR

Dickey-Fulle	r test for unit	root	Number of obs	6 = 129
		I nte	rpolated Dickey-Ful	l er
	Test	1% Critical	5% Critical	10% Critical
	Statistic	Val ue	Value	Value
Z(t)	-0. 861	-3.500	-2.888	-2. 578

The series are both I(1) so I run a cointegration test. The Johansen test for cointegration indicates that there exists one cointegrating relationship (the hypothesis of one or less cointegrating vectors is not rejected, but the hypothesis of no cointegrating vectors is rejected, both at 5% level). This is an important finding since long-run equilibrium spread between LIBOR and UK T-bills is stationary if the two series are cointegrated.

Table 7 - Johansen cointegration for 3-month LIBOR and UK T-bills

Trend: co Sample:	onstant 1997m5 -	2007m10			Number	of obs = Lags =	126 2
maximum rank 0 1 2	parms 6 9 10	LL 253. 02353 263. 38995 264. 66485	ei genval ue 0. 15172 0. 02003	trace statistic 23.2826 2.5498 <u>*</u>	5% critical value 15.41 3.76		

Granger causality tests reveal the extent to which LIBOR market leads the UK T-bills market (uni-directional), is led by the UK T-bills market (reverse-directional), or if the LIBOR market both leads the UK T-bills market and is led by the UK T-bills market (bi-directional). According to Granger (1969, 1986) a variable X_t Granger-causes another variable Y_t if, given information of both X_t and Y_t , the variable Y_t can be better predicted in the mean square error sense by using only past values of X_t than by not doing so.

According to the information criteria, 2 lags are used for the variables in order to compute Granger causality.

ag	LL	LR	df	р	FPE	AIC	HQI C	SBIC
0	-65. 4268				. 010963	1. 16253	1. 1818	1. 21001
1	205. 128	541.11	4	0.000	. 000111	-3. 43324	-3. 37542	-3. 29081
2	243. 744	77. 232*	4	0.000	. 000061*	-4.03007*	-3. 9337*	-3. 79269*
3	245.016	2. 5443	4	0. 637	. 000064	-3. 98303	-3.84813	-3. 6507
4	248.63	7. 2278	4	0. 124	. 000064	-3. 97638	-3.80293	-3. 5491
5	250. 956	4. 6514	4	0. 325	. 000066	-3. 94751	-3. 73551	-3. 42528
6	253. 439	4. 9668	4	0. 291	. 000068	-3. 92136	-3. 67082	-3. 30418
7	255.872	4. 8661	4	0. 301	. 00007	-3.89435	-3. 60526	-3. 18221
8	256. 921	2.0975	4	0. 718	. 000074	-3.84346	-3. 51583	-3.03638
9	257.872	1. 9016	4	0. 754	. 000078	-3.79089	-3. 42471	-2.88885
10	261. 398	7.0537	4	0. 133	. 000079	-3. 78273	-3. 37801	-2. 78574
11	265.489	8. 1804	4	0. 085	. 000079	-3. 78429	-3. 34102	-2. 69235
12	265. 821	. 66534	4	0. 956	. 000084	-3. 72106	-3. 23925	-2. 53417

 Table 8 - Lags selection according to the information criteria

Table 9 - Granger causality UK T-bills and LIBOR

Equation	Excl uded	chi 2	df	Prob > chi 2
Yields	LI BOR	4. 5299	2	0. 104
Yields	ALL	4. 5299	2	0. 104
LI BOR	Yields	47. 111	2	0.000
LI BOR	ALL	47. 111	2	0.000

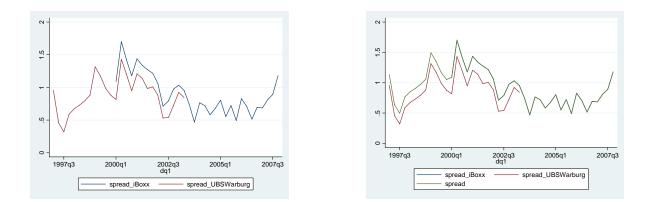
The p-value in the first row (0.104) indicates that one can not reject the null hypothesis that LIBOR does not Granger causes the UK T-bills yields. The p-value on the third row (0.000) indicates that one can reject the null hypothesis that UK T-bills yields do not Granger cause LIBOR. One can say that UK T-bills yields Granger cause LIBOR (reverse directional causality).

2. I further introduced in the regression the credit spread. The intuition was that its coefficient will be positive and significant. This means that when the credit spread is high, LIBOR is also high - corporate yields much higher than UK T-bills yields, indicating a period of difficult credit⁴; banks "prefer cash" and do not lend money easily to other banks, which pushes up LIBOR.

⁴ The credit spread tends to widen in a recession and to shrink in an expansion.

I obtained only quarterly data from Watson Wyatt. There are two indexes, iBoxx AA and UBS Warburg AA for AA UK corporate bonds. I computed the differences over the 10y UK UK Tbills and I plotted the series. Then I lifted up the UBS Warburg series and created one series for the studied period, see Fig 2.

Fig. 2 - iBoxx AA and UBS Warburg AA UK corporate bonds indexes



I run the regression of 3m LIBOR over 3m UK T-bills and the credit spread. As suspected, the coefficient on spread is positive and significant.

Table 10 - Regression	of LIBOR on UK T-bills	vields and credit spread

Source	SS	df	MS		Number of c F(2, 41	bs = 44) = 3772.87
Model Resi dual	57. 2925404 . 311300522		462702 592696		Prob > F R-squared Adj R-square	= 0.0000 = 0.9946
Total	57.6038409	43 1.33	962421		Root MSE	= .08714
LI BOR	Coef.	Std. Err.	t	P> t	[95% Cor	nf. Interval]
Yi el ds spread _cons	1.075022 .1407114 2198442	. 0126233 . 0447196 . 0718071	85. 16 3. 15 -3. 06	0.000 0.003 0.004	1. 049528 . 0503983 3648615	1. 100515 . 2310244 074827

Romanian Treasury Bills - Primary and Secondary Market

Since 2005, the primary market for the Romanian Treasury Securities is organized by the National Bank of Romania (Regulation 11, September 29, 2005). The NBR sells the T-bills (up to two years maturity) and T-notes (more than two years and less than ten years maturity) by means of auction or public subscription. In 2007, T-bills and T-notes issued in the first quarter represented about 9% of the total outstanding debt of the government of Romania, according to the Ministry of Economy and Finance. The participants on the market are financial institutions which are authorized as primary dealers. The Ministry of Economy and Finance issues T-bills (with 6 and 12 months maturity) and T-notes, also called benchmark bonds, with 3, 5 and 10 years maturity. The auction is sealed-bid and it starts at 1 p.m. The bidders submit sealed bids to buy a specific quantity at a specific yield. The methods to determine the price are: multiple price and uniform price. Multiple price means that all bids with yields below the cut-off rate are completely awarded at the yield submitted by the participant. In this case, the NBR acts as a price discriminating monopolist⁵. Uniform price means awarding all the bids at the highest yield that was accepted. There are three different yields which characterize an auction in general: the low yields is the lowest yield bid in the auction, the topout yield or cut-off yield is the highest yield which is accepted in the auction, the average yield is the volume-weighted average yield of the accepted bids. Apart from the competitive round there is also a non-competitive round in which the bidder specifies the quantity but not the yield. These are awarded at the volume weighted average yield in the competitive round (in the case of multiple price) or at the final yield in the competitive round (in the case of uniform price).

The settlement is done through the SaFIR system and is usually done within two business days after the auction (the legal term for spot transactions).

The secondary market is organized also at the NBR, but starting from June 2008 the T-bills and T-notes will be also traded at the Bucharest Stock Exchange, in an attempt to increase their liquidity. This was also a measure taken for the pension funds which can start investing money from May 2008, in order to provide them with this investment opportunity.

⁵ see Varian (2005): in terms of allocation, the price discriminating solution produces the same results as the market solution, that is the *same* people get the goods. However, the price they pay is different in the two situations, the price discriminating monopolist receives all consumer surplus.

The market participants are the financial and non-financial sectors in Romania. Starting with 2006 foreigners also have access to the secondary market (a step connected to the liberalization of the capital account).

I have secondary market data for the period 2006-2008. In 2006 there was no new issuing of Tbills or T-notes, so the only available data is from the secondary market. In 2007, however, I have data both from the primary and secondary market. I was interested to study the differences in yields between the two markets. Auction theory states that yields on the primary market are higher (and prices lower) than on the secondary market. That is T-bills and T-notes are cheaper at the auction than on the market. The explanation auction theory gives is that bidders will bid a lower price than their true valuation for the bills and notes when submitting bids for the auction. When a bidder is awarded a bill, for example, on the primary market he realizes that his opponents who are not awarded any paper demanded a higher yield for the bills in the auction and thus the winning bidder might not be able to resell his bill on the secondary market. In order to evade this phenomenon which is called *the winner's curse*, bidders will tend to increase their yield bid above their true valuation.

In order to compute the yields on the secondary market I made some maturity approximations. I computed the difference between the trading day and the maturity, in months. Then I considered the bill or note to be of 3m, 6m, 12m, etc. if the time to maturity was in the 2m-4m, 5.5-6.5m, 11m-13m, etc. intervals.

Months	2-4m	5.5-6.5m	11-13m	23-25m	34-38m	57-63m	81-87m	117-123m
to								
maturity								
Approx.	3	6	12	24	36	60	84	120
maturity								

 Table 11 - Maturity approximations (for 2007, secondary-market data)

Indeed, I observed that yields on the primary market are in most cases greater than yields on the secondary market.

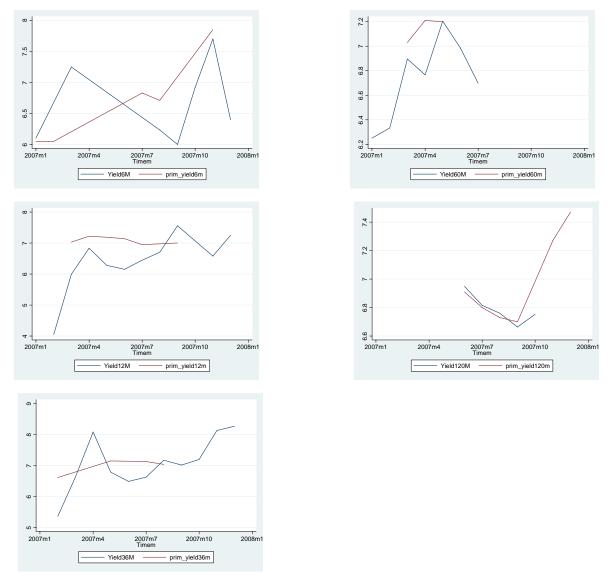


Fig. 3 - Yields on the primary and secondary market, on different maturities. Monthly data in 2007. Red line -yields on the primary market. Blue line - yields on the secondary market.

In order to make use of all the data available when creating the yields series, I use primary market yields when there are no secondary market yields, secondary market yields when there are no primary market yields (for example in 2006) and a weighted average of yields when both primary and secondary yields are available. To find the weights I compute the volatility of the series. As easily seen from the above graphs, the volatility for the secondary market is higher than for the primary market (0.5805 as compared to 0.2995). Then I take the yields proportional to $1/\sigma^2$, that is 80% primary market yields and 20% secondary market yields.

BUBOR and the Romanian Yield Curve

As with LIBOR and UK Bonds yields, I tried to see what the connections are between BUBOR⁶ and Romanian T-bills. I constructed a panel with the panel variable Maturity (3M, 6M, 12M) and with time variable months between 1997m1 and 2008m2 (however, the first yields that I have begin in 1999).

I ran a regression with fixed effects and a regression with random effects. Then I performed a Hausman Test to choose the better model.

Table 12 - BUBOR-Yields regression w/ fixed effects	
Fixed_effects (within) regression	Numł

Fixed-effects (Group variable:		ressi on		Number of	of obs = groups =	= 206 3
				Obs per g	roup: min = avg = max =	64 68. 7 71
corr(u_i, Xb)	= 0. 1435			F(1 , 202) Prob > F	= =	17940. 95 0. 0000
Bubor	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval
Yi el ds _cons	1. 033943 1. 902365	. 0077192 . 2392283	133. 94 7. 95	0.000 0.000		1.049164 2.374069
sigma_u sigma_e rho	. 45671169 1. 9245958 . 0533105	(fracti on	of varia	nce due to	u_i)	
F test that all	u_i =0:	F22, 202) =	3. 76		Prob > F	= 0.0250

The small correlation between fixed-effects residuals and the fixed-effects predicts values indicate that the model make be a good candidate for the random effects model (which assumes the correlation to be 0).

⁶ The methodology for BUBOR was improved in March 2008 (and the name of the index changed to ROBOR). Now there are 10 contributing banks, and the fixing takes place at 11:00 a.m., Romanian time. The owner is the NBR and, like with LIBOR, the index is computed by Reuters as an arithmetic average, after trimming out the extreme values.

Table 13 -	BUBOR	-Yields	regression	w /	random	effects

Random-effect Group variabl		sion			of obs of groups =	= 206 = 3
betwee	= 0. 9889 n = 0. 9965 l = 0. 9889			Obs per	group: min = avg = max =	68.7
Random effect corr(u_i, X)				Wald chi Prob >		= 18126.00 = 0.0000
Bubor	Coef.	Std. Err.	Z	P> z	[95% Cont	f. Interval
Yi el ds _cons	1.035202 1.861953	. 0076891 . 2893328	134.63 6.44	0.000 0.000	1. 020132 1. 294871	1.050273 2.429035
sigma_u sigma_e rho	. 28355145 1. 9245958 . 02124509	(fracti on	of varia	ince due t	co u_i)	

Table 14 - Hausman Test

	Coeffi (b)	cients —— (B) re	(b-B) Difference	sqrt(di ag(V_b-V S.E.	_B))
Yi el ds	1. 033943	1.035202	001259	. 0006816	
	= inconsistent	t under Ha, et	t under Ho and Ha fficient under Ho ts not systematic	; obtained from	
	chi 2(1) = = Prob>chi 2 =	(b-B)' [(V_b-V 3. 41 0. 0648	_B)^(-1)](b-B)		

The computed W (=3.41) is smaller than the critical value in the table for a 0.05 level (=3.48). The null hypothesis that the coefficients from the two models do not differ systematically can not be rejected, so I use the random effects model.

The implied equation is:

BUBOR = 1.862% + 1.035 x Yields

Again, the coefficient on Yields is very close to 1. The constant is higher than in the case of UK, but this may be explained by the difference in Yields (and BUBOR) across time (average 3m Yield in 2001 was 40.77%, average 3m BUBOR in 2001 was 43.74%, while average 3m Yield

in 2006 was 7.09%, average 3m BUBOR is 8.76%). Once again, I ran the random effects regression for each particular year:

Year	β	α (%)	\mathbf{R}^2
2000	1.136	-2.892	0.97
	(25.84)	(-1.22)	
2001	0.919	5.788	0.98
	(38.39)	(5.65)	
2002	0.952	4.210	0.99
	(46.59)	(7.41)	
2003	0.891	4.926	0.67
	(7.91)	(2.72)	
2004	1.165	0.155	0.93
	(15.46)	(0.11)	
2005	Insufficient	Insufficient	Insufficient
	observation	observation	observation
2006	-0.178	10.155	0.00
	(-0.80)	(6.40)	
2007	0.034	7.639	0.01
	(0.44)	(14.70)	
1999-2008	1.035	1.862	0.99
	(134.63)	(6.44)	

Table 15 - α 's and β 's for individual years (t-stats in brackets); α 's in percents

There are puzzling results for years 2006 and 2007 (where I introduced data from the secondary market, exclusively in 2006 where there was no issuing on the primary market, and in addition to the primary market data in 2007).

The Johansen test for cointegration cannot be made because there are gaps in the date (which the *vecrank* command does not allow). I go on to make the test for Granger causality. First I select the number of lags, according to the information criteria.

lag	LL	LR	df	р	FPE	AIC	HQI C	SBIC
0	-274.876				448.645	11. 782	11.8116	11. 8607
1	-175. 315	199. 12	4	0.000	7. 69152	7.71553	7.8044	7. 95171
2	-162. 367	25.896	4	0.000	5. 26255	7.33475	7.48289	7.7284*
3	-156. 703	11. 327	4	0. 023	4. 91691	7.26397	7.47136	7.81508
4	-148.859	15. 689*	4	0.003	4. 1963*	7. 10038*	7.36702*	7.80895

Table 16 - Lags selection according to the information criteria

I use four lags of BUBOR and Yields and I run the Granger causality test (when Maturity equals 3m). The results show the two variables Granger cause each other (we can reject the null hypothesis that one does not Granger cause the other) - bi-directional causality. This indicates that the alternative regression (of Yields on BUBOR) has significance - this is also intuitive because the T-bills market is not yet developed and bidders for T-bills clearly guide after BUBOR when participating in the auction for T-bills.

This regression (with random effects) produces the equation:

Yields = -1.4889% + 0.955 x BUBOR

Testing the Expectations Hypothesis in Romania

According to the classical expectations hypothesis of the term structure of interest rates, longterm interest rates are determined by the expectations of the future short-term interest rate. The term premium is zero, i.e. forward rates are equal to the expected short rates:

 $EH: f_j = E(r \sim_j)$

These expected rates, along with an assumption that arbitrage opportunities will be minimal, is enough information to construct a complete yield curve. For example, if investors have an expectation of what 1-year interest rates will be next year, the 2-year interest rate can be calculated as the compounding of this year's interest rate by next year's interest rate. More generally, rates on a long-term instrument are equal to the geometric mean of the yield on a series of short-term instruments. This theory perfectly explains the stylized fact that yields tend to move together. However, it fails to explain the persistence in the shape of the yield curve.

In order to test this hypothesis, I compute the forward rates and compare them with the respective yield. The yields in percent are divided by 100.

 $(1+YTM_{j})^{j} = (1+YTM_{i})^{i} x (1+f_{i:j})^{j-i}$, YTM=yield to maturity, f=forward rate, j>i maturities

Computed forward rate	Comparing yield
f_2	YTM ₁ , 1 year from now
f ₃	YTM ₁ , 2 years from now
f _{2:5}	YTM ₃ , 2 years from now
f _{3:5}	YTM ₂ , 3 years from now
f _{2:7}	YTM ₅ , 2 years from now
f _{5:7}	YTM ₂ , 5 years from now
f _{3:10}	YTM ₇ ,3 years from now
f _{5 : 10}	YTM ₅ , 5 years from now
f _{7:10}	YTM3, 7 years from now
f _{2 : 12}	YTM ₁₀ , 2 years from now
f _{5 : 12}	YTM ₇ ,5 years from now
f _{7 : 12}	YTM ₅ , 7 years from now

Table 17 - Forward rates

f _{10:12}	YTM ₂ , 10 years from now
f _{3:15}	YTM_{12} , 3 years from now
f _{5:15}	YTM ₁₀ , 5 years from now
f _{10:15}	YTM ₅ , 10 years from now
f _{12:15}	YTM ₃ , 12 years from now

I ran a panel regression, where the panel variable was the Maturity of the forward contract. The two series were Forward rates and the Comparing Yields. The use of cross-section data to test the expectation hypothesis has a number of advantages over the time-series approach. Firstly, it is possible to include bond maturities for which there are only short time-series of data available (very useful in my case). Second, the estimated regressors are free of the finite sample biases that may be inherent in time-series regressions.

The results presented below show that the market correctly anticipated future rates, but with a bias. This is why I prefer not to fill in the yields table with yields computed based on forward rates.

Fixed-effects Group variabl					of obs fgroups =	= 93 8
betwee	= 0. 8185 n = 0. 9915 l = 0. 8762			Obs per g	group: min = avg = max =	1 11.6 52
corr(u_i, Xb)	= 0. 5584			F(1 , 84) Prob > F	= =	378. 83 0. 0000
comparing_~d	Coef.	Std. Err.	t	P> t	[95% Conf.	Interval]
forward _cons		. 0328651 . 9002826	19. 46 6. 05	0.000 0.000	. 5743141 3. 660638	. 7050259 7. 241259
sigma_u sigma_e rho	1. 7643606 4. 7425659 . 12157705	(fraction	of varia	nce due to	0 u_i)	
F test that a	II u_i=0:	F 7 , 84) =	1. 56		Prob > F	= 0. 1591

Table 18 - Results of panel regression Comparing Yields on Forward rates w/ fixed effects

Expectation hypothesis doesn't hold, as the coefficient is not 1, and the constant is not 0. However, the market still anticipates the direction, but not the degree of change in the rates.

Constructing the Yield Curve - Examples

Based on the data that I have, I build the yield curves for each of the following dates: 2005m6, 2007m3. In order to have a continuous, differentiable curve, I use the cubic spline method. The cubic spline is a function defined piecewise by third-order polynomials, which passes through a set of control points (the yields that I have). The polynomials have the following representation: $Y_i(t) = a_i + b_i t + c_i t^2 + d_i t^3$

Fig. 4 - Yield curve in June 2005. Blue line - cubic spline of yields; green line - 5-month moving average spline

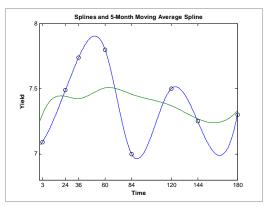


Fig. 5 - Yield curve in March 2007. Blue line - cubic spline of yields; green line - 5-month moving average spline

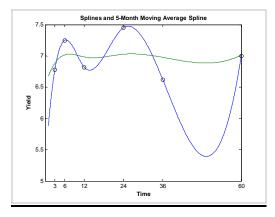
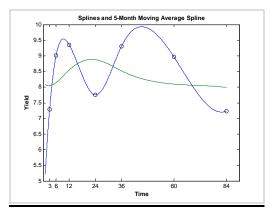


Fig. 6 - Yield curve in February 2008. Blue line - cubic spline of yields; green line - 5-month moving average spline



According to the February 2008 yield curve, and assuming that the expectation hypothesis holds, the market expects interest rates to grow over the medium run and then to decrease slightly over the long run.

Risk Factors Affecting Yield Curve Movements: Slope, Level, Curvature

The variance in yields can be described in terms of a few factors, typically a "level", "slope" and "hump" (or "curvature factor"). This can be seen from a maximum-likelihood analysis or from a simple eigenvalue⁷ decomposition of yields. I group the maturities into three categories: short - 3M, 6M, medium - 12M, 24M, 36M, 60M, and long - 84M, 120M, 144M, 180M. I take average over the groups and then run a principal component analysis for the three groups. The results, reported below, show that the first eigenvector has fairly constant values, the second is increasing and the third has a convex shape. 68.22% of the variance in yields is explained by factors that move the yield curve similarly across the maturities (hence the "level" factor). The statistical interpretation is that the level factor is the one whose covariance with the initial series is the highest, that is the vector of covariances between the first factor and the initial series has the highest length.

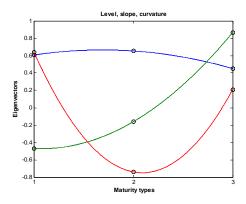
The following 25.44% of the variance of the yield curve is explained by factors that have a different influence on maturities.

ncipal compone Rotation: (un				Number of obs Number of comp. Trace Rho	= = =	9 3 3 1.0000
Component	Eigenvalu	Je Diffe	erence	Proportion	Cum	ul ati ve
Comp1 Comp2 Comp3	2. 0465 . 76328 . 19013	.5	28329 73152	0. 6822 0. 2544 0. 0634	0). 6822). 9366 . 0000
ncipal compone	nts (eigenve	ctors)				
Variable	Comp1	Comp2	Comp3	Unexpl ai ned		

Table 19 -	- Principal	component	analysis	for short run.	medium run	and long run
		eomponene.				

⁷ These are the eigenvalues of the covariance matrix, which is symmetric. This ensures that the eigenvalues are real numbers.

Fig. 7 - Spline of level, slope and curvature



In the above figure, the blue line indicates the level, the green line the slope and the red line the curvature.

If I run a principal component analysis for maturities 3M, 6M, 12M and 24M (introducing more maturities reduces the number of observation below a reasonable limit), the level, slope and curvature components are also well represented, but this time the level component explains 98.64% of the movements in the yield curve!

	ipal compone otation: (un	nts/correla rotated = p			Number Number of Trace Rho		= = =	18 4 1. 0000
_	Component	Ei genva	ue Diff	erence	Propo	ortion	Cum	ulative
_	Comp1 Comp2 Comp3 Comp4	3.945 .04285 .009362 .002299	.03 .03 .12 .007	90263 334917 '06218	0. 0.	9864 0107 0023 0006	0	. 9864 . 9971 . 9994 . 0000
ri nc	ipal compone	nts (eigenv	ectors)					
	Variable	Comp1	Comp2	Comp3	Comp4	Unexpl	ai nec	— I
	variable				1			

Another method to identify the level, slope and curvature factors is presented in Evans&Marshall (1998). For each separate observation they make a quadratic approximation by regressing yields on a constant, maturity and maturity squared. The coefficients (which are time-

varying because of regressing each observation) represent the level, slope and curvature factors. To see how the shape of the yield curve changes as response to a shock, one estimates VARs in which the yield is replaced by one of these coefficients. If, for example, the curvature - which is usually negative - has a positive response, it means the yield curve flattens.

Just for comparison, I make the same analysis for BUBOR, so I take a principal component for 1M, 3M, 6M, 9M, 12M over the M8 1999 - M4 2008. I expect the first component (the level) to explain over 95% of the variation in the term structure of BUBOR, given that the maturities are equal or less to 1 year. Indeed, as seen from the table below.

Table 21 - Principal component analysis for BUBOR 1M, 3M, 6M, 9M, 12M

, , , , , , , , , , , , , , , , , , , ,	/correlation	Numbe	er of obs = Number o Trace		105 5 5
Rotation: (unro	tated = principal)	Rho		=	1.0000
Component	Ei genval ue D	i fference	Proportion	Cumulative	
Comp1	4. 98854	4. 97909		0. 9977	0. 9977
Comp2	. 00944758	. 00766518		0. 0019	0. 9996
Comp3	. 0017824	. 00163691		0.0004	1.0000
Comp4	. 000145489	. 0000594958		0.0000	1.0000
Comp5	. 0000859932	•		0.0000	1.0000
i pal components Vari able	(eigenvectors)	p2 Comp3	Comp4 Coi	np5	Unexpl ai ned
· ·	Comp1 Corr	p2 Comp3		•	Unexpl ai ned
Vari abl e Robor1m Robor3m	Comp1 Com 0. 4469 0 0. 4473 0	. 5720 0. 649 . 4166 -0. 448	98 -0. 224 81 0. 650	1 0. 0241 7 -0. 0470	0
Vari abl e Robor1m Robor3m Roboróm	Comp1 Com 0.4469 0 0.4473 0 0.4476 -0	. 5720 0. 649 . 4166 -0. 444 . 0072 -0. 53	98 -0. 224 91 0. 650 71 -0. 651	1 0. 0241 7 -0. 0470 7 0. 2939	0 0 0
Vari abl e Robor1m Robor3m	Comp1 Com 0.4469 0 0.4473 0 0.4476 -0 0.4474 -0	. 5720 0. 649 . 4166 -0. 448	98 -0. 224 31 0. 650 71 -0. 651 22 -0. 082	1 0.0241 7 -0.0470 7 0.2939 3 -0.7964	0

Macroeconomic Factors Affecting the Yield Curve - Definitions

I used two classes of macro variable, one denoting "inflation" and the other one denoting "real activity". The variables used have traditionally appeared in the VAR literature. There are two ways in which I picked these measures:

- a) principal components for inflation and IP for real real activity, where I first seasonally adjust the data, then I take logs, and first differences. (Notation: PCA_Inflation_SA, IP Realact SA)
- b) consumer price index as a measure for inflation, and industrial production as a measure for real activity. The data is seasonally adjusted, in logs and in first difference. (Notation: CPI_Inflation_SA, IP_Realact_SA)

The time range is M8 1999 (the first date I start to have yields for the T-bills) and M10 2007. In the first class I included several measures and used a principal component analysis (PCA) to extract the components. For the "inflation" class I used the consumer price index (CPI), an index for the price of a commodity, here oil, (PCOM) and the production price index (PPI). PCOM is usually thought as a leading indicator for inflation.

	Central moments				Autocorrelations			
	Mean	Stdev	Skew	Kurt	Lag 1	Lag 2	Lag 3	
СРІ	2.2422	0.1565	-0.8816	-0.2993	0.9607	0.9219	0.8845	
Brent	3.0127	0.2034	-0.3185	-0.8029	0.9320	0.8816	0.8384	
PPI	2.2815	0.1883	-0.6920	-0.5693	0.9625	0.9257	0.8898	
IP	2.0750	0.0572	-0.2211	-0.3171	0.8553	0.7820	0.7470	

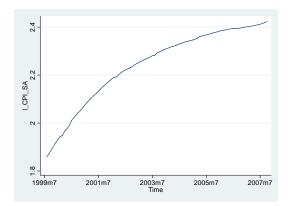
Table 22 - Summary statistics of data (logs), over the period M8 1999 - M10 2007

The Original Series:

Consumer Price Index (CPI)

The series is an index, where 2000=100, over the M8 1999-M10 2007 period. It is obtained from IMF Statistics. The series is seasonally adjusted then used in logs and tested for stationarity (unit root test). I use difference in logs (t - t₋₁).

Fig. 8 - CPI series (sa, logs)



In order to deseasonalize, I regressed the CPI on a constant term and the 11 seasonal dummies (I chose only 11 instead of 12 dummies to avoid the dummy variable trap - perfect collinearity). I used this method instead of X- 12-ARIMA, which is not built in STATA. I obtained a small R^2 and a significant F-statistic, so I had to find another method to deseasonalize the data. I finally used the Tramo/Seats procedure in Demetra; the procedure is recommendable in data sets where I do not have a large number of observations, which is my case.

Price of a commodity, Brent Europe oil, (PCOM)

The series will capture the price of a commodity, here the price of oil measured as Brent⁸ Europe, FOB. The data are from EconStats - U.S. Energy Information Administration (EIA). They are monthly data, from M8 1999 to M10 2007. I transformed the data from USD to RON. I introduced the price of oil for several reasons: first, when constructing the CPI, the National Institute for Statistics&Economic Studies (INSEE) considers "Housing, water, gas, electricity and other fuels" as 13.7% of the basket, so the CPI may not measure accurately the impact of oil price on the economy (a value which depend however on the pass-through of fuel prices to other prices in economy); second, the measure for real activity considers industrial production (GDP is not available in monthly data) - change in oil price and the price of commodity accounts for the unexpected inflation.

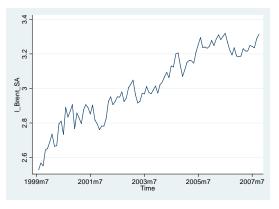
⁸ Brent oil is sourced from the North Sea and is used to price 2/3 of the world's internationally traded crude oil supplies.

The data is deseasonalized (Tramo/Seats in Demetra), used in logs and the series is tested for unit roots. As the Augmented Dickey-Fuller test indicates, the series is I(1) so difference in logs is used (I used the t-t₋₁ difference).

Dickey-Fuller	r test for unit	rœt	Number of	obs =	99
	Test Statistic	1% Cri ti cal Value		ed Dickey-Fuller 10% Critical Value	
Z(t)	-2.06	0	-3. 511	-2. 891	-2. 580

Table 23 - Unit root test for log(Brent)

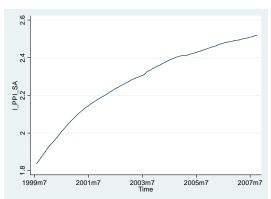
Fig. 9 - Brent series (sa, logs)



Producer Price Index (PPI)

The series is an index, where 2000=100, over the M8 1999-M10 2007 period. The series is obtained from IMF Statistics. Difference in logs is used (I used the t-t₋₁ difference).

Fig. 10 - PPI series (sa, logs)



Industrial production (IP)

Industrial production measures production over the analyzed period. GDP can not be used because only quarterly data exist, and not monthly data. IP is an index, where 2000=100. The series covers the M8 1999 - M10 2007 period in logs and in first difference. I tried to take the series in real terms (that is divide by CPI and multiply by 100), but the results (IP actually declined from 700 to 50 – index numbers, 2000 values = 100) indicated that the series was already adjusted for inflation.

Fig. 11 - Industrial production (sa, logs)

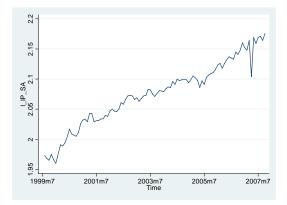


Table 24 - Unit root test for IP

лскеу-FullTe	r test for unit ro	ωι	Number of ol		99
	Test Statistic	1% Cri ti cal Val ue	5% Critical Value	l Dickey-Fuller 10% Critical Value	
Z(t)	-1.061		-3. 511	-2. 891	-2. 580

The Measures for Inflation and Real Activity:

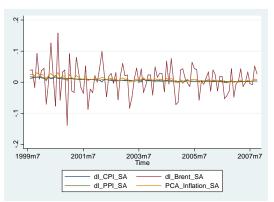
a) principal component for inflation and IP for real activity, where I first seasonally adjust the data, then I take logs, and first differences. (Notation: PCA_Inflation_SA, IP_Realact_SA) **Inflation**: I have three measures of inflation (CPI, price of commodity, PPI). In order to reduce the number of RHS variables in the subsequent estimations, I extract a principal component. This method is based on computing the eigenvectors and corresponding eigenvalues for the variance-covariance matrix. The eigenvalues are then sorted in a descending order and I use only the eigenvector corresponding to the highest eigenvalue. We can see form the analysis that the first component explains 63.35% of the total variation. The first principal component loads positively on the CPI, PCOM and PPI so I multiply the eigenvector corresponding to the highest eigenvalue to the matrix of the series to obtain the new measure of inflation.

cipal components/	correlation	Numb	er of obs = Number of comp. = Trace =	99 3 3
Rotation: (unrot	ated = principa) Rho		1.0000
Component	Ei genval ue	Di fference	Proportion Cumulative	
Comp1 Comp2	1. 9005 . 99453	2.889599	0. 6335 0. 3315	0. 6335 0. 9650
Comp3	. 10493	· · ·	0. 0350	1.0000
pal components	(eigenvectors)			
pal components Variable		Comp2 Comp3	Unexpl ai ned	
· ·	Comp1 (Comp2 Comp3 -0.0884 0.70 0.9955 0.03	054 0	

Table 25 - Principal component analysis for inflation

The new measure for inflation is obtained by multiplying the first eigenvector by the vector containing the CPI, the PCOM and the PPI.

Fig. 12 - CPI, PCOM, PPI, PCA_Inflation



The inflation factor is closely correlated to the CPI (79.92%) and the PPI (82.62%) and less correlated with Brent (59.65%).

	PCA_In~Adl_	_CPI ~A dlBr	∼e~A dI _PPI	~A
PCA_Inflat-A dl_CPI_SA dl_Brent_SA dl_PPI_SA	1.0000 0.7992 0.5965 0.8262	1.0000 0.0310 0.8937	1. 0000 0. 0795	1.0000

Table 26 - Correlation between PCA_Inflation_SA, CPI, Brent and PPI

The unconditional correlation between the inflation factor (PCA_Inflation_SA) and the real activity factor (IP Realact SA) is negative and very small (-0.0023).

I further look at the conditional correlation, from estimating a VAR for the macro factors. I included 3 lags for inflation and real activity (consistent with the information criteria).

Table 27 - Lag length selection in VAR(3)

ag	LL	LR	df p	FPE	AI C	HQI C	SBI C	
0	630. 466				6.2e-09	-13. 2309	-13. 2091	-13. 1771
1	664.87	68.809	4	0.000	3.2e-09	-13. 8709	-13. 8058	-13. 7097
2	674.809	19.877	4	0. 001	2.9e-09	-13. 996	-13. 8873	-13. 7271
3	686. 21	22.803	* 4	0.000	2.5e-09*	-14. 1518*	-13. 9997*	-13. 7754*
4	689.459	6. 4978	4	0. 165	2.5e-09	-14. 136	-13. 9405	-13. 6521

A positive shock to inflation produces a decrease in the real activity (inflation sets back the production), the it fluctuates before dying in about half a year. Inflation increases after a positive shock to production, then it fluctuates before dying also after more than half a year. A surprising response of inflation could also have been expected, because the inflation has a commodity component (international price of oil) which is not influenced by the production in Romania. Anyway, the response of inflation is very small (less than 5 bp), which is not economic significant, so the above explanation may be the reason.

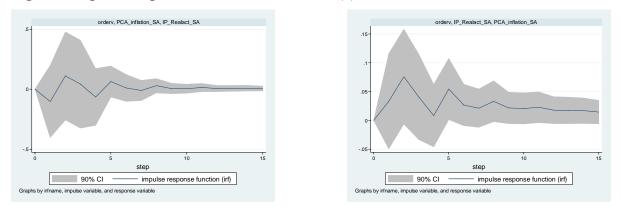


Fig. 13 - Impulse response functions in the VAR(4)

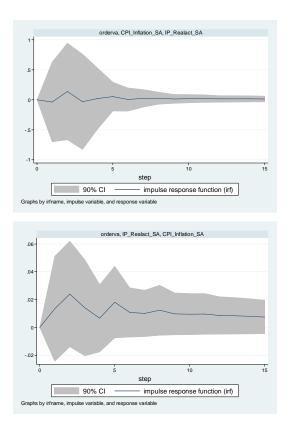
b) consumer price index as a measure for inflation, and industrial production as a measure for real activity. The data is seasonally adjusted, in logs and in first difference. (Notation: CPI_Inflation_SA, IP_Realact_SA)

If I use only CPI and IP, the correlation between them is slightly positive (0.0124). I run a VAR with 3 lags, consistent with the information criteria.

Table 28 - Lag length selection

ag	LL	LR dt	fр	FPE	AI C	HQI C	SBI C	
0 1 2	679. 655 735. 482 749. 537	111. 66 28. 108	4	0.000	2. 2e-09 7. 3e-10 5. 9e-10	-14. 2664 -15. 3575 -15. 5692	-14. 2447 -15. 2923 -15. 4606	-14. 2127 -15. 1962 -15. 3004
3 4	759. 536 761. 108	19. 999* 3. 1436	4 4	0. 000 0. 534	5. 2e-10* 5. 5e-10	-15. 6955* -15. 6444	-15. 5434* -15. 4488	-15. 3191* -15. 1605

Fig. 14 - Impulse response functions in the VAR(3)



Taylor Rule - The Dynamics of the Short Rate

According to the Taylor rule (1993), short rate movements are explained by contemporaneous macro variables f_t^0 and another component which is orthogonal on the macro variables - a shock v_t . Ang and Piazzesi (2003) survey the commonly used models that trace the movements in the short rate.

1. Taylor rule (1993): $r_t = a_0 + a'_{l}f_t^0 + v_t$

Taylor's original specification uses two macro variables as factors in f_t . The first is an annual inflation rate, similar to the inflation factor I computed, and the second is the output gap (which I may be able to compute using a Hodrick-Prescott filter with a smoothing parameter of 1600 for the quarterly GDP). But GDP data are only available at a quarterly frequency, while my computed measure of real activity has monthly data (because it uses IP instead of GDP).

2. Backward looking Taylor rule: $r_t = b_0 + b'_1 X_t^0 + v_t$, where $X_t^0 = (f_t^{0'} f_t^{0'} I_t, ..., f_t^{0'} I_{t-1})'$, so lagged macro variables are introduced as arguments. This type of policy rule has been proposed by Clarida et al. (2000).

3. Affine term structure models (Duffie and Kan, 1996) are based on a short rate equation (like in the Taylor rule model) together with an assumption on risk premia. The difference between the short rate dynamics in affine term structure and the Taylor rule is that in affine term structure models the short rate is specified to be an affine (constant plus linear term) function of underlying latent factors X_t^u :

$$r_r = c_0 + c_1 X_t^u$$

Combining the above equations, I obtain: $r_t = \delta_0 + \delta_{11} X_t^0 + \delta_{12} X_t^u$

The approach I follow is the one specified in Ang and Piazzesi (2003), where the latent factors X_t^u are orthogonal to the macro factors X_t^0 . In this case, the short rate dynamics of the term structure model can be interpreted as a version of the Taylor rule with the errors $v_t = \delta_{12} X_t^u$ being unobserved factors.

The coefficients on inflation and real activity in the short rate equation $r_t = \delta_0 + \delta_{II} X_t^0 + \delta_{I2} X_t^u$ can be estimated by ordinary least squares because of the independence assumption on X_t^0 and X_t^u . I run two regressions: the original Taylor rule and a backward-looking Taylor rule, which incorporates lags of the macro variables. The regression results give a preliminary view as to how much of the yield movements is explained by the macro factors. The R² of the estimated Taylor rule is small, 4.74 %, but it increases in the estimated backward-looking version of the Taylor series - R² is 67.41 %. These numbers suggest that macro factors should have explanatory power for yield curve movements.

Source	SS	df MS		Number of F(59 2.44
Model Resi dual	. 043917486 . 504571521		21958743 09010206		Prob > F = R-squared =	0. 0966 0. 0801 0. 0472
Total	. 548489007	58 .00	9456707	Adj R-squared = Root MSE =		. 09492
dl_yields3bp	Coef. S	Std. Err.	t P> t	[95% (Conf. Interval]	
CPI_Inflat~A IP_Realact~A _cons	. 724039 2. 016274 0321878	2.881056 .9296478 .02384	0. 25 2. 17 -1. 35	0. 802 0. 034 0. 182	-5. 04741 . 1539659 0799452	6. 495488 3. 878583 . 0155696

Table 29 - Regression 3m yields on Inflation and Real activity - original Taylor rule

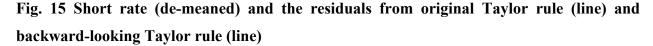
Source	SS	df MS		Number of		50
Model Resi dual	. 330314128 . 065885499		3763089 0263542		24, 25) = Prob > F = R-squared =	5. 22 0. 0001 0. 8337
Total	. 396199627	49 . 00	8085707		i R-squared = Root MSE =	0. 6741 . 05134
l_yi el ds3bp	Coef. S	itd. Err.	t P> t	[95% (Conf. Interval]	
Pl_Inflat~A	(- ····		
L1.	-6. 902027	8. 169195	-0.84	0.406	-23.7268	9.922745
L2. L3.	4. 843132 15. 49198	6. 761217 4. 237388	0. 72 3. 66	0. 480 0. 001	-9.081855 6.764917	18. 76812 24. 21904
L3. L4.	5. 461745	4. 535843	1.20	0.240	-3.879999	14.80349
L5.	. 8959059	4. 467295	0.20	0.843	-8. 304661	10. 09647
L6.	4.051777	3.882792	1.04	0.307	-3.944984	12.04854
L7.	3. 527515	3.994039	0.88	0.386	-4. 698362	11.75339
L8.	-1. 417098	3.807087	-0. 37	0. 713	-9. 257941	6. 423744
L9.	-3. 484693	3. 453706	-1.01	0. 323	-10. 59773	3. 628348
L10.	-6. 659316	3. 69759	-1.80	0. 084	-14. 27465	. 9560138
L11.	-6. 205538	3.804552	-1.63	0. 115	-14. 04116	1.630084
L12.	-8. 456825	3. 905115	-2.17	0. 040	-16. 49956	4140894
P_Realact~A	4 (01000	0407400	4 00	0 000	6 544004	0 (57/00
L1.	-4.601308	. 9437482	-4.88	0.000	-6.544994	-2.657622
L2. L3.	7100309 -1. 894723	1.394362 1.654385	-0. 51 -1. 15	0. 615 0. 263	-3.581773 -5.301993	2. 161711 1. 512547
L3. L4.	1. 114812	1. 707621	0.65	0. 203	-2. 402099	4. 631724
L5.	. 7967269	1. 660716	0.48	0.636	-2. 623582	4. 217036
L6.	-2.856102	1.606771	-1.78	0.088	-6. 165308	. 4531042
LO. L7.	-2. 520625	1.453388	-1.73	0.095	-5. 513934	. 4726844
L8.	2. 193679	1. 494141	1.47	0.155	8835624	5. 27092
L9.	-2. 411545	1. 390764	-1.73	0.095	-5. 275878	. 4527877
L10.	3. 180031	1. 562622	2.04	0.053	0382481	6. 398311
L11.	1. 59746	1. 496761	1.07	0. 296	-1. 485177	4. 680097
L12.	9488062	1. 390613	-0. 68	0. 501	-3. 812828	1. 915215
_cons	. 0110825	. 0188085	0. 59	0. 561	0276544	. 0498194

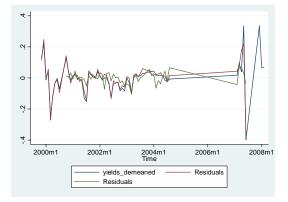
 Table 30 - Regression 3m yields on Inflation and Real activity with 12 lags - backwards-looking Taylor rule

 Table 31 - Autocorrelations in the Taylor rule (calculated at lag 1)

	Residuals from the	Residuals from the	Short rate (3m
	original Taylor	backward-looking	Yields)
	rule	Taylor rule	
Autocorrelation	0.1413	0.1039	0.0199
Durbin-Watson test (H ₀ : no	1.36	1.63	-
autocorrelation, cannot be			
rejected if D-W close to 2)			
Breusch-Godfrey	Computed	Computed	-
(H ₀ : no autocorrelation)	Chi2=1.72; Critical	Chi2=0.72;	
	value Chi2(1)=3.84	Critical value	
	at 95% confidence;	Chi2(1)=3.84 at 95%	
	Can't reject H ₀	confidence; Can't	
		reject H ₀	

The residuals will follow the same broad pattern as the short rate, unless a variable which mimics the short rate is placed on the right-hand side of the short rate equation. This can be seen from Fig. 15, which plots the residuals together with the de-meaned short rate.





The coefficients in the original Taylor rule are significant for real activity, but insignificant for inflation. In the backward-looking Taylor rule lags 3, 10 and 12 of the inflation are significant, and lags 1, 6, 7, 9, 10 of the real activity are significant. I evaluate the models using an information criterion test (a likelihood ratio test is not available because there is a different number of observations in the two regressions).

Applying the Bayesian Information Criterion (BIC) to the models yields the following results: BIC(original Taylor)=-101.266, BIC(backward-looking Taylor)=-91.898⁹. I should choose the model with the lowest BIC, that is the original Taylor rule model.

Further study of the performance of the Taylor rule should also take into account that:

- a. the rate depends on a larger set of macroeconomic factors. In case of the reference rate (the equivalent of the federal funds rate), the NBR looks at many indicators when it sets this rate
- b. the Taylor rule is sensitive to the measures taken for inflation and real activity; using GDP or output gap can yield different results (here I preferred IP because it is computed

 $^{^{9}}$ BIC = -2lnL + kln(n), L=the maximized value of the likelihood function, n=number of observations, k=number of free parameters to be estimated. If lnL is positive and the sample size and/or the number of parameters is small, BIC will be negative.

monthly); also, one can include measures such as the deviation of the rate of unemployment form the NAIRU

- c. the Taylor rule has a forward looking component, that is the national bank tries to respond to the expected inflation
- d. there exists an interest rate smoothing, that is the national bank tries to adjust the rate in small successive steps, rather that in large amounts.

Vector Autoregressions - Yields and Macroeconomic Variables

a. VAR with yields, principal component for inflation and industrial production for real activity

I want to find out what predictive power the macroeconomic factors have for the yields. I use a VAR to be able to estimate the model with lags. I introduce as endogenous variables the yields (short term and medium term; long term yields have only few observations), inflation and real activity.

The first step is to decide how many lags to include in the model. Although some of the information criteria suggest 1 lag, economically it would make sense to include 3 lags (also considering that the yields have maturities of 3m and 6m, it makes sense to use a larger number of lags, but not too many as there are 46 observations).

Table 32 - Information criteria for the selection of lags

ag	LL		LR	df	р	FPE	AI C	HQI C	SBIC	
0	432.	179					9. 7e-14	-18. 6165	-18. 5569	-18. 4575
1	482.		99.		16	0.000	2.2e-14*			
2	496.		29.		16	0.022	2.4e-14	-20.0282	-19.4921	-18.597
3	510. 522.		27.	791* 003	16 16	0. 033 0. 114	2.7e-14 3.6e-14	-19. 9367 -19. 7411	-19. 1623 -18. 7284	-17.8695 -17.0379

I run the VAR with 3 lags. The results are presented below:

Table 33 - VAR short and medium term yields, inflation, real activity - only equation of yields is reported

Vector autoregres	isi an					
Sample: 2001m Log likelihood = FPE = Det(Sigma_ml) =	6 - 2007m10 533.181 2.44e-1 2.64e-1	4	gap	No. of c AIC HQIC SBIC	bs = = = =	48 -20. 04924 -19. 28318 -18. 0221
Equation	Parms	RMSE R-sq	chi 2	P>chi 2		
dl_sy dl_my PCA_i nflation_SA IP_Realact_SA	13 13 13 13 13	. 050326 . 063077 . 003752 . 010927	0. 8011 0. 5203 0. 2925 0. 5626	193. 3454 52. 06052 19. 84612 61. 742	0.0000 0.0000 0.0701 0.0000	
	Coef.	Std. Err.	z P> z	[95% Co	onf. Interval]	
dl _sy						
dl _sy L1. L2. L3.	6352997 1534975 . 1063533	. 1718416 . 1986173 . 0973791	-3.70 -0.77 1.09	0. 000 0. 440 0. 275	972103 5427803 0845063	2984963 . 2357853 . 2972129
dl_my L1. L2. L3.	. 6827013 . 1869645 . 0596461	. 1446863 . 1892039 . 1434111	4. 72 0. 99 0. 42	0. 000 0. 323 0. 677	. 3991214 1838682 2214345	. 9662812 . 5577973 . 3407266
PCA_i nfl at-A L1. L2. L3.	2. 767214 -3. 669213 -6. 205082	1.661111	1. 48 -2. 21 -3. 30	0. 140 0. 027 0. 001	9061479 -6. 924931 -9. 890117	6. 440575 4134948 -2. 520048
IP_Realact~A L1. L2. L3. _cons	-4. 522671 -3. 389482 7640785 . 0618882	1. 12708	-6.80 -3.42 -0.68 3.33	0. 000 0. 001 0. 498 0. 001	-5.826516 -5.330319 -2.973115 .0254974	-3.218827 -1.448646 1.444958 .098279
dl_my						
dl_sy L1. L2. L3. dl_my	6173598 1708596 0370595	. 2153809 . 2489407 . 1220519	-2.87 -0.69 -0.30	0. 004 0. 492 0. 761	-1. 039499 6587744 2762769	1952211 . 3170553 . 2021579
L1. L2. L3. PCA inflat-A	. 7163584 . 0411931 . 1116248	. 1813452 . 2371422 . 1797469	3. 95 0. 17 0. 62	0. 000 0. 862 0. 535	. 3609283 423597 2406727	1. 071788 . 5059832 . 4639223
L1. L2. L3. IP Real act~A	4. 297315 -6. 020888 -5. 606993	2. 349061 2. 081984 2. 356526	1.83 -2.89 -2.38	0. 067 0. 004 0. 017	3067606 -10. 1015 -10. 2257	8.90139 -1.940274 9882878
L1. L2. L3. _cons	. 5856489 -4. 706022 889516 . 0541023		0. 70 -3. 79 -0. 63 2. 32	0. 482 0. 000 0. 529 0. 020	-1.048548 -7.138605 -3.658253 .0084912	2. 219846 -2. 273438 1. 879221 . 0997134

 R^2 is 80.11% for the short-term yields equation and 52.03% for the medium-term yields (Ang & Piazzesi find that macro factors explain up to 85% of the US yields). The intuition is that there are other factors that explain the yields, which have not been introduced in the model - the so called latent factors, maybe.

The next concern is the stability of VAR. In the model $y_t = \mu + \Delta y_{t-1} + v_t$, dynamic stability is achieved if the characteristic roots of Δ have modulus less than one (the roots may also be complex as Δ need not be symmetric). As seen from the table, all the roots are within the unit circle, so the VAR satisfies the stability condition.

 Table 34 - Stability check of the VAR

Ei genval ue					
.5884309 + .5200247/ .58843095200247/ .2601674 + .7342503/ .26016747342503/ .3158536 + .5642882/ .31585365642882/ .5860938 + .1364676/ .58609381364676/ .5758197 + .1692106/ .57581971692106/ .5031627 .1838709					

VAR satisfies stability condition.

The residuals contain valuable information. I run the tests for autocorrelation and normal distribution. The residuals are correlated at lag 2. Further, that the errors are not normally distributed (i.e. the VAR is not a Gaussian process) indicates any likelihood ratio test should be interpreted with caution (the LR test assumes errors to be normally distributed) - for example the LR test in the lag selection table.

 Table 35 - LM test for residual autocorrelation and the Jarque-Bera test for normally

 distributed disturbances

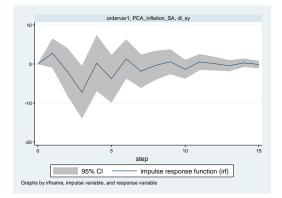
ag	chi 2 d	df Pro	b > chi 2			
1 2	13. 2122 25. 5081					
: no aut	ocorrelation a	atlagio	rder			
arque-Ber	a test					
	Equati on		chi 2	dſ	Prob >	> chi 2
	dl_sy dl_my flation_SA Realact_SA ALL		4.3 16.0 0.2 79.7 100.4	94 61 83	2 2 2 2 8	0. 11575 0. 00032 0. 87779 0. 00000 0. 00000

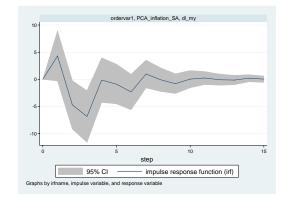
Granger causality shows if one variable x can predict another variable y. This is not necessary causation, it may well mean that another variable z, correlated with both x and y was omitted from the model (a case named in the literature "spurious causal relation"). In the yields equations, there is Granger causality, but not in the inflation and real activity ones.

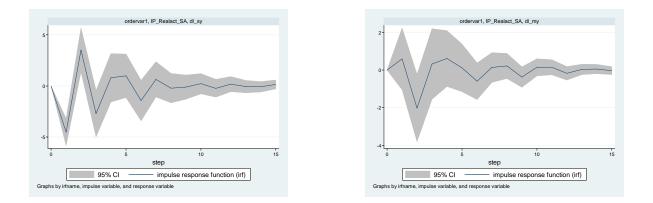
anger causality Wa				
Equati on	Excl uded	chi 2	df Prob	> chi 2
dl_sy	dl_my	24. 395	3	0.000
dl_sy	PCA_i nfl ati on_SA	24. 9	3	0.000
dl_sy	IP_Real act_SA	49. 698	3	0.000
dl_sy	ALL	166. 51	9	0.000
dl _my	dl_sy	8. 2727	3	0. 041
dl _my	PCA_i nfl ati on_SA	21. 989	3	0. 000
dl _my	IP_Real act_SA	17. 819	3	0. 000
dl _my	ALL	38. 127	9	0. 000
PCA_inflation_SA	dl_sy	4. 5545	3	0. 207
PCA_inflation_SA	dl_my	4. 1102	3	0. 250
PCA_inflation_SA	IP_Realact_SA	3. 3147	3	0. 346
PCA_inflation_SA	ALL	9. 4331	9	0. 398
I P_Real act_SA I P_Real act_SA I P_Real act_SA I P_Real act_SA I P_Real act_SA	dl_sy dl_my PCA_i nfl ati on_SA ALL	2. 9848 6. 5704 2. 5941 13. 96	3 3 3 9	0. 394 0. 087 0. 459 0. 124

The impulse response function shows how the system responds when a shock is injected into one variable for one period. In particular, I am interested to see how the yields respond to shocks in inflation and in real activity, respectively. The yields fluctuate after a shock, and die in less than 10 months.

Fig. 16 - Impulse response functions







b. VAR with yields, consumer price index for inflation and industrial production for real activity

I test the same VAR as above, but with CPI instead of the principal component. For real activity I use the IP, same as above.

The information criteria indicate 1 or 2 lags. I choose to use 3 lags, for comparability with the previous model, and because of the economic significance.

	LL		LR	df	р	FPE	AI C	HQI C	SBIC	
)	454.	321					3.7e-14	-19. 5792	-19. 5196	-19. 4202
	508.	949	109.	26	16	0.000	6. 9e-15*	-21. 2586*	-20. 9608*	-20. 4636*
	523.	472	29.0	47*	16	0. 024	7. 5e-15	-21. 1944	-20. 6583	-19. 7633
	530.	775	14.6	05	16	0. 554	1. 1e-14	-20. 8163	-20. 0419	-18. 7491
	539.	697	17.8	44	16	0. 333	1.7e-14	-20. 5086	-19. 4959	-17.8053

Sample: 2001m Log likelihood = FPE = Det(Sigma_ml) =	16 - 2007m10, 554.2539 1.01e-14 1.10e-15	but with a	gap	No. of c AIC HQIC SBIC	bs = = = =	48 -20. 92724 -20. 16119 -18. 90011
Equati on	Parms RM	ISE R-sq	chi 2	P>chi 2		
dl_sy dl_my CPI_Inflation_SA IP_Realact_SA	13 13 13 13 13	. 059907 . 07317 . 001926 . 010986	0. 7182 0. 3545 0. 5640 0. 5579	122. 3215 26. 36096 62. 09353 60. 57382	0.0000 0.0095 0.0000 0.0000	
	Coef. S	itd. Err.	z P> z	[9 5% Co	onf. Interval]	
dl_sy dl_sy L1. L2. L3.	4477072 . 0244213 . 1303196	. 1970114 . 2201754 . 1148755	-2. 27 0. 11 1. 13	0. 023 0. 912 0. 257	8338423 4071145 0948322	061572 . 4559572 . 3554713
dl_my L1. L2. L3. CPI_Inflat~A	. 7567212 1233803 . 104505	. 1668714 . 1986428 . 1682544	4. 53 -0. 62 0. 62	0. 000 0. 535 0. 535	. 4296592 512713 2252675	1.083783 .2659523 .4342775
L1. L2. L3. I P_Real act~A	. 853559 -7. 030619 2. 284331	4. 432183 4. 086259 4. 124778	0. 19 -1. 72 0. 55	0.847 0.085 0.580	-7.833359 -15.03954 -5.800086	9.540477 .9783009 10.36875
L1. L2. L3. _cons	-4. 437552 -2. 545494 . 2015858 . 021192	. 8183082 1. 182692 1. 289851 . 0191613	-5. 42 -2. 15 0. 16 1. 11	0. 000 0. 031 0. 876 0. 269	-6.041407 -4.863527 -2.326475 0163635	-2.833697 227461 2.729647 .0587475
dl_my dl_sy						
L1. L2. L3. d1_my	3959291 0638908 0149941	. 2406268 . 2689191 . 1403072	-1.65 -0.24 -0.11	0. 100 0. 812 0. 915	8675491 5909625 2899912	. 0756908 . 4631809 . 260003
L1. L2. L3. CPI_Inflat~A	. 723586 2594818 . 1736654	. 2038143 . 2426194 . 2055035	3.55 -1.07 0.85	0. 000 0. 285 0. 398	. 3241172 7350071 229114	1. 123055 . 2160434 . 5764449
L1. L2. L3. I P_Real act~A	737777 -7. 375426 . 9276107	5. 413404 4. 990897 5. 037945	-0. 14 -1. 48 0. 18	0. 892 0. 139 0. 854	-11. 34785 -17. 1574 -8. 946579	9. 8723 2. 406554 10. 8018
L1. L2. L3. _cons	. 6088361 -3. 799064 4855707 . 0279107	. 9994698 1. 444523 1. 575405 . 0234034	0. 61 -2. 63 -0. 31 1. 19	0. 542 0. 009 0. 758 0. 233	-1. 350089 -6. 630276 -3. 573308 0179591	2.567761 9678517 2.602166 .0737805

Table 38 - VAR(3); only equations for yields are reported

The computed VAR is stable:

Table 39 - Stability of VAR

Ei genval ue	Modul us	
.8875566	. 887557	
548109 + .4451612/	. 70611	
5481094451612/	. 70611	
1886607 + .6260124/	. 653823	
18866076260124/	. 653823	
447698 + .3282827/	. 55516	
.4476983282827/	. 55516	
.3477834 + .4234154/	. 547936	
.34778344234154/	. 547936	
.4455476	. 445548	
.01998428 + .1798331/	. 18094	
.019984281798331/	. 18094	

The residuals are not correlated at lags 1 or 2. From this perspective, this model is better than the first, where the residuals are correlated at lag 2. The errors are not normally distributed.

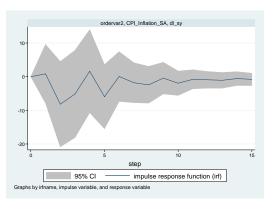
 Table 40 - Correlation in the residuals

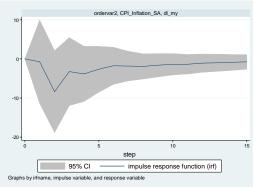
lag	chi 2 c	lf Prot	o > chi 2		
1 2	9. 8436 18. 1555	16 16	0. 87467 0. 31487		
10: no a	utocorrelation a	nt lag or	der		
Jarque-B	era test				
	Equati on		chi 2 d	f Prob	> chi 2

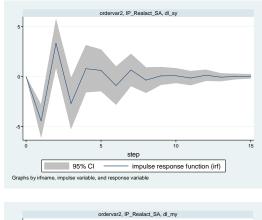
The yields are Granger-caused by the other variables, but not the inflation and the real activity equations. The fact that the yields seem to be better predicted in absence of inflation raises a serious question mark on the validity of the model.

Table 41 -	Granger	causality
------------	---------	-----------

Equati on	Excl uded	chi 2	df Prob >	> chi 2
dl_sy	dl_my	21. 335	3	0. 000
dl_sy	CPI_I nfl ati on_SA	3. 4469	3	0. 328
dl_sy	IP_Real act_SA	32. 324	3	0. 000
dl_sy	ALL	103. 39	9	0. 000
dl _my	dl_sy	2. 7519	3	0. 431
dl _my	CPI_I nfl ati on_SA	4. 0128	3	0. 260
dl _my	IP_Real act_SA	9. 353	3	0. 025
dl _my	ALL	16. 006	9	0. 067
CPI_Inflation_SA	dl_sy	1. 8941	3	0. 595
CPI_Inflation_SA	dl_my	. 33446	3	0. 953
CPI_Inflation_SA	IP_Realact_SA	3. 4406	3	0. 329
CPI_Inflation_SA	ALL	5. 6057	9	0. 779
l P_Real act_SA	dl_sy	2.384	3	0. 497
l P_Real act_SA	dl_my	6.2901	3	0. 098
l P_Real act_SA	CPI_Inflation_SA	2.0555	3	0. 561
l P_Real act_SA	ALL	13.3	9	0. 149







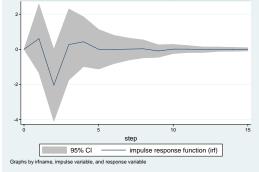


Fig. 17 - Impulse response functions

Conclusions

(a) Up to 1 year, BUBOR is a good approximation of the Romanian Treasury Bill yields. This suggests that when bidding for T-bills people follow BUBOR closely. I verify this connection also in the case of GBP LIBOR and UK T-bills. Clinebell, Kahl, Stevens (2000) verify the same relationship for the USD-denominated LIBOR and US T-bills. This fact allows me to test the Taylor rule using 3-month yields instead of the alternative 3-month BUBOR rate

(b) On the primary market, yields are higher than on the secondary market, a fact known in the literature as the *winner's curse*. This happens because people want to be able to resell the titles, so they bid a lower price (and thus demand a higher yield) than their true valuation. This is in contrast with an althernative theory, the liquidity premium theory. According to this, secondary market bonds are less liquid, and thus demand a higher yield premium. This theory is not supported in the Romanian bond market.

(c) The expectation hypothesis does not hold, as the slope coefficient is not 1, and the intercept is not 0. However, the market still anticipates the direction, but not the degree of change in the rates. Fama-Bliss (1987) also find that forward rates do not have explanatory power for rates on a short horizon of time, but once the horizon is expanded, this power begins to increase. Further tests will have to be done when more data is available, especially on the longer maturities.

(d) Consistent with the foreign fixed income literature, I find that a large part of the movements in the yield curve is explained by the "level" factor, which produces parallel shifts in interest rates. I run a principal component analysis and find that the level factor accounts for 68.22% of the yield curve movements, with "slope" and "curvature" factors explaining the rest. (e) The Taylor rule is verified in backwards-looking form, but not in the original, no-lag, form. The macroeconomic factors explain 67.41% of the movements in yields. By contrast, Ang & Piazzesi (2003) found that macroeconomic factors explain 85% of the movements in yield curve. This may be because of the volatility of the Romanian market which makes it more difficult to link the yields only to the economic activity.

(f) The connections between the yields and the real economy are difficult to assess because of the scarcity and volatility of data; however, with the two models used, the one that incorporates the price of a commodity (oil) is better for predicting short term yields, and the one without the price of commodity is better for predicting medium-term yields (in terms of R^2). This suggests that the

price of oil has a more powerful impact on the short-term yields, than on the medium-term ones. There are two caveats: First, in the model without the price of oil one cannot reject the hypothesis that inflation does not Granger cause yields, which raises a serious question mark Second, the response of yields to inflation in the model including oil prices seems more plausible (there is an increase at the beginning, although it drops afterwards; in the other model, the rates do not seem to increase at all). As a response to real activity, in both models yields fluctuate, but the impulse dies after less than a year.

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