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ESTIMATING THE TERM PREMIUM FROM A GAUSSIAN DYNAMIC TERM STRUCTURE MODEL – THE CASE OF ROMANIA

Abstract. *The present article aims at deriving the time-varying term premium in a Gaussian Dynamic Term Structure (GDTSM) framework, using yield curve information for Romania's sovereign debt instruments. Currently, empirical literature on term structure models is relatively scarce for CESEE economies due to the degree of financial market development and, consequently, the limited market data availability. Therefore, our approach contributes to this line of research by estimating the model using term structure data starting from 2011 and comparing the results with public information on term premia published by the Federal Reserve. We find that the term premium estimated for Romania generally follows international dynamics, signaling a high degree of sensitivity to external events, with several episodes of diverging behavior largely explained by internal factors. Finally, we analyzed the ways in which the term premium can been used for macro-financial purposes. In this regard, we investigated the manner in which the information set carried by the evolution of term premium can been exploited for predictability of the industrial production, CPI and private credit, as proxies for the business cycles, monetary policy stance and financial cycle/macroprudential stance.*

Key words*: term structure, term premium, macro-financial linkages, monetary policy, macroprudential policy.*

JEL Classification: E43, E52, G28

1. Introduction

It is widely agreed that the yield curve plays a central role in the macro-financial framework of any market economy and that monitoring term structure dynamics is important to investors and policymakers alike. In the financial field, it can be used as a reference point for private issuance of debt instruments, as well as for estimating discounting factors for insurance companies and pension funds or duration mapping the balance sheet of credit institutions. At the same time, from a macroeconomic perspective, it has been shown in several studies that yield curve dynamics have predictive power over the general state of the economy and that monitoring the term structure shape is useful in anticipating future booms and busts of the business cycle. Additionally, laying the groundwork for a liquid and efficient sovereign debt market can contribute to fulfilling government financing needs at a reduced cost. Moreover, from a macroprudential policy point of view, current yield curve dynamics associated with significant compression of yields and the general low interest rate environment strongly affects financial institutions' business models and encompasses new structural vulnerabilities which require a close monitoring by macroprudential authorities. Interactions between term premium and financial cycle dynamics are another innovative field at the border of monetary and macroprudential policy, due to the important effects of a decreasing or increasing premium on the amplitude of the financial cycle. Therefore, the term premium can be consideredan important indicator in achieving a successful coordination between monetary and macroprudential policy. However, many emerging market economies presently suffer from the low degree of financial market development and a lack of financial instrument diversification, which naturally leads to limited market data availability regarding sovereign debt markets. One of the negative consequences stemming from low development is the limited maturity horizons associated with sovereign debt instruments, which in turn implies that yield curve estimates have a higher degree of uncertainty as compared to well-developed liquid markets.

Several theoretical, as well as practical, modelling techniques applied at a wide-scale level in developed economies have proven to be infeasible or even impossible to implement in the absence of reliable statistical data regarding sovereign bond market activity. Many economies from the CESEE region (such as Romania, Hungary, Bulgaria and others) have only recently started to develop a fully functioning bond market for sovereign market instruments, while corporate issuance still remains at modest levels. Therefore, the relatively short time series available for empirical modelling of the yield curve place a high degree of uncertainty on the robustness of estimates for affine term structure models.

The Global Financial Stability Report (GFSR) of the IMF first mentions the growth of local sovereign bond markets in the CEE area in 2002, highlighting the fast pace of countries such as Poland, Hungary or the Czech Republic. Starting from 2007, Romania's bond market growth embarks on a similar trend, while

Bulgaria still has a modest turnover in the sovereign debt instrument market (Figure 1).

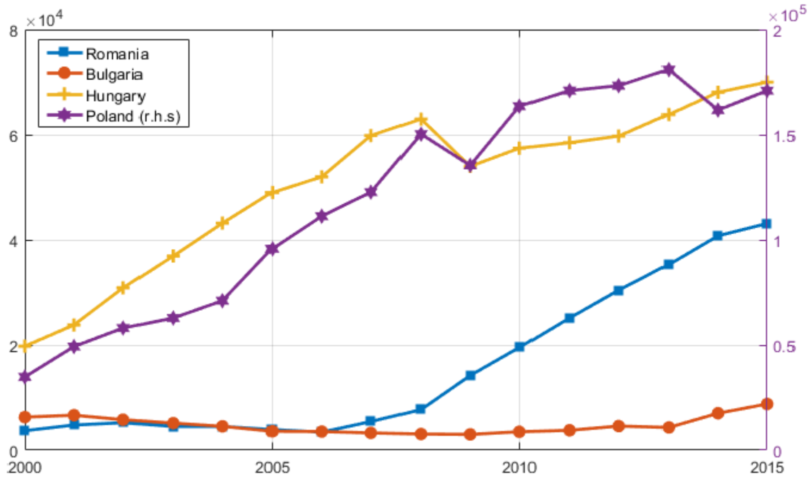

Figure 1.Sovereign Debt issuance in selected CEE countries (mln. Euro)

Recently, overcoming the aforementioned qualitative shortfalls has allowed researchers to engage in the in-depth study of term structure dynamics, with promising results regarding the fundamental drivers of bond market yields and the sensitivity of the sovereign yield curve to external and internal factors.

2. Literature Review

Disentangling different fundamental forces driving yield curve dynamics has been at the center of several strands of empirical literature. Policymakers have been preoccupied with uncovering changes in the expected path of short rates as well as the risk premium that investors require for buying long-term debt instruments. The implications of term premium dynamics are important from a monetary policy point of view, due to the fact that the perceived risk for holding long-term debt can have a significant impact on the transmission mechanism, when moving along the term structure from the short-term rates towards the long-end of the yield curve.

Term structure empirical literature is mainly concentrated on two types of modelling approaches: Nelson-Siegel Models (NSM) and Affine Term Structure Models (ATSM), with particular assumptions and underlying stochastic processes (Cochrane, 2001). Although Nelson-Siegel Models present several appealing features from a modelling point of view, we chose to concentrate on the ATSM class of models. The name of this class of models derives from its underlying assumptions regarding the fact that the price of risk is affine in the state variables and that the pricing kernel is exponentially affine in the shocks that drive the economy (Adrian, Crump and Moench, 2008).

One of the first empirical studies to estimate multi-factor affine models of the term structure is Chen and Scott (2003). The authors use a version of the Cox, Ingersoll and Ross model (1985), estimated using US treasury market data via nonlinear Kalman filter methodology. The results show that a three-factor model is capable of adequately capturing short term and long term dynamics as well as interest rate volatility. Dai and Singleton (2000), confirm earlier empirical findings of Campbell and Shiller regarding contradictions of traditional expectations theory exhibited by the slope of the yield curve by using Gaussian Affine Term Structure Models (GATSM).Kim and Wright (2005) use a simple three-factor arbitrage-free term structure model to explain the decline in long-term yields observed in the USA since 2004 and Duffe (2000) extends the classical affine framework by allowing an independent variation in risk compensation from interest rate volatility and finds an overall better forecasting accuracy. Adrian, Crump and Moench (2008) develop a three-step linear regression approach for a fast estimation of models with several pricing factors and show that the results are robust, when compared to other similar approaches.

A novel approach of estimating GDTSM models was proposed by Joslin, Singleton and Zhu (2011) in which the pricing factors are observable portfolios of yields. Using a data set of US Treasury bond yields, the authors show that maximum likelihood algorithms exhibit a rapid convergence towards the global optimum in their setting. Several recent papers, as McCallum (1994), discussed about the necessity of introducing the long-run rate in the Taylor rule for monetary policy. Other papers, as Söderlind (1999), also used the long rate in the specification of IS equation. Therefore, as it is emphasized in each of the two examples provided before, the long-run rate poses effects on the business cycle dynamics in a New-Keynesian framework and consequently on the monetary policy transmission mechanism.

3. The Model

In order to derive a time-varying term premium, we chose to apply the approach formulated by Joslin, Singleton and Zhu (2011), by considering the following representation for Gaussian Affine Term Structure Models (GATSM):

$$\Delta X_t = K_0^P + K_1^P X_{t-1} + \Sigma_x \varepsilon_t^P$$
$$\Delta X_t = K_0^Q + K_1^Q X_{t-1} + \Sigma_x \varepsilon_t^Q \qquad (1)$$
$$r_t = \rho_0 + \rho_1 X_t$$

Where X_t denotes the state vector (risk factors), r_t is the one-period spot interest rate, $\Sigma_X \Sigma_{X'}$ is the variance-covariance matrix of the state vector and$\varepsilon_t^P, \varepsilon_t^Q \sim N(0, I_N)$. If X_t is n-dimensional and we observe $J > n$ yields (y_t), we can write:

$$\mathcal{P} = W y_t$$
$$y_{t,m} = A_m(\Theta_X^Q) + B_m(\Theta_X^Q) X_t \qquad (2)$$

where Θ_X^Q is a vector of pricing parameters $\Theta_X^Q = (K_0^Q, K_1^Q, \Sigma_x, \rho_0, \rho_1)$. The pricing factors $\mathcal{P}$ are linear combinations of the observed yields and focus on the first *N* principal components.

Joslin, Singleton and Zhu use invariant affine transformations to show that any GATSM has a unique equivalent representation:

$$\Delta \mathcal{P}_t = K_{0\mathcal{P}}^P + K_{1\mathcal{P}}^P \mathcal{P}_{t-1} + \Sigma_{\mathcal{P}} \varepsilon_t^P$$
$$\Delta \mathcal{P}_t = K_{0\mathcal{P}}^Q + K_{1\mathcal{P}}^Q \mathcal{P}_{t-1} + \Sigma_{\mathcal{P}} \varepsilon_t^Q \qquad (3)$$
$$r_t = \rho_{0\mathcal{P}} + \rho_{1\mathcal{P}} \mathcal{P}_t$$

where$K_{0\mathcal{P}}^P, K_{1\mathcal{P}}^P, \rho_{0\mathcal{P}}, \rho_{1\mathcal{P}}$ are functions of $(\lambda^Q, k_\infty^Q, \Sigma_{\mathcal{P}})$ - λ^Q is the vector of eigenvalues of K_1^Q and k_∞^Q is the long-run mean parameter.

The key result in Joslin, Singleton and Zhu's approach is that $K_{0\mathcal{P}}^P$ and $K_{1\mathcal{P}}^P$ cab be estimated by OLS independently of $\Sigma_{\mathcal{P}}$. In turn, these estimates are used in the final step when maximizing the likelihood function to obtain $\lambda^Q, k_\infty^Q, \Sigma_{\mathcal{P}}$and Σ_ε.

McCallum (1994) shows that the short-term rate can be formulated as:

$$i_t = \rho i_{t-1} + \gamma(R_t - i_t) + \varphi_t$$
$$\varphi_t = \tau \varphi_{t-1} + \eta_t \qquad (4)$$

where R_t is the long-run rate and φ_t is the term premium, modelled as a Gaussian AR(1) process. This relationship, derived on the basis of rational expectations hypothesis applied for term structure modelling, emphasizes positive effects from the unanticipated movements in term premium on the evolution of short-term interest rates. Given the negative relationship between interest rates and inflation, an increase in term premium would generate a decrease in prices.

Söderlind (1999) formulated a New-Keynesian with long rate entering in the standard IS equation. By having in mind a contraction map metaphoric idea and putting together the approaches of McCallum (1994) and Söderlind (1999), it follows that the term premium negatively affects output-gap evolution.

4. The Dataset

Sovereign yield market information is obtained from the National Bank of Romania's website, which publishes daily fixing quotes from secondary market activity, starting from 2011. The available maturities are limited to 6M, 1Y, 3Y, 5Y and 10Y due to the underlying portfolio structure of debt instruments issued by the Romanian Government. The dataset is comprised of approximately 1,600 data points for each maturity (Figure 1, Annex).

The macroeconomic data employed in the second part of the paper was extracted from the Eurostat database: the industrial production index, as a proxy for real economic activity and the harmonized index of consumer prices (HICP), while credit data was taken from the NBR's statistical database. The time series used for estimation are at monthly frequency and span the period between February 2011 and April 2017.

5. Results

We estimate the model via maximum likelihood, as described by Joslin, Singleton and Zhu (2011), using term structure data starting from 2011 and comparing the results with public information on term premia published by the FED, in order to uncover any evidence of co-movement with international yield curves. We find that the term premium estimated for Romania, for a maturity of 5 years, generally follows international dynamics, signaling a high degree of sensitivity to external events, with several episodes of diverging behavior largely explained by internal dynamics (Figure 2).

Figure 2. Estimated 5Y Term Premium for Romania and USA (FED data)

A proper understanding of the term premium evolution is important for policy makers, analysts, treasury dealers or risk managers from several points of view. Of course these points of view could be different among the stakeholders mentioned before. While it is pretty clear how a proper understanding of the term premium is useful for analysts, treasury dealers or risk managers, not so many papers focused on the importance of such an information in the policy-making process. In this paper, we address the importance of term premia for monetary and macroprudential policy design as well as for business cycle dynamics.

What we intended was to investigate the predictability power of the term premium in respect to different interest macro-financial variables and to different time horizons. In this regard, we investigated if the evolution of the term premium carries information on the future dynamics of the HICP, industrial production and private credit. For this purpose, we resorted to constructing predictability regressions of each of the three variables mentioned on the term premium. At the first glance we used univariate specification of the predictability regressions:

$$Y_t = c + tp_{t-i} + \varepsilon_t \tag{5}$$

where $Y = \{Ip, CPI, Credit\}$, *c* stands for the intercept, *tp* is the term premium and $\varepsilon_t$are the related standard errors.The obtained results are reported below:

Table 1. Predictability regressions (term premium and macro variables) results

1 Month				
	Intercept	β	R^2(%)	$\sigma(\varepsilon)$%
IP	0.3799; (0.0763***)	0.3042; (0.5962)	0.24	1.83

CPI	0.1140; (0.0265**)	-0.4988; (0.0524***)	9.6	0.45
Credit	0.2182; (0.4655)	0.9782; (0.9782)	1.2556	2.56
3 Month				
	Intercept	β	R^2(%)	σ(ε)%
IP	0.3837; (0.0733***)	0.6677; (0.2935)	1.15	1.85
CPI	0.0931; (0.0932***)	-0.1755; (0.2236)	1.23	0.47
Credit	0.2935; (0.3373)	-0.4615; (0.6816)	0.29	2.57
6 Month				
	Intercept	β	R^2(%)	σ(ε)%
IP	0.4183; (0.0710***)	-1.2275; (0.1828)	3.79	1.86
CPI	0.1013; (0.0819***)	0.0118; (0.9291)	0.01	0.48
Credit	0.2115; (0.4678)	1.6881; (0.1425)	0.0413	2.45
12 Month				
	Intercept	β	R^2(%)	$\sigma(\varepsilon)$%
IP	0.4307; (0.0888***)	-0.0820; (0.8900)	0.02	1.9775
CPI	0.0878; (0.1736)	0.2275(0.3230)	2.10	0.48
Credit	0.2376; (0.4397)	0.8256; (0.3941)	1.12	2.41

As it can be observed from the table above, we investigated predictability for horizon of 1, 3, 6 and 12 months. Therefore, term premium timing is indexed by $i = \{1, 3, 6, 12\}$. For the estimation, we used a standard least squares estimator with Newey-West standard errors to ensure robustness related to the estimated figures. For HICP, industrial production and private credit we used growth rates, while the term premium was expressed separately in growth rates, respectively in levels. Therefore, we ran the regressions twice, once for the term premium in growth rates and once for the term premium in levels. In the table above, we reported the results for which the term premium was expressed in growth rates.

Obtained results showed no predictability for the industrial production and private credit by using the term premium as an only source of information. On the other hand, term premia can be used as predictor for the future evolution of inflation in the next month. As in the other two cases, growth rates of prices cannot be predicted for horizon of time longer than one month by using the information contained in term premium evolution. By looking at the figures reported in the table, we observe that the estimated value of β for inflation predictability at 1-month horizon is significant at 5% confidence level, with an $R^2$of around 10%. This means the introduction of other predictors has the potential to improve the forecast accuracy.

On the other hand, the negative coefficient is consistent with predictions emphasized by McCallum (1994): an increase in the term premium determines a contemporaneous increase in the short-rate which will further be correspondent with a decrease in inflation. As we stated, we ran the same regression by using this time the level of term premium. The results are broadly similar. The main difference is that the obtained β in the case of inflation is much lower (-0.15), while the related p-value is 11.78 %. For this reason, further investigations are based solely on the use of growth rates for the term premium. This approach is in line with Rudebusch (2006), who argues for an approach in growth rates as reflecting changes in the monetary policy stances and finds a higher degree of predictive power in this setup.

Table 2. VAR (1) estimation (term premium and macro variables) results

1 Month				
	Intercept	β	R^2 %	$\sigma(\varepsilon)$%
IP	0.5532; (0.0046*)	0.3133; (0.6094)	19.29	1.65
CPI	0.0888; (0.0439**)	-0.4691; (0.0819***)	14.43	0.44
Credit	0.2430; (0.4142)	0.9470; (0.4692)	5.04	2.51

Given the obtained results, we went further and investigated the issue of predictability in a multivariate approach for a 1-month horizon case. For this reason, we ran a VAR (1) with intercept, by using as before an OLS approach with Newey-West standard errors. For comparability with the univariate case, in the above table we only reported the intercept and the β related to term premium from inflation equation. Obtained results are pretty much the same: no predictability for credit and industrial production and a negativeβin the case of inflation, with a similar magnitude and also a statistical significance at 10% confidence level. In the case of inflation, we repeated the estimation exercise by using a simple least squares estimator this time. Obtained figures are pretty similar, except the fact that the p-value for term premium's β shows statistical significance at 1% confidence level. Of course, the latter result could be put on the base of a bias effect.

Putting together the obtained results, from here on, we solely focused on the predictability issue of inflation by using the one-period time lagged growth rates of the term premium. More exactly, further on we investigate the likelihood of the estimated parameters, given that their statistical likelihood is somewhat questionable. In these circumstances, our aim at this stage is to use several consecrated approaches to stress the confidence in the obtained figures. But above all, in order to set a proper investigation, we started by looking at the stochastic properties of the term premium's growth rates. In this regard, we analyzed the likelihood of an AR(1) for the term premium's dynamic. So, we computed the unconditional and conditional likelihood for an AR(1) process for the term premium's evolution. For a sample size *T*, the unconditional likelihood for a Gaussian AR(1) process is given by the following formula:

$$\mathcal{L}_U(\theta) = -\frac{1}{2}log(2\pi) - \frac{1}{2}log\left(\frac{\sigma^2}{1-\rho^2}\right) - \frac{1}{2}\frac{tp_1 - \frac{c}{1-\rho}}{\frac{\sigma^2}{1-\rho^2}} - \frac{T-1}{2}log(2\pi) - \frac{T-1}{2}log\left(\frac{\sigma^2}{1-\rho^2}\right) - \sum_{t=2}^{T}\left[\frac{(tp_t - c - \rho\, tp_{t-1})^2}{2\sigma^2}\right] \quad (6)$$

where θ is the set of parameters, c and σ^2 denote the intercept, respectively the variance of the process, while ρ is the auto-regressive coefficient. The exact estimators obtained via maximum likelihood approach are obtained by taking derivatives of $\mathcal{L}_U(\theta)$ in respect with c, σ^2 and ρ and setting them equal to 0. The conditional likelihood function for the underlying Gaussian AR(1) model for the term premium evolution is:

$$\mathcal{L}_C(\theta) = -\frac{T-1}{2}log(2\pi) - \frac{T-1}{2}log\left(\frac{\sigma^2}{1-\rho^2}\right) - \sum_{t=2}^{T}\left[\frac{(tp_t - c - \rho\, tp_{t-1})^2}{2\sigma^2}\right] \quad (7)$$

Therefore, the difference between $\mathcal{L}_U(\theta)$ and $\mathcal{L}_C(\theta)$ consists in considering the first observation as being deterministic and not stochastic. The exact estimators are found in the same manner. By computing the unconditional and conditional likelihood for an AR(1) process for the term premium's growth rate, we sequentially considered as being deterministic a time span of 1 month, respectively 6 months. In the Annex, Figure 1 shows the unconditional and conditional likelihood densities, considering a sequence of 6-month as being deterministic.The figure reveals no difference between the two likelihood function, both emphasizing that term premium is described by a white noise process. Given this, our further investigations consider a univariate specification.

The maximum likelihood approach is based on finding a local maximum for the likelihood function $\mathcal{L}(\hat{\theta})$, where $\hat{\theta}$ denotes the set of parameters obtained at the attained maximum. In fact, the derived formulas (under the asymptotic laws) for the underlying process are obtained under the aegis of attaining a local maximum. Another way to look at the statistical confidence related to the parameters is to numerically implement a least-squares approach for our predictability regression. In this regard, we resorted to a gradient-based procedure to find an *extremum* point as a proxy for $\hat{\theta}$. In fact, we used two approaches for this purpose. The first one is based on the implementation of a standard gradient:

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{N}\left[\frac{1}{T-1}\sum_{t=2}^{T}\left(c^i + \beta^i tp_{t-1} - CPI_{t-1}\right)^i\right]^2 \tag{8}$$

where θ is a Nx2 vector that stores grids for the two parameters. Given the parameters estimates and the standard errors that we obtained in our regression exercises, we constructed the grids: $c\, \epsilon[0{:}\,0.5]^{Nx1}$ and $\beta\, \epsilon[0{:}\,-1]^{Nx1}$, with N=180. Therefore, we searched for $\min J(\hat{\theta})$, which signifies the point where the cost function J reaches a minimum and, consequently, the parameters $\hat{\theta}$ reach their optimal values, similar to the case of $\mathcal{L}(\hat{\theta})$.

The second gradient procedure is based on a stochastic gradient, where even though the principle is fairly similar, the mechanic isslightly different. The stochastic gradient is based on a supervised learning rule, which implies running sufficient iterations, starting from an initial guess of the parameters θ_0, in order toachieve convergence to the optimal set of parameters $\hat{\theta}$. The mechanic of the stochastic gradient is defined as:

$$\begin{aligned} \theta_{i\epsilon[1:N]} &= \theta_{i\epsilon[1:N]} - \Psi\frac{\vartheta\, J(\theta)}{\vartheta\, \theta_{i\epsilon[1:N]}} = \\ &= \theta_{i\epsilon[1:N]} - \Psi\left[\frac{1}{T-1}\sum_{t=2}^{T}\left(c^i + \beta^i tp_{t-1} - CPI_{t-1}\right)\right] \end{aligned} \tag{9}$$

where Ψ is a learning rate, that we set at 0.03 in order to ensure a monotone convergence. The initial guess for the parameters was set as $\theta_0 = \left[\hat{c} - \hat{\sigma}^c, \hat{\beta} - \hat{\sigma}^\beta\right]$, with $\hat{c} - \hat{\sigma}^c = 0.0613$ and $\hat{\beta} - \hat{\sigma}^\beta = -0.6767$. According to this approach, the optimal set of parameters $\hat{\theta}$ is obtained at $\theta_{i=N}$.

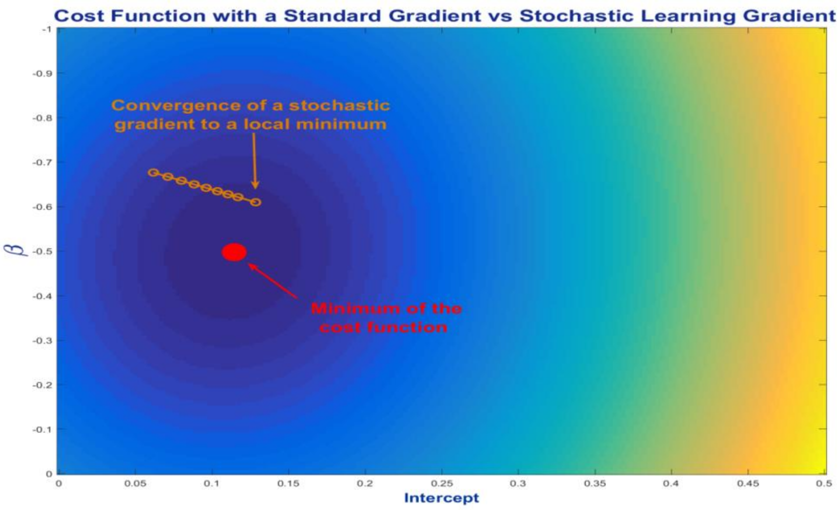

Figure 3. Gradient based implementation of the least-square approach

In the figure above, we plotted the results obtained on the basis of the two previously described approaches. The contour plot shows the basin of attraction for $J(\theta)$, computed with standard gradients. On the xOy axes, the two grids defined for the intercept and the β coefficientare reported. The red dot denotes $\min J(\hat{\theta})$, where the optimal parameters' set is obtained. On the other hand, we plotted the sequence $\theta_{i\epsilon[1:N]}$, which shows the convergence of the stochastic gradient to the optimal set of parameters. By comparing the $\hat{\theta}$ resulted from running the two gradient-based approaches with estimates from the least-square estimator, we can observe that the values provided by the standard gradient are closer to the econometric estimates than those provided by the stochastic gradient. In any case, the difference between the stochastic gradient and the standard gradient are related to β, while for the intercept, the difference is very small.

The next exercise that we ran to stress the significance of obtained parameters consists in a Monte-Carlo experiment. In this regard, we analyzed the asymptotic bias in our estimates. Given this objective, we proceeded in the following manner: by using the $\hat{\theta}$ from the least-squares estimation with Newey-West standard errors, we simulated 100,000 paths of a length equal to T for the evolution of inflation. For each of the simulated paths, we used the OLS method with Newey-West standard errors in order to obtain a set of parameters θ.

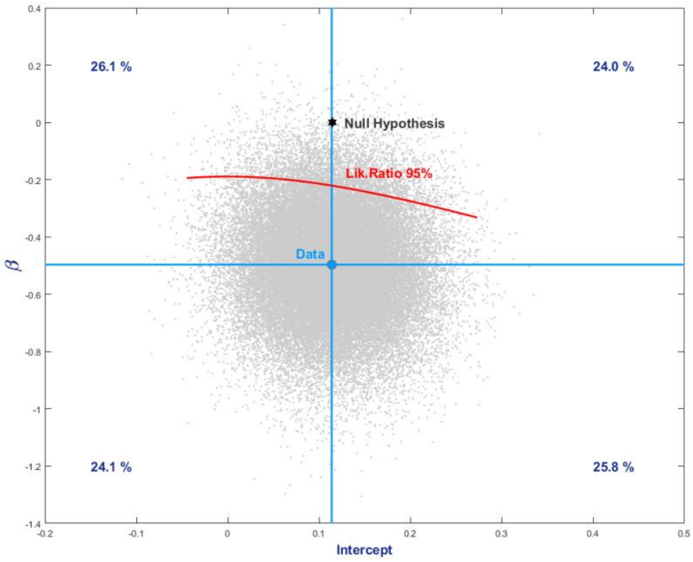

Figure 4. Joint distribution of regression parameters on the base of Monte-Carlo simulations

For the simulation exercise, we set the standard deviation of ε_t at the level obtained from the estimation approach. Another important specification is that, within the simulation exercise, we modelled the term premium as a white noise process with intercept, setting these two parameters on the basis of the estimation results. In Figure 4, the joint distribution for β and the intercept for the 100,000 paths is plotted. In the center of the figure, the estimates of the two parameters from data can be found. Above, the null hypothesis according to which β is zero is displayed, while the intercept is set at the long-run empirical mean, observed in the growth rate of HICP. In each quadrant the share in which the obtained simulation estimates depart from those resulted by using empirical data for estimation, is reported. We can observe that the resulted weights are pretty much the same, which underlines no sign of dependence in the scatter. Therefore, no interlinkages between the intercept and β can be found. On the hand, the joint distribution shows that a higher uncertainty can been attached to the statistical significance of β.

Until now, we called for a one-side test (as it is depicted with a black star in the figure above), by investigating if β shows statistical significance. Even in this case, as we stated before, the joint distribution of the two parameters provides no signs of dependence between them, a more powerful test would be to look at the confidence of β by setting limits for the intercept. A proper tool for such an analysis would be the use of a likelihood ratio (LR) test. For our regression, the derived LR statistics is given by:

$$LR \approx (T-1)ln\left[1+\frac{\hat{c}^2}{\sigma^2(\varepsilon_t^{CPI})}+\hat{\beta}^2\frac{\sigma^2(\varepsilon_t^{tp})}{\sigma^2(\varepsilon_t^{CPI})}\right] \tag{10}$$

which is χ^2asymptotically distributed. To implement this test we used the least-squares estimates and the empirical standard deviation for the term premium. To construct the region depicted in red, we constructed a grid for the intercept, by adding and subtracting three times its related standard deviation from the estimation process: $\hat{c} \in [\hat{c}-3\hat{\sigma}^c, \hat{c}+3\hat{\sigma}^c]$. We can see the LR curve is somewhat downward slopping, but this is not surprising given there is no (or at least very small) dependence between the two parameters. Relatively contrary to the prediction of the LR test, enough information is outside the predicted delimited area according to a 95 % confidence level.

6. Conclusions

The paper contributes to yield curve strand of related research by estimating an GATSM model using Romania’s term structure data starting from 2011 and comparing the results with public information on term premia published by the FED. We find that the term premium estimated for Romania generally follows international dynamics, signaling a high degree of sensitivity to external events, with several episodes of diverging behavior largely explained by internal dynamics.

The investigation carried out in order to uncover the manner in which information contained in term premium could be used to anticipate future movements in industrial production, CPI and private credits reveals predictability power only for the case of inflation. Even in this case, introduction of other variables could improve the ability to predict future movements in inflation. Moreover, the last phrase could be valid also for the case of industrial production and private credit. The lack of predictability could be explained by the fact that an important share of variability in the two mentioned variables are mainly explained by other sources of fluctuations. Therefore, using a univariate representation with term premium as predictor could prove insufficient to understand future developments in real activity and credit, also given the short time frame of analysis severely limited by the lack of sovereign yield curve data.

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Annexes

Figure 1. Secondary market sovereign yields, NBR fixing data

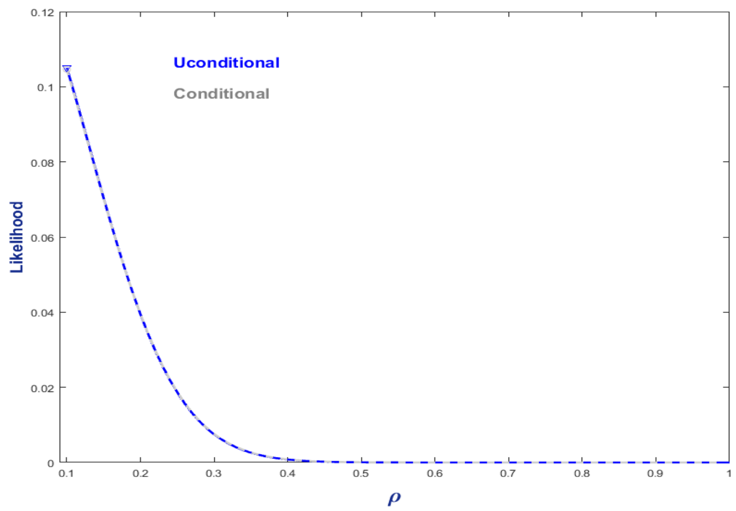

Figure 2. Likelihood functions from fitting a Gaussian AR(1) process for the growth rate of term premium