Making decisions on issuing sub-federal bonds in Russia: key factors modeling

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Abstract. Recently, Russian regions have been more active in using sub-federal bonds to finance regional debt. However, the Russian sub-federal bonds market’s liquidity is still low while regional authorities often use commercial bank loans to finance the regional budget deficits. The purpose of this study is to identify the key factors influencing the regional authorities’ decisions to issue sub-federal bonds. The impacts of the following factors were assessed: the regional budget deficit volume, the Central Bank key rate, the budget loan proportion of the regional debt, the regional debt burden, average per capita cash income in the region, the employed in the region. We used monthly data for 85 regions (constituent entities of the Russian Federation) for the period 2015–2019.

Various regression models for panel data have been developed: those predicting probabilities of a non-zero value of regional bond volume, the volume itself, and combined generalized linear mixed hurdle model with a negative binomial distribution (estimated with glmmTMB contributed package of R). The latter showed non-significant dependence of regional bond volume on region budget surplus, prioritizing unobserved region-specific random factors.

1. Introduction

Regional bond issuance is one of the well-known borrowing instruments for regional authorities. Regional bonds are especially popular in federal states with a high degree of regional economic independence. In terms of the regional bonds market turnover, the USA is in the lead, and also a significant market share belongs to European countries [1].

Currently, many Russian regions have also started using this tool. By the beginning of 2020, a particularly high bond share in regional debt was in the Siberian (42.42%), Ural (35.84%), and Central (32.05%) federal districts. Moscow, St. Petersburg, and some other regions by 2020 have completely switched to bonds in their debt financing. For the period 2015–2019, the nominal volume of issued sub-federal bonds in the Russian Federation increased by 33% [2].

However, in general, the Russian sub-federal bond market is still characterized by low liquidity and low turnovers in the secondary market. To attract financial resources, regional authorities are much more likely to use more traditional sources for loans of Russia from commercial banks and direct budget transfers.

In 2019, the economic situation for the regions to enter the bond market in order to attract long-term finance resources was extremely favorable [3]. Against the background of the decrease
in the Bank of Russia’s key rate, the yield on sub-federal bonds dropped to 7.2% per annum, which is lower than the values of the pre-crisis 2013. However, there was no boom of the sub-federal bonds issuing. In 2019, the aggregate volume of issued regional and municipal bonds remained at the level of 2018. The number of issuances, as well as the number of issuers, decreased. The average maturity of new bond issues decreased by four months down to 4.4 years. For the federal level, however, 2019 was the most successful year in terms of attracting financing via bonds. Despite the federal budget surplus, the total volume of federal bonds issues in 2019 more than doubled as compared to 2018 and amounted to 2.1 trillion rubles.

The regional budget revenues growth and the consistent decrease in the need for debt financing were blamed as the main reasons for the Russian regions' low interest for the issuing of the bonds. The number of regions with a budget deficit in 2019 almost halved compared to 2017.

In addition, the sub-federal bonds’ growth supply was restrained due to the federal government’s support to the regions aimed at reducing the regional debt burden. The maturity of the federal budget loans to regions has been increased, and the regions’ authorities were motivated to make commitments to reduce the regional debt level. As a result, the regions’ needs for new borrowings have decreased. An additional incentive for the regional debt reduction was the changes introduced in 2019 to the Budget Code of the Russian Federation in order to ensure control over the debt burden of Russian regions.

The decline in interest rates throughout 2019 has been also blamed to contribute to the non-increase in the sub-federal bond market activity. With continuing declining interest rates, the regions preferred bank loans. Early redemption of regional bonds is mostly impossible, while bank loans are more flexible in this way – with an interest rates decrease, bank loans can be repaid ahead of schedule and replaced with cheaper credit resources.

In 2020, there is a chance that bonded loans will replace some of the bank debt of the regions. Some growth in sub-federal bond issuing may be facilitated by the changes in the Russian Budget Code adopted in mid-2019 to ensure control over the debt burden of regions and municipalities, as well as stabilization of interest rates at the current low level. However, experts believe that a noticeable increase in the sub-federal bond volume is unlikely.

2. Tested Hypotheses and Data

The purpose of this study is to identify the key factors influencing the decision of the regional authorities to issue sub-federal bonds. The following hypotheses are tested:

(i) the regional budget deficit increase leads to an increase in the volume of sub-federal bonds;
(ii) the expectations of a key rate cut reduce the volume of sub-federal bonds;
(iii) an increase in the share of the federal budget loans issued to the region reduces the volume of the regional bonds;
(iv) an increase in the level of the regional budget debt burden reduces the volume of the regional bonds;
(v) the higher the level of the regional economic development, the greater the volume of the regional bonds (since it is easier for more developed regions to place bonds).

The following indicators were used to test the above hypotheses:
- the Russian region’s valid bond volume at the beginning of the month, thousand rubles;
- the volume of the Russian region’s budget deficit (surplus) at the beginning of the month, million rubles;
- the level of the Bank of Russia key rate at the end of the month, %;
- the budget loan proportion of the Russian region’s debt at the beginning of the month, %;
• the level of the Russian region’s debt burden (the ratio of the public debt volume and the volume of tax and non-tax revenues of the regional budget) at the beginning of the month, %;
• the average per capita cash income in the Russian region at the beginning of the month, rubles;
• the number of employed in the Russian region at the beginning of the month, a thousand people.

We used monthly data for 85 regions (constituent entities of the Russian Federation) for the period 2015–2019. Data on the regions’ valid bond volumes, the amount of the regions’ debt, the number of budget loans received by the regions were taken from the official website of the Ministry of Finance of the Russian Federation [4]. Data on the volume of the Russian regions’ budget deficits (surpluses) and the amount of tax and non-tax revenues of regional budgets were obtained from the site “Open Budget of the Moscow Region” [5], and also from the site “Open budget of the Saratov region” [6].

Data on the Russian regions’ debt burden levels were taken from the Single portal of the budget system “Electronic budget”, the section “Budget” subsection “Public debt” [7]. The debt burden indicator was assessed as the ratio of the region’s state debt to the budget annual income, excluding gratuitous receipts.

Key rate data was taken from the official website of the Central Bank of the Russian Federation [8].

To incorporate the regions’ economic development levels in the model, we used data on average per capita cash income, as well as the number of employed by regions, which were taken, respectively, from the sites of the Open Budget of the Saratov Region [9] and the Open Budget of the Moscow Region [10].

3. Literature Review

Different aspects of bonds as public debt instruments have been discussed in the economics and finance literature. S. Valseth is exploring price discovery in government bond markets using Norwegian data including trades from both tiers of the market and dealer identities [11]. S. Annisa, M. Combo, and A. Afaf are investigating the issuance of regional bonds and the risk of public bonds registration in Indonesia [12]. Lots of studies are devoted to government bond returns factors (see, e.g., [13–15]).

A few studies are devoted to the optimization of public bond issues. A. Adamo, et al. described an optimization model for the issuances of Public Debt securities to determine the composition of the monthly issued portfolio which minimizes a specific “cost function” [16]. A. Consiglio and A. Staino proposed a multistage stochastic programming model to select portfolios of bonds, where the aim of the decision-maker is to minimize the cost of the decision process [17]. In their model, sovereign states issue fixed and floating securities to fund their public debt. The value of such portfolios strongly depends on the fluctuations of the term structure of interest rates.

M. Bernaschi, et al. are looking for an optimal strategy for the issuance of Public Debt securities using methods employed for the generation of possible scenarios for term structure evolution [18]. The basic idea was to split the evolution of each rate into two parts: the component driven by the evolution of the official rate and the component represented by the fluctuations having a null correlation with the official rate.

A. Shadrin discusses the situation in Russia’s municipal and sub-federal debt market in 2018 [19]. The role of Russian regions bonds in funding the regional debt is being assessed by A. Yakunina and Y. Semernina [2]. The authors show that the importance of sub-federal bonds as a funding instrument for the Russian regions’ debt on average has grown over the last few years.
Table 1. Statistical indicators used (all observed at the beginning of the month)

| Variable | Indicator                                                                 |
|----------|---------------------------------------------------------------------------|
| RBV      | Regional (sub-federal) bond volume, 1000 rubles                            |
| BLP      | Budget loan proportion, %                                                 |
| KR       | Key rate (refinancing rate), %                                            |
| ACCI     | Average per capita cash income, rubles                                    |
| DL       | Debt level (public debt/volume of tax and non-tax revenues), %            |
| RBS      | Regional budget surplus, million rubles                                   |
| EMPL     | Employed, 1000 people                                                     |

However, this growth is uneven across periods and regions – most regions are increasing the issue of bonds, but there are also those that refuse to use a bond to fund regional debt. However, this study did not estimate the effects that different factors have on the issued sub-federal bond volume.

4. Model Description and Results

Panel data comprises 85 regions of Russia (not all at the top level of territorial hierarchy) with time ranging from January 2015 to April 2020 (64 months). The indicators used are represented in table 1, the corresponding summary statistics in table 2.

Table 2. Summary statistics of input data

| Statistic | N   | Min | Median | Mean     | St. Dev.  | Max     |
|-----------|-----|-----|--------|----------|-----------|---------|
| RBV       | 5,440 | 0   | 0      | 5,803,268,000 | 11,796,174,000 | 111,255,238 |
| BLP       | 5,440 | 0.000 | 50.419 | 51.655 | 27.962 | 100.000 |
| KR        | 5,440 | 6    | 9      | 9.324     | 2.454 | 17 |
| ACCI      | 5,100 | 5,223,000 | 26,332,500 | 29,742,540 | 12,952,260 | 150,843,000 |
| DL        | 5,133 | 0.000 | 55.360 | 55.137 | 34.171 | 230.190 |
| RBS       | 5,097 | −67,511,000 | 303,900 | 4,782,966 | 24,254,230 | 381,541,200 |
| EMPL      | 5,434 | 19.130 | 555.690 | 849.577 | 960.401 | 7,294,200 |

The response variable RBV takes on 51.4% zero values, so in view of subsequent use of models for zero-inflated count data, it was transformed to integers according to the following formula:

\[ RBV_{\text{rnd}} = \text{round}(RBV/10^5). \]

Such a transformation induces some loss of precision, including 16 observed values of RBV, equal or smaller to 1 thousand rubles, which were mapped to zero. However the relative error of approximation decreases with increasing RBV to 0.04%. The transformed RBV features 51.9% zero values with the maximum of 1113.

The study of distributions of six predictor variables BLP, KR, ACCI, DL, RBS, EMPL showed high positive asymmetry of ACCI, EMPL and DL; therefore the first two were log-transformed (logACCI, logEMPL), and DL was square-root transformed (sqrtDL). The distribution of RBS, which takes on both positive and negative values, has very heavy tails, so we decided to transform it with the “signed fourth root” function:

\[ \text{transRBS} = \text{sgn}(RBS) \left( \text{sgn}(RBS) \right)^{1/4}, \]
which has roughly symmetric distribution without outlying values. The composite scatter plot of variables RBVrnd, BLP, KR, logACCI, sqrtDL, transRBS, logEMPL, which were used in subsequent modeling is shown in figure 1. The upper row contains scatter diagrams of response RBVrnd vs. each predictor.

The first approach to model RBVrnd values consisted in modeling of indicator variable $RBVnz = 1$ if $RBVrnd > 0$, otherwise $RBVnz = 0$. Generalized linear model (GLM) for panel data with binomial family, logit link and random intercept for the regions was used. The Model 1 was estimated with `pglm` function of `pglm` contributed package [20] of R package for statistical computing and graphics [21]. This and subsequent models were estimated using maximum likelihood method.

Visual inspection of the RBVrnd values suggests addition of a dummy regressor – indicator for December 2018, characterized by massive sub-federal bonds issuing by most regions (Model 2). The results of estimation of Models 1 and 2 are shown in table 3.

Comparison of the Models 1 and 2 with `AICtab()` function of `bbmle` package [22] shows advantage of Model 2 with AIC 245.7 less and a highly significant positive estimate of D201812 coefficient.

As the range of models estimable in `pglm` package doesn’t include models with zero inflated response distribution and AR(1) dependence structure in random effects, thereafter we used `glmmTMB()` function of the eponymous package [23]. This choice was determined by a wide range of estimable models, including various zero-inflation models and correlation structures of random effects, high computing speed, availability of random factors’ individual values estimates, and compatibility with `DHARMa` package (see further).

The Model 3 is similar to Model 2 but is estimated with `glmmTMB()` function (table 3). Model 3 has the lowest AIC which is by 73.2 less than that of Model 2. We note also that Model 3 has much larger standard deviation of the region-specific random intercept $\sqrt{60.844} \approx 7.8$ comparing to that of Models 1 and 2 (parameter sigma about 5.5), while coefficient of logACCI loses its significance.

In order to assess Model 3 adequacy we use `DHARMa` package [24]. The corresponding diagram, cf. figure 2 shows reasonable fit.

We tried also a model similar to Model 3 containing random effects both for region and time, but it’s AIC was by 1.4 higher than that of Model 3.
Table 3. Response RBVnz: Models 1, 2 estimated with pgls, Model 3, 4 with glmmTMB

|              | Model 1    | Model 2    | Model 3    | Model 4    |
|--------------|------------|------------|------------|------------|
| (Intercept)  | -32.057*** | -27.792*** | -29.865*** | 16.312     |
|              | (3.410)    | (3.729)    | (7.936)    | (41.461)   |
| BLP          | -0.069***  | -0.100***  | -0.087***  | -0.078     |
|              | (0.004)    | (0.006)    | (0.007)    | (0.065)    |
| KR           | -0.478***  | -0.550***  | -0.575***  | -5.231***  |
|              | (0.039)    | (0.045)    | (0.051)    | (1.258)    |
| logACCI      | 2.067***   | 1.676***   | 0.966      | -0.653     |
|              | (0.271)    | (0.297)    | (0.509)    | (3.447)    |
| sqrtDL       | 0.548***   | 0.873***   | 1.012***   | 0.550      |
|              | (0.042)    | (0.058)    | (0.128)    | (0.768)    |
| transRBS     | 0.007      | 0.011      | 0.022      | -0.115     |
|              | (0.012)    | (0.013)    | (0.015)    | (0.160)    |
| logEMPL      | 2.296***   | 2.103***   | 3.587***   | 1.821      |
|              | (0.128)    | (0.126)    | (0.850)    | (1.766)    |
| sigma        | 5.748***   | 5.435***   | -          | -          |
|              | (0.272)    | (0.266)    | -          | -          |
| D201812      | -          | 9.527***   | 11.103***  | 37.927***  |
|              |            | (0.857)    | (1.004)    | (6.513)    |

Coefficients with $p < 0.05$ in **bold**.

Figure 2. DHARMa adequacy assessment for Model 3
In general all variables being modelled are slowly varying, which suggests introduction of lagged dependent variable as a predictor or some form of covariance between time-specific values of random effects. This leads to Model 4, similar to Model 3 but featuring homoscedastic random effects with AR(1) covariance structure (table 3). Model 4 is radically different from Model 3: all predictor variables excluding KR and D201812 have non-significant coefficient estimates, while the standard deviation of random effects increased more than twenty-fold: \(\sqrt{4890.591} \approx 221.2\) (the same estimated variances for months 3 – 59 are omitted). Inter-temporal correlation, which equals autoregressive coefficient is about 0.99 (not shown in the table). This suggests that the decision to issue sub-federal bonds (of any non-zero volume) is governed mainly by some slowly varying region-specific factors, and is also (negatively) influenced by Central Bank of Russia’s Key Rate and positively by an unknown country-wise factor specific to December 2018. Comparison of AICs for Models 1–4 shows that the latter is much better than all the former ones: AIC for Model 4 is less by 948.2 than that for Model 3. DHARMa adequacy tests for model 4 show reasonable fit.

Modeling of the (scaled and rounded) Region’s Bond Volume, RBVrnd requires a combination of two mechanisms: the first one sets if zero or non-zero volume of bonds will be issued by a region during a specified month; the second determines the volume itself provided that it is non-zero. The first mechanism can be reasonably described by Model 4, while the second one requires a distribution for discrete random variate taking on the values 1, 2, etc. A popular candidate is truncated Poisson distribution:

\[
\Pr (Y = y) = \frac{e^{-\lambda} \lambda^y}{(1 - e^{-\lambda}) y!}, \quad y = 1, 2, \ldots
\]

The combination (mixture) of two mechanisms is called Poisson hurdle model or zero-inflated Poisson model (see, for example, [25]).

The glmmTMB package features truncated poisson family of distributions which permits to estimate corresponding Model 5 (table 4). Using the experience of building previous models as a basis, for this model we set up predictors for zero-inflation and count process of exactly the same form, including six predictors used in the former models, and AR(1) covariance structure for time-specific random effects. The “zero model” part of Model 5 incorporates “inverted version” of Model 4: while the latter predicts issuance of any non-zero volume of bonds, the former predicts zero volume. This feature is reflected in mirroring values of all coefficients’ estimates, apart from a small computational error. For example, the KR coefficient in Model 4 is -5.231, while in the “zero model” part of Model 5 it is 5.231. The “count part” of Model 5 has much smaller standard deviation of random effects, \(\sqrt{0.982} \approx 0.99\), and the random effects are also slowly varying: first-order autocorrelation, which equals AR(1) coefficient, is about 0.984. DHARMa adequacy test for Model 5 (figure 3) shows a strange pattern on the right-hand side of the plot, but, to our opinion, it is due to the nature of the model – the residuals for two different parts of the Model 5 being combined.

As table 4 suggests, various predictors have non-significant coefficients, even with p-values very close to 1. Consequently we tried to exclude them from the model. But a number of similar models with reduced set of predictors all have larger value of AIC criterion, that is why we left the initial model.

One of the very convenient features of glmmTMB package is the possibility to estimate individual values of random effects. Such effects from Model 4 and 5 for Saratov region are shown in figure 4. As was noted before, the coefficients of zero-inflation part of Model 5 are reversed with respect to those of Model 4, and so individual values of random factors. We use the latter from Model for due to more convenient interpretation. As can be seen from figure 4, for Saratov region, the opportunities to issue sub-federal bonds enlarged gradually up to November 2017 and expanded rapidly in December. After attaining maximum in February 2019 they began
Table 4. Response RBVrnd: Model 5 estimated with glmmTMB

| Model 5 |  |
|---|---|
| Count model: (Intercept) | 0.373 |
| | (0.786) |
| Count model: BLP | −0.004*** |
| | (0.001) |
| Count model: KR | −0.001 |
| | (0.010) |
| Count model: logACCI | 0.004 |
| | (0.030) |
| Count model: sqrtDL | 0.019 |
| | (0.019) |
| Count model: transRBS | −0.002 |
| | (0.001) |
| Count model: logEMPL | 0.564*** |
| | (0.102) |
| Count model: D201812 | 0.390*** |
| | (0.029) |
| Zero model: (Intercept) | −16.318 |
| | (41.462) |
| Zero model: BLP | 0.078 |
| | (0.065) |
| Zero model: KR | 5.231*** |
| | (1.258) |
| Zero model: logACCI | 0.653 |
| | (3.448) |
| Zero model: sqrtDL | −0.550 |
| | (0.768) |
| Zero model: transRBS | 0.115 |
| | (0.160) |
| Zero model: logEMPL | −1.821 |
| | (1.766) |
| Zero model: D201812 | −37.928*** |
| | (6.514) |

AIC: 20159.511
Log Likelihood: −10059.755
Num. obs.: 4879
Num. groups: region 85
Var (count model): region monthmonth2 0.982
Var (count model): region monthmonth60 0.982
Var (zero model): region monthmonth2 48909.636
Var (zero model): region monthmonth60 48909.636

Coefficients with $p < 0.05$ in **bold**.
to contract. The lower plot indicates a peak of issued bonds volume in December 2018 more pronounced than peak characteristic to most regions and modeled by indicator dummy D201812.

![Figure 3. DHARMa adequacy assessment for Model 5](image)

![Figure 4. Model 4’s and Model 5’s estimated random effects for Saratov region](image)

Formatting of the models was done with texreg package [26]. The data and commands for its exploration and transformation, followed by complete modeling and presentation steps are available at [https://github.com/alxymitr/regional-bonds-Russia.git](https://github.com/alxymitr/regional-bonds-Russia.git).

5. Conclusions

Our main aim was to try to elucidate the process of sub-federal bonds issuing based on panel data on Russia’s regions. The data on the response variable – Regional Bond Volume (RBV) includes more than a half of zero values, suggesting the use of a model consisting of two parts: the first one predicting the probability of any non-zero RBV volume, the second one predicting the volume itself provided it is positive.

In our opinion, ordinary regression analysis (for panel data), trying to predict condition \( RBV > 0 \) and \( RBV|RBV > 0 \) using a limited set of predictors, such as Budget loan proportion, Key (Refinancing) rate, Average per capita cash income, Debt level, Regional budget surplus, Employed hardly lets us get closer to the goal. Sure enough, there exist some dependencies between RBV and these factors, and the regression model reproduces them as much as possible, but clearly, regression coefficients don’t reflect a two-subject (the region’s government and the Central Bank of Russia) decision process, leading to the stated RBV.

So we decided to change the approach to modeling starting to consider models with slowly varying region-specific latent factors. From the technical point of view it required introduction of inter-temporal dependence for each region-specific latent factor. This approach was supported by the possibility given by software used to estimate individual values of these latent factors. In fact, the final model constructed for each region gave separate estimates of such factors, one predicting condition \( RBV > 0 \), another predicting \( RBV|RBV > 0 \). As a result of introduction of latent factors, the set of predictors, having a meaningful additional impact on RBV, considerably reduced.

For the non-zero volume of RBV these are Key (Refinancing) Rate of Central Bank of Russia, influencing negatively, and time-specific factor of December 2018, influencing positively.
For the volume of RBV provided it is positive, these are Budget Loan Proportion (the share of budget loans in the structure of the state debt of the regions) (influencing negatively), the size of region’s economy, measured by logarithm of Employed and the same time-specific factor of December 2018 (both positively).

The negative dependence to issue non-zero volume of regional bonds might reflect the regions incentive to reduce current cost of borrowing.

As for the time-specific factor of December 2018, it can be explained by the fact that 2018 was the first full year of implementation of budget loans restructuring agreements between the Russia Ministry of Finance and most Russian regions achieved in 2017. Since 2018, the Federal Ministry of Finance has stopped issuing long-term budget loans. The restructuring program participants are required to reduce the debt burden by about 2% per year.

The vast majority of Russian regions tried to meet the restructuring terms and reduced debt at the end of 2018. The total debt of all Russian regions for the year decreased by 5% or 109 billion rubles. The share of budget loans in the regions’ debt began to decline. This is due to the repayment of existing restructured loans (5% each in 2018 for program participants) and the termination of issuing new ones. The debt on all budget loans decreased by 7%. Also, the regions’ total debt to banks decreased by 5%. At the same time, debt on bonds increased by +0.5% [27]. This change in the structure of regional debt in favor of bonded loans meets the federal requirements of the procedure for the regional finance management quality assessment, which assigns a higher rating to regions with a balanced debt repayment schedule.

At the same time, experts suggest that the regions traditionally borrow to finance the budget deficit at the very end of the year. In December 2018, the total debt burden of the regions increased by 7.4% [28]. 68 regions increased the volume of the regional bonds in December 2018.

The negative influence of Budget Loan Proportion is possibly explicable by the fact that regions having access to the most beneficial budget loans have less incentives to use regional bonds as a financing instrument.

The hypothesis (1) stated above that the regional budget deficit increase leads to an increase in the volume of sub-federal bonds is not confirmed – the dependence on RBS is weak for \( RBV > 0 \) as well as for \( RBV \mid \text{RBV} > 0 \).

The hypothesis (2) that the expectations of a Key rate cut reduce the volume of sub-federal bonds remains unclear due to the absence of data on these expectations; the Key Rate itself influences negatively the condition \( RBV > 0 \), but not the positive volume of RBV itself.

The hypothesis (3) that an increase in the share of the federal budget loans issued to the region reduces the volume of the regional bonds is confirmed.

The hypothesis (4) that an increase in the level of the regional budget debt burden reduces the volume of the regional bonds is not confirmed – no significant dependence on the Debt level was found.

The hypothesis (5) that the higher the level of the regional economic development, the greater the volume of the regional bonds is confirmed.

Rounding the response variable RBV allowed to use models for count data at the cost of a small loss of accuracy. The hurdle models, typical for ecological statistics [25], offer interesting possibilities to reveal details of decisions, underpinning issuance of sub-federal bonds in Russia, and, possibly, are applicable in many similar situations. The key here is the possibility to estimate slowly-varying region-specific random effects. More traditional GLMs for panel data with random intercepts give not easily interpretable results. In line with remarks in [29], the generalized linear mixed models offer valuable extension to traditional econometric toolbox. An attempt to simplify the model by elimination of predictors with non-significant coefficients did not succeed, as AIC criterion growd, which requires further study.

Areas of further research include: 1) testing/adding spatial dependence structure for random factors; 2) using more detailed data on the process of issuing regional bonds.
References

[1] Syrbu A P, Dmitrieva E V and Ya O Z 2018 Sub-federal bonds: is the game worth the candle? *Quest. Mod. Sci. Pract.* **67** 86–95
[2] Yakunina A V and Yu V S 2020 Sub-federal bonds as a tool for financing the state debt of Russian regions *Bulletin of the Saratov Soc. Econ. Univ.* **82** 149–53
[3] Pershin M and Anisimova E 2020 Regional bond market: reasons for stagnation
[4] State debt of constituent entities of the Russian Federation and municipalities 2020
[5] Open budget of the Moscow region 2020
[6] Open budget of the Saratov region 2020
[7] State debt of the Saratov region 2020
[8] Refinancing rate of the Central Bank of the Russian Federation 2020
[9] Monthly monitoring of socio-economic development (in the context of RF subjects) – Saratov region 2020
[10] Monthly monitoring of socio-economic development (in the context of RF subjects) – Moscow region 2020
[11] Valseth S 2013 Price discovery in government bond markets *J. Fin. Mark.* **16** 127–51
[12] Annisa S, Rahmaawati M and Alaf A 2019 Prosperity of the process and issuance of regional bonds and risk of public bonds registration in indonesia *Notaire* **2** 89–110
[13] Boubaker S, Nguyen D K, Piljak V and Savvides A 2019 Financial development, government bond returns, and stability: international evidence *J. Int. Fin. Mark. Instit. Mon.* **61** 81–96
[14] Zaremba A and Schabek T 2017 Seasonality in government bond returns and factor premia *Res. Int. Bus. Fin.* **292**–302
[15] Sola S and Palomba G 2016 Sub-nationals’ risk premia in fiscal federations: Fiscal performance and institutional design *J. Int. Mon. Fin.* **63** 165–187
[16] Adamo A et al 2004 Optimal strategies for the issuance of public debt securities *Int. J. Theor. App. Fin.* **7** 805–22
[17] Consiglio A and Staino A 2012 A stochastic programming model for the optimal issuance of government bonds *Annals of Oper. Res.* **159**–172
[18] Bernaschi M, Briani M, Papi M and Vergni D 2007 Scenario-generation methods for an optimal public debt strategy *Quantitative Finance* **7** 217–29
[19] Shadrin A 2019 Russia’s Municipal and Sub-Federal Debt Market in 2018 *Russian Econ. 2018. Trends and Outlooks* 156–74
[20] Croissant Y 2020 Pglm: Panel generalized linear models
[21] R Core Team 2020 *A language and environment for statistical computing* (Vienna: R Foundation for Statistical Computing)
[22] Bolker B and R Development Core Team 2020 bbmle: tools for general maximum likelihood estimation
[23] Brooks M E, Kristensen K, van Benthem K J, Magnusson A, Berg C W, Nielsen A, Skaug H J, Maechler M and Bolker B M 2017 GlmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling *The R J.* **9** 378–400
[24] Hartig F 2020 DHARMa: Residual diagnostics for hierarchical (multi-level / mixed) regression models http://florianhartig.github.io/DHARMa/
[25] Zuur A, Ieno E, Walker N, Saveliev A and Smith G 2009 Mixed Effects Models and Extensions in Ecology with R Springer Science+Business Media
[26] Leifeld P 2013 Texreg: Conversion of statistical model output in R to LaTeX and HTML tables *J. Stat. Software* **55** 1–24
[27] Anisimova E S 2019 Regional debts – 2018: key trends and figures
[28] State debt of Russian regions: results of 2018 2019
[29] Croissant Y and Millo G 2008 Panel Data Econometrics in R: The plm Package *J. Stat. Software Articles* **27** 1–43