Forecasting tax revenues in an emerging economy: The case of Albania

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Abstract

Fiscal balance is one of the main concerns of fiscal policy. Although academic and political choices on budget deficit vary due to perspective differences, improving the quality of revenue and expenditure forecasting has become prominent. The seminal researches on this topic present that tax revenue forecasts suffer from high positive biases. As tax forecasts have chain implications on the expenditures side as well, this might lead to high unexpected deficits. According to the IMF 2016 country report on Albania, emerging market economies are suffering higher than advanced ones in tax revenue forecasting. The aim of this paper is to implement new forecasting models and to apply forecast combinations for Albania, where forecast errors are higher than average. The estimation results show that influence of internal and external factors on tax revenue forecasting create a significant improvement on tax revenue accuracy. The estimations and forecast combinations of this paper perform lower errors than official forecasts, which indicate that revision of tax forecasting methodology can increase the accuracy of predictions for emerging market economies.

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1. Introduction

In the simplest form, budgetary process contains two building blocks: 1. Forecasting the revenues. 2. Allocating the revenues to expenditures. Taxes are primary source of budget revenues. If government expenditures go beyond the revenues, government appeals to finding new sources such as borrowing, increasing taxes, privatization of public sector assets. History of modern economics is full of lessons which prove that resort to this alternative revenue sources can create various complications and may have negative impact on economy. The analysis of budget deficit may vary according to schools in economic thought, the ideology of the ruling party etc. Yet, avoiding miss-estimations, or narrowing the forecasting errors have crucial importance to policy makers in decreasing uncertainty in tax and expenditure side; regardless of abovementioned variables.

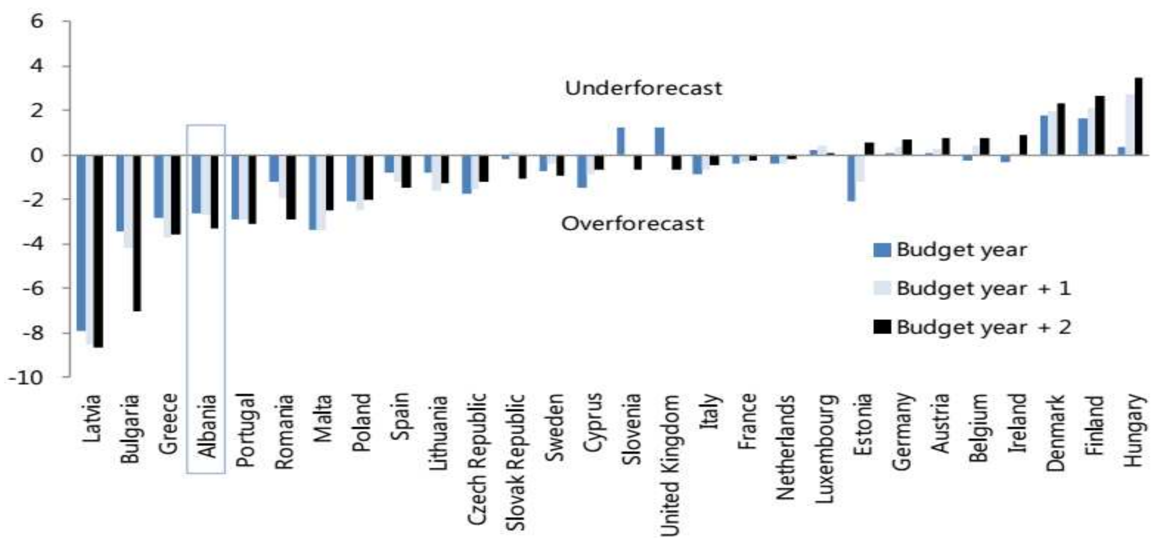
Fiscal policy rules are key elements of fiscal policy. Designing a set of prosperous fiscal policy rules requires forecast accuracy of the budget, particularly of tax revenues. Tax revenue forecasting is an important element in designing fiscal policies as they give us a perception of what fiscal actions are sustainable over the longer term. Given the role played by fiscal forecasts in policymaking as mentioned by Leal et al (2008), ex-ante forecasts pointing to risks in public finances might prompt corrective actions resulting in an ex-post fiscal outcome completely different than initially planned, so tax changes might be suggested in the case of tax forecasts.

Tax revenue forecasting remains an important issue in many developing countries. Though it has not been studied a lot in the literature compared to the issues of GDP forecasting, its effects are of utmost importance in developing countries. Several researchers conducted researches on this field and concluded that under or over-prediction of tax revenues in government budgets persisting over a period of years has emerged as a problem both in developed and developing countries. Institutional weakness, technical errors, inefficient tax administration are listed as a source of high forecast errors. Leal et al (2010), confirm the same results, by bringing evidence of the existence of the political and institutional bias in revenue forecasting in the case of the European countries. This happens more in the countries where the minister of finance has strong discretionary powers and can adjust the budgetary totals in the course of the budget cycle.

With reference to political budget cycle literature Strauch et al (2004), explain, that if voters see higher targets, and they believe these forecasts about the health of the economy and of the state of the budget, they will think the government is doing well and they would continue to vote for government. Forecasting higher tax revenues would allow the governments to increase the expenditures during election years, by maintaining the same level of the deficit. Leal et al (2008), revising revenue forecasting literature, find that optimistic budget forecasts, which might come from overestimating tax revenues forecasts, are worst in terms of budget balance projections than when we have an underestimation of tax revenues.

Beyond the valuable arguments above, setting up a precise tax revenue forecast is a tough task. It requires to take into account a wide set of variables, from the most basic macroeconomic variables to fiscal policy, tax structures and possibly people's behavior towards uncertainty. This paper addresses these questions. Together with omitting the reason of biases this paper focuses to improve the forecasted revenues. In order to improve tax revenue forecasting in developing countries, different estimators and combination of estimates are used in a small open or transition economy. In our paper, Albania has been chosen as a country case because Albania's average medium-term revenue forecast errors were among the highest among the EU member and candidate countries during the period 2002–12, as shown by the IMF country report on Albania (2016) report on fiscal transparency evaluation in Figure 1.

Figure 1: Revenue forecasts errors in selected EU countries, (2002–12, %)



Source: IMF country report on Albania 2016.

Over the past decade, revenue forecasts errors for Albania have been consistently optimistic. Budget-year forecast revenue errors averaged −3.0 percentage points, which was the highest amongst the countries shown in the figure. This high revenue forecast errors make Albania an interesting country in experimenting different forecasting techniques and methods as we will show in the following sections. Main motivation of paper is to beat the official ministry forecasts and prove that only with technical improvement inaccuracy can be lowered.

The paper is organized as follows. Section 2 reviews the literature about forecasting techniques applied on tax revenues by different countries. Section 3 presents the theoretical framework, the methodology of this paper, and gives a description of the data used. Section 4 presents the empirical results and analysis. Finally, in section estimation and combination results are discussed together with research question.

2. Literature review

There is a growing literature on tax revenue forecasting, more on advanced economies than emerging ones. An important work on the forecasting of tax revenues, Jenkins et al (2000), identify several methods on how to forecast tax revenues starting from macro-foundations methods, tax elasticity, tax buoyancy, GDP based models, and micro-simulation techniques. On the Eurozone, Favero and Marcellino (2005) use ARMA models, VAR(s), small scale structural models and pooling to forecast fiscal variables, where they find that forecasts based on simple time-series models or pooled forecasts outperform forecasts based on multivariate time-series or semi-structural small models for fiscal variables. Keene and Thompson (2007) revise the tax revenue models used by New Zealand Treasury and conclude that simple benchmark models where tax revenue is expressed as a product of a tax ratio and a suitable macroeconomic variable regarded as a proxy for the tax base are the best models that are adopted. Koester and Priesmeier (2012) suggest a dynamic approach evaluating the long run and short run elasticities through a two-step (2S) regression method based on an error correction method (ECM) to improve German tax revenue forecast. Error correction models are also used by Corvalão et al (2010) in specific tax revenues forecasting such as the VAT in the state of Santa Caterina in Brazil, by Rudzkis and Maciulaity (2007) in profit tax revenues forecasting in Lithuania, by Zhang and Ciui (2008) in total tax revenues forecasting in China etc. Krol (2010) sees the using of the Bayesian methods on a vector autoregression, showing superiority in forecasting compared to random walk forecasts and simple VAR(s), as more appropriate for forecasting German tax revenues. Fullerton (1989) examines the effectiveness of composite forecasting of sales tax revenues in Idaho, creating a linear combination of an econometric model forecast and Box-Jenkins univariate ARIMA technique. Using quarterly frequencies, Pedregal et al (2014) develop a temporal aggregation model to forecast Spanish central government components including tax revenues. In the case of Ireland, Hannon et al (2015) sum up the forecasting procedure of tax revenues by taking into account one-off factors of current and upcoming year, projected next year growth as appropriate macroeconomic driver, and policy changes projected to happen next year, adding a judgement factor. The forecasting of tax revenues seems to be more problematic on emerging economies, where, according to Kyobe and Danninger (2005), the forecasting methods on low-income countries consist 83.9% in basic extrapolations as main forecasting method, and only 12.9 percent of their sample of 34 low-income countries use econometric methods. On other transition countries such as Croatia, Botrić and Vizek (2012) argue that alternative econometric models such as trend model, random walk model, ARIMA model and error correction models should be used for forecasting each component of tax revenues. Forecasting government revenues for Nepal, Koirala (2012) finds seasonal ARIMA and Winter method (Winter (1960) as appropriate for forecasting government revenues. The Exponential Smoothing Holt-Winters (2004) method is also used as a suitable tool for forecasting revenues (and budget items) for Latino-American countries and the Caribbean mentioned by Cepal (2015). Alamdari et al. (2016) show that using non-linear methods such as neural networks approach gives minimal errors in forecasting tax revenues for the case of Iran. Jensen et al. (2015) revise Albanian tax revenue forecasting methodology, where for each tax, the current year tax revenue is grown by real growth in GDP and the change in the GDP Deflator. In addition, if there has been a change to the tax laws, the revenue impact is calculated separately and added to the expected future revenues and each year are taken into account tax administration efficiency improvements. Other Authorss such as Coulharde et al (2010), using mainly simple regressions and ARIMA(s) which take into account the tax bases for each tax, prefer forecasting Albanian tax revenues through a bottom-up approach tax by tax.

3. Theoretical framework

3.1. Modelling Albanian Tax revenues

In modelling the Albanian Tax revenues and finding the most adequate forecast, we start using the simplest approach, the Random Walk model, and then move forward to more complicated models. Finding the best models for the exchange rate, Meese and Rogoff (1983) on their empirical study came up the conclusion that most structural and time series models fail to beat the Random walk forecast. The Random Walk forecast has always been used as a benchmark or a comparing model since then. Our Random Walk model would be:

$Y_t = Y_{t-1} + \in_t$ Equation (1) $\in$, is a stationary random disturbance term.

The series has a constant forecast value, conditional on t and the variance is increasing over time. As Cepal (2015) mentions, another method suitable for forecasting revenues (and budget items) is the Exponential Smoothing Holt-Winters (2004) method, which can be used when forecasting a series that can be modelled as a time trend, with a constant term and the time-slope varying over time and exhibiting local trends. The two types of Holt-Winters method we use are the Holt-Winters—Multiplicative method (three parameters) and the Holt-Winters—Additive (three parameter).The Holt-Winters—Multiplicative method would be expressed:

$y_{t+k} = (a + bk)c_{t+k}$ Equation (2) Where a is permanent component or intercept, b is the trend, c_t multiplicative seasonal factor.

The Holt-Winters—Additive method would be expressed:

$y_{t+k} = a + bk + c_{t+k}$ Equation (3) Where a and b are permanent component and trend, while c is the additive seasonal factor.

The Error Correction Models are another possibility for forecasting tax revenues although not widely used on this area:

$\ln TAX_{it} = \sum_{j=1}^{p} \emptyset_{ij} lnTAX_{i,t-j} + \sum_{j=1}^{p} \theta_{ij} lnGDP_{i,t} + \varepsilon_{it,}$ Equation (4)

Where TAX_{it} denotes tax revenue in type i in year t, and GDP stands for the level of GDP and $\varepsilon_{it}$is the error term. For estimation purposes we further transform the equation 4 in:

$\Delta ln\, TAX_{it} = \mu_i(ln\, TAX_{i,t-1} - \beta_i lnGDP_{i,t-1)} + \theta_{i,0\theta} \Delta lnGDP_{i,t} + \varepsilon_{it}$ Equation (5)

Where $\beta_i = -\frac{\theta_{i,0}+\theta_{i,1}}{\mu_i}$ and $\mu_i = -(1-\theta_{i,1})$, where θ is the short term elasticity, β the long term elasticity, μ is the speed of adjustment of the growth in tax revenue to its long term growth rate.

Vector autoregressions (VARs) and Bayesian-vector autoregressions (BVARs) are another type of model we use in forecasting the Albanian tax revenues, where our basic VAR specification would be:

$$Y_t = c + A(L)Y_{t-1} + e_{t,} \qquad E\{e_t e_t'\} = \sum e \qquad \text{Equation (6)}$$

Where *y* contains *n* variables and *p* lags in the VAR. Initially our variables will be Tax revenues and GDP_nominal_sa. Moving forward with the VAR specification as Litterman (1986) says, the use of the Bayesian approach to VAR allows for interaction between variables and flexible specification of how likely we believe the interaction does exist, therefore we will use Bayesian methods to estimate our vector autoregression. Following a similar approach as Box-Jenkins (1994), we will use the autoregressive integrated moving average forecasting (ARIMA), where according to Newton (1999) we need at least 50 observations long to forecast revenues with this method. ARIMA model can be useful to understand how exogenous shocks of one period *t* affect the future outcomes. When the method deals with quarterly or monthly data seasonal effects are to be considered turning the method into a Seasonal ARIMA. The general form of the ARIMA model for forecasting Albanian Tax revenues would be:

$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q} \qquad \text{Equation (7)}$$

ϕ and θ represent respectively the effects of the AR and MA terms. Initially, we take into account our ARIMA domestic explanatory factors such as the nominal GDP, the total imports of goods, inflation and the Bank of Albania Economic Sentiment Index. On a more advanced second step, as most of the econometric models we have seen rely solely on domestic information, they do not take into account any external or globalization effects that might come and influence the tax revenue realization. Fioramanti et al (2016) raise the question that to what extent projection errors are due to external assumptions that *ex post* turn out to be different. To answer this question, we also take into account external factors related to globalization effects when forecasting Albanian tax revenues. The globalization effects in our models ARIMA and VAR is introduced through taking into account for variables effects such as: (i) the LEK/EURO exchange rate, (ii) Brent oil prices and the (iii) GDP in the main EU partners[1] (on imports side). As seen by Jenkins et al (2000), one approach to forecast tax revenues is to forecast each of its components by taking into account each tax base and then aggregate them. Disaggregating the Albanian tax system revenues, we would have 6 main group of taxes: 1. VAT tax revenues divided into vat collected from tax Authorsities and from custom Authorsities, 2. Custom duties, 3. Excises, 4. National taxes, 5. Profit tax and 6. Personal income tax. Coulharde et al (2010), use as explanatory variables in their ARIMA(s) for forecasting Albanian tax revenues 1. For VAT, they consider the consumption of households, the total imports of goods and the VAT rate, 2. For Custom duties, they consider custom tariffs and the total imports of goods, 3. For Excises, the imports of fuel and food and alcohol, 4. For national taxes, they consider as tax base GDP, 5. For the profit tax, they consider the payroll and 6. For the Personal income tax, they consider GDP and the Corporate Income Tax rate. We add into their approach also other domestic factors such as the Inflation, the Economic Sentiment Index, dummy variables in the years where main tax changes have happened, and external factors such as the ones mentioned above to be included in the equation 7. In table 6 in the annex, we present the estimations of the 2 best models for each of the specific taxes of the Albanian tax system, aggregating them in two different forecasts for the total tax revenues in the end.

3.2. Combining forecasts

Armstrong (2001), on 30 empirical comparisons of different papers, arrived under ideal conditions on the conclusion that combining forecasts were sometimes more accurate than their most accurate components. When we are uncertain about a situation, which method to use or when we want to avoid making huge forecasts errors, combining forecasts comes to help. What is problem-solving about combining is the fact that it can be done regardless of the different data or method used. Bates and Granger (1969) is considered to be the seminal article on combining forecasts, which inspired Clemens (1989), bringing a review of the literature on combining forecasts and showing that the combination of different forecasts of the same variable improves prediction performance. Combining forecasts, since then, has shown to be

[1] Here are chosen only EU partners such as Italy, Greece, Germany, France and Spain.

practical, economical, and useful. Carabotta and Clayes (2015) bring forward a reason for this prediction performance improvement. The fact that different methods, either econometric techniques or judgement ones, capture different type of errors, averaging them reduces the errors. In the case of combing experts-adjusted forecasts, Dijk and Franses (2016) say that combining or averaging works because: "It is not the way in which experts agree in their judgement, but it is the way that they do not agree that can make the average expert-adjusted forecast to work well." Clements and Hendry (2004) show that combining forecasts adds value, and can even dominate the best individual device if occurs that the forecasting models are differentially miss-specified, and is likely to occur when the DGP[2] is subjected to location shifts. In this case, averaging may dominate over estimated weights in the combination. The effectiveness of forecast combinations in producing accurate forecasts by using evidence from all models rather than using the best single model is also pointed by Timmermann (2006). He also lists key reasons for using forecasts combinations, such as providing hedging against model uncertainty, avoiding the problems of structural breaks and producing robust forecasts against misspecification problems and individual forecasters errors found in the dataset. There are plenty of studies that use combining in forecasting macro-fiscal variables mainly for countries that have large datasets and use different methods for forecasting, such as the US, the OECD countries etc. Combining forecasts is not usually applied in low income countries as they use poor estimation techniques and lack data availability according to Kyobe and Danninger (2005). Marcellino (2004) compares alternative forecast pooling methods and 58 forecasts from linear, time-varying and non-linear models, using a very large dataset of about 500 macroeconomic variables for European Monetary Union countries, and on average, he finds that combination methods work well but single non-linear models can outperform them for several series. Stock and Watson (2004) combine forecasts of output growth in a seven country data set, while Favero and Marcellino (2005) consider and use combinations in modelling and forecasting fiscal variables in the Euro-Area. Ghysels and Ozkan (2015), in making real-time predictions for the US budget, combine MIDAS regressions models and show that combinations provide forecasts gains over the traditional models. Carabotta and Clayes (2015) improve the accuracy of the budget deficit of Italy by combining the forecasts of both private and public agencies over the period 1993-2012. No studies were found regarding combining forecasts for tax revenues; therefore, we try apply this approach for the case of

[2] Data Generating Process

Albania.

Clemens (1989) states that simple averages are found to be the most robust forecast when combining forecasts for macro-economic variables, showing that forecasters on average are right. Stock and Watson (2004) point out the simple combination forecasts, using the simple mean, the simple median and the trimmed mean computed with 5% systemic trimming. Carabotta and Clayes (2015) use, among others, the simple averages mentioned by Stock and Watson (2004), plus the geometric and the harmonic average to combine forecasts for the fiscal deficit of Italy. A combined forecast is a weighted average of the M forecasts:

$$\hat{Y}^{c}_{T+h} = \sum_{i=1}^{M} W_{T,h,i} X_{T,h,i} \qquad \text{Equation (8)}$$

Where $W_{t,h,i}$ is vector of weights, Y_t is the value of Y at time t (today is T), $X_{t,h,i}$ is an unbiased (point) forecast of Y_{t+h} made at time t, h is the forecasting horizon, i = 1,...M is the identifier of the available forecast, M is the total number of the forecasts, $e_{t+h,i} = Y_{t+h} - X_{t,h,i}$ is the forecast (prediction) error, $L(e_{t,h})$ is the loss from making a forecast error, $E[L(e_{t,h})]$ is the risk associated to a forecast, $\hat{Y}^{c}_{T+h}$ is the forecast combination.

The forecast combination “problem” can be formally stated as: Choosing weights $w_{T,h,i}$ to minimize $E[L(e_{t,h})]$ subject $\sum_{i=1}^{M} w_{T,h,i} = 1$. The quadratic form for the loss function is used by Artis and Marcellino (2001), while Granger (1999) highlights that when the loss function is not on this form, then the standard properties of optimal forecasts will not hold. Other loss functions to be taken into account are the Absolute error loss, Linex loss etc. The choosing of the optimal weights to minimize the squared errors loss is not an easy process. Healy and Sandberg (2016) say that it makes sense to (in terms of minimum squared error) to use equal weights: When the variance of the forecast errors, are the same; and all the pair wise covariances across forecast errors are the same; and the loss function is symmetric. According to Stock and Watson (2004) and Smith and Wallis (2009), the equal eights tend to perform better than many estimates of the optimal weights. There are several ways of choosing the optimal weights as such, and one way to achieve this is to “shrink” the optimal weights towards equal weights (Stock and Watson (2004)).

$$\omega^{s}_{T,h,i} = \Psi\, \omega_{T,h,i} + (1-\Psi)(\tfrac{1}{M}), \qquad \Psi = max(0,1 - (\tfrac{kM}{T-h-M-1})) \qquad \text{Equation (9)}$$

Other types of weights would be according to: the relative performance, shrinking relative performance, recent performance, adaptive weights and non-parametric (trimming[3] and indexing).

In combining the produced tax forecasts for Albania, we use methods starting from simple averages to others more complicated ones, such as weighted averages. Our combinations will be: 1) the simple mean averaging method which takes the arithmetic mean of the forecasts at each observation in the forecast sample and gives to each forecast the same weight; 2) the simple median method which calculates the median of the forecasts at every observation in the forecast sample and the implicit (0, 1) weights used will be time-varying[4]; 3) the trimmed mean which is calculated in the same way as the simple mean, but here we drop, from the mean calculation, at each observation the highest 12%[5] and the lowest 12% of the forecast values[6], 4) the geometric average; 5) the harmonic average; 6) the least squares weighting[7]requires knowledge of the true values of the forecasted variable for some of the forecast period and it is calculated by regressing the forecasts against the actual values and then using the coefficients from the regression as weights; 7) the mean square error (MSE weighting, see also Stock and Watson (2004)), compares the individual forecasts with the actual values over some forecast period. The MSE of each forecast is computed and used to form individual forecast weights. Here we will use as discount factor 1 which is the most commonly used power, the produced weights here are based on the ratio of each forecast's MSE to the total of all the MSE-s. 8) MSE ranks[8] method is similar to the mean square errors method outlined above, but rather than computing the ratio of MSE vales, this method computes the MSE of each forecast, ranks them, and then computes the ratio of the inverse of the ranks, so that each forecast's weight is its rank divided by the sum of all ranks.

[3] For trimming, Aiolfi and Favero (2003) recommend ranking the individual models by R^2 and discarding the bottom and top 10 percent.

[4] As each forecast method may be the median for some observations but not others.

[5] 12% is chosen for the reason that this % removes at least best forecast and worst forecast model, since only 18 forecasts series are produced by the models we have chosen.

[6] The selection of which forecasts to remove as part of the trimming is recalculated at each observation in the forecast sample so that the weights are time-varying

[7] See for details Eliot and Timmermann (2013)

[8] For further details see Aiolfi and Timmermann (2006)

3.3. Forecasts evaluations and applied tests

The forecast error can be measured as shown in equation (1):

$where\ FE_t = \hat{Y}_i - Y_i,\ and \quad Bias = \frac{1}{f}\sum_{t=i}^{f} FE_t$ Equation (10)

The smaller the forecast error, the better the work of the forecaster in forecasting. In measuring the forecast quality and accuracy of our models and forecasters, we use following statistics illustrated in the equations 11 – 15, where:

The Standard Error is measured as: $SE = \sqrt{\frac{1}{f}\sum_{i=1}^{f}(FE_t - BIAS)^2}$ Equation (11)

The Mean Square Error[9] as $MSE = \frac{1}{f}\sum_{i=1}^{f} FE_i^2$ Equation (12)

The Root Mean Square Error as $RMSE = \sqrt{\frac{1}{f}\sum_{i=1}^{f} FE_i^2}$ Equation (13)

The Mean Absolute Error[10] $MAE = \frac{1}{f}\sum_{i=1}^{f}|FE_t|$ Equation (14)

Mean Absolute Percentage Error $MAPE = \frac{1}{f}\sum_{i=1}^{f}\left|\frac{FE_t}{Y_t}\right|$ Equation (15)

The Theil's 1 statistic is used to measure forecast accuracy, where $U_1 = 0$, is the best forecast (no observed error) and is shown as:

Theil 1 $U_1 = \frac{\sqrt{\frac{1}{f}\sum_{t=1}^{f}(\hat{Y}_t - Y_t)^2}}{\sqrt{\frac{1}{f}\sum_{t=1}^{f}(\hat{Y}_t)^2} + \sqrt{\frac{1}{f}\sum_{t=1}^{f}(Y_t)^2}}$ Equation (16)

The Theil's 2 statistic, which is a measure of forecast quality and compares the forecast with a benchmark (naïve) method. If $U_2 < 1$, the forecasting technique being used is better than the (naïve) method.

The Theil 2 $U_2 = \sqrt{\frac{\frac{1}{f}\sum_{t=1}^{f}(\frac{\hat{Y}_t - Y_t}{Y_{t-1}})^2}{\frac{1}{f}\sum_{t=1}^{f}(\frac{Y_{t-1} - Y_t}{Y_{t-1}})^2}}$ Equation (17)

The next test we use will be the encompassing test or combination test of Chong and Hendry, (1986); and Timmermann (2006). The idea of this test is whether a single forecast contains all the information included in the other individual forecasts or not, with the scope of seeing if that forecast will be as good as a combination of all the forecasts. The null hypothesis of this

[9] The mean square and absolute error assume a symmetric cost associated with positive and negative forecast errors

[10] Negative errors cannot cancel positive ones, therefore MAE does not limit the size of the error. The MAE, however, does not provide information on the direction of the error (underestimation or overestimation).

test H0 would be: Forecast *i*, includes all information contained in others or the forecaster is as good as the combination of the forecast. The Diebold-Mariano test of Diebold and Mariano (1995) is a test of whether two competing forecasts have equal predictive accuracy. The null hypothesis of this test states that our models perform better than the naïve forecast used as benchmark.

The DM test statistic comes on the following formula representation:

$$S = \frac{\frac{1}{T}\sum_{t=1}^{T}\{g(e_{1t})-g(e_{2t})\}}{\sqrt{\frac{2\pi f(0)}{T}}} \qquad \text{Equation (18)}$$

Where $g(e_{1t})$ and $g(e_{2t})$ are respectively the error functions of each model tested.

As final step we will check the performance of our forecasts through time and see if they capture the tax revenues dynamic trend. To prove this, it comes to help the Wilcoxon signed rank test, which is a non-parametric test and tests the null hypothesis that: H_0: median (E) = 0, where E is our variable of interest. Rejecting the null hypothesis would bring evidence that at first the models might fail at capturing the tax revenue trend.

3.4. The data description

In our study we will use mainly quarterly data, with a sample that starts from 2005q1 – 2016q1, with a minimum of 55 observations in total for each of the models used. As explanatory variables we will use domestic and external information as explained in section 3.1 and in table 1 where there is given information about the variables used in the models. We have used in the cases where only yearly data is available for some variables the Litterman (1983) interpolation method to recreate quarterly data. Where in the regressions we haven't added seasonal dummies seasonal components the data are seasonally adjusted using Tramo/Seats method. The main economic EU partners of Albania are respectively Italy, Germany, Greece, France and Spain, while the euro was chosen the exchange rate that might affect Albanian Tax revenue forecasts. The main sources of data are the Albanian Ministry of Finance for Tax Data, Albanian Institute of Statistics of real sector data, Bank of Albania for the data on Economic Sentiment and Exchange rate quarterly data, and the U.S. Energy Information Administration for the data on oil prices. The econometric software(s) used for this work is Eviews.

4. Empirical results

We have estimated in total 18 models[11] for forecasting tax revenues in Albania as grouped[12] in Table 3, 4, 5, and 6 in the Annex. In table 3, we can see that the factors taken into account for constructing our Seasonal Arima(x) models seem all to explain on average more than 90% of the variance models. The second difference of the log form of tax revenues is taken into account into the models presented in table 3, for dealing with the lack of stationarity in the variable level form. The positive sign in front of the coefficient of our models suggest that the independent variables have a positive impact (when they rise) on tax revenues as it seems to be the case of nominal GDP and vice-versa when the coefficients are negative. Judging by the variables statistical importance[13] it seems that the domestic factors taken into account into our models seem to be significant, while the external factors mostly are insignificant, but as they influence the overall fit of the model and make our errors more normally distributed we have decided to keep them in our models. On average the external factors included in the Sarima models 5-9 increase slightly. The overall variance explanation of the models, especially in sariama06 and sarima07 models. In table 4, we can notice that the Vector Regression Estimates VAR02 that takes into account also external factors such as oil prices and main partners GDP seem to improve slightly the explanation of tax revenue estimates compared to the VAR01 taking into account only the domestic factors and the Bayesian form of the VAR. In table 5 we present the simple form of the regression for forecasting tax revenues, the Random Walk model and the Error Correction model, where in the first case we can conclude that a large variance of tax revenues estimates are explained by its past performance. While in the second case our ECM[14] shows that past performance of tax revenues and GDP past and current performance have a high impact in the tax revenues output, being it in the long run or in the short term. In table 6 in the annex are shown 2 versions of the estimates of the regressions according to the bottom up approach for each of the main taxes in the Albanian tax system. The taxes which are supposed to be influenced by the external factors, are custom duties, the vat revenues coming from imports and excises. As external factors, oil prices influencing excises and the exchange

[11]All the models estimated are checked if they fulfill Gaus-Markov assumptions for the OLS method. We have checked for Heteroskedasticity (Breuch-Pagan test, White test etc), Normality in the errors (Jacque-Bera test), for Serial Correlation (this explains the AR(s) and MA(s) added into the regression.

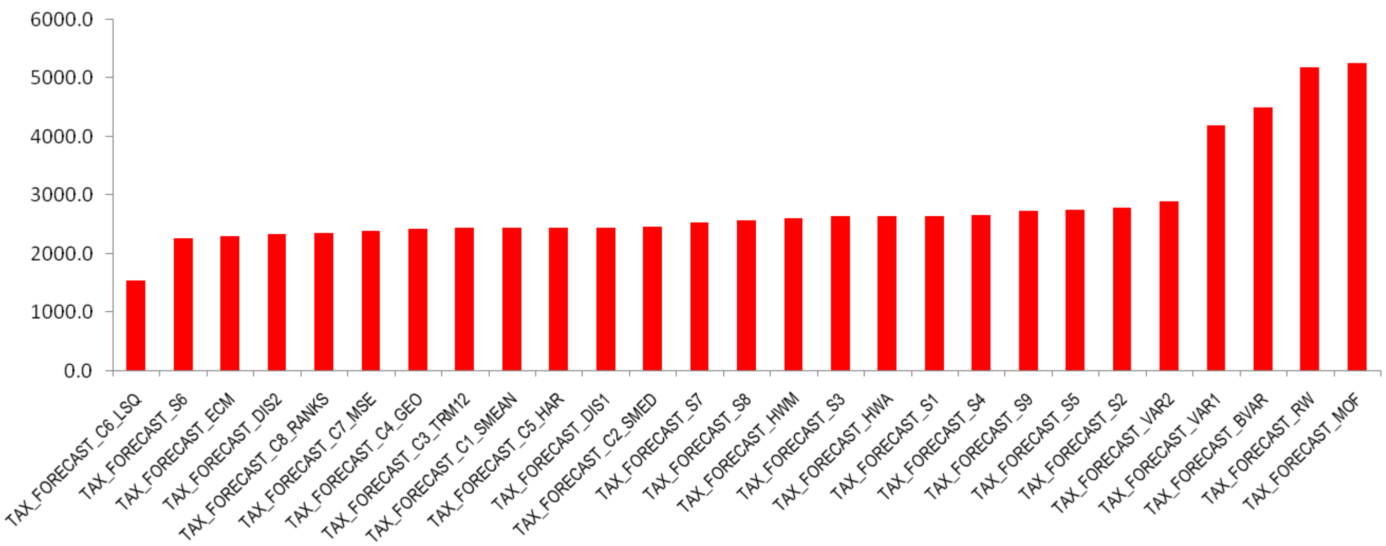
[12]The Holt Winter Additive and Multiplicative Smoothing methods are not presented in the tables as they do not take regression form.

[13]At a $\alpha = 0.05$

[14]Johansen cointegration procedure was taken into account in defining the ECM form, with our variables transformed into being I(0) variables.

rate vis-à-vis the euro influencing vat and custom duties are shown to be statistically significant, while the GDP of our main trading partners taken into account as factors for influencing vat coming from imports shown neither economic nor statistically significance. The overall statistical significance of the models presented by the F statistics is important at 5%. In Figure 2 we have put the forecasts evaluation according to the RSME statistics for our 18 models together with our 9 model combinations that we used to obtain forecasts for the Albanian tax revenues. The forecasts are ranked from the best[15] to worst according to this criteria the RSME criteria, where a smaller value of RSME indicates a better model. In the top six models, according to the RSME criteria, 3 of them are combinations of models, respectively the ones who use the combination averaging of the least squares method, of the mean square error with ranks and the mean square error weighting.

Figure 2: Tax Revenue forecasts evaluations



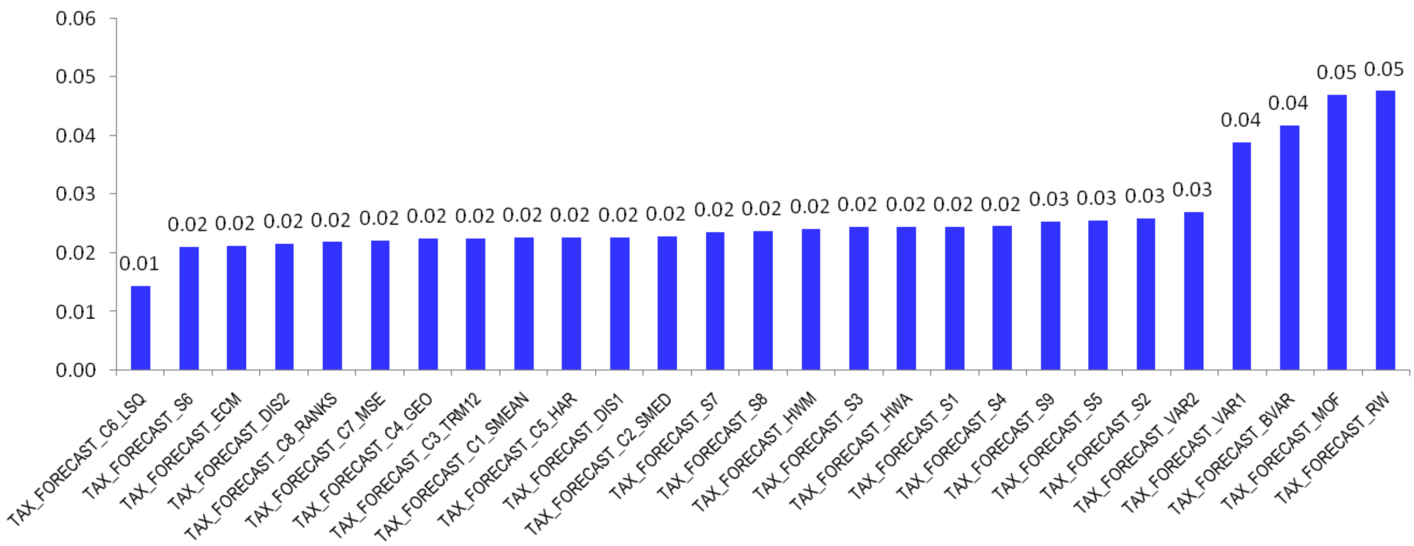
Source: Authors 2016

The Error Correction model, the second variant of disaggregation method and Sarima 6 model version that takes into account external factors such as the oil prices and Euro/Lek exchange rate made it to the top 6 models list. As it can be seen from the ranking in figure 2, all the forecasts taken through the combination techniques make to the top part of the median of all the forecasters, suggesting that on average combination forecasts perform better than all

[15]The forecasts with the lowest RSME, MAE, MAPE values are the ones which perform the best.

the other models. Similar results are found also when forecasting is done at tax by tax level than on aggregate level, where both the disaggregated versions tax by tax show on average better forecasts results than the models that forecasts taxes on an aggregate base. On average the models taking into account external factors[16] seem to perform better than the individual models that do not take into account globalization effects. Returning the focus on the individual models that do not take into account the above characteristics, the best models are the Error Correction model, followed by the Holt Winter Additive and Multiplicative smoothing techniques, and the Sarima03, that takes into account only domestic factors such as nominal GDP and the total imports of goods. The ranking shown in Figure 1, is also supported by the MAE and MAPE statistics given in table 7 in the Annex. In figure 3, we have illustrated the forecasts in increasing order according to the Theil's U1, Forecast accuracy statistic, where $U_1 = 0$, is the best forecast (no observed error).The results of the Theil's 1 statistic are shown on Figure 3, where we can see that almost all of our forecasters have the statistic less than 0.5. The forecasts accuracy results shown from Theil's 1 statistics re-confirms that the combination using least squares weighting is the most accurate forecast.

Figure 3: Theil's U1: Forecast accuracy

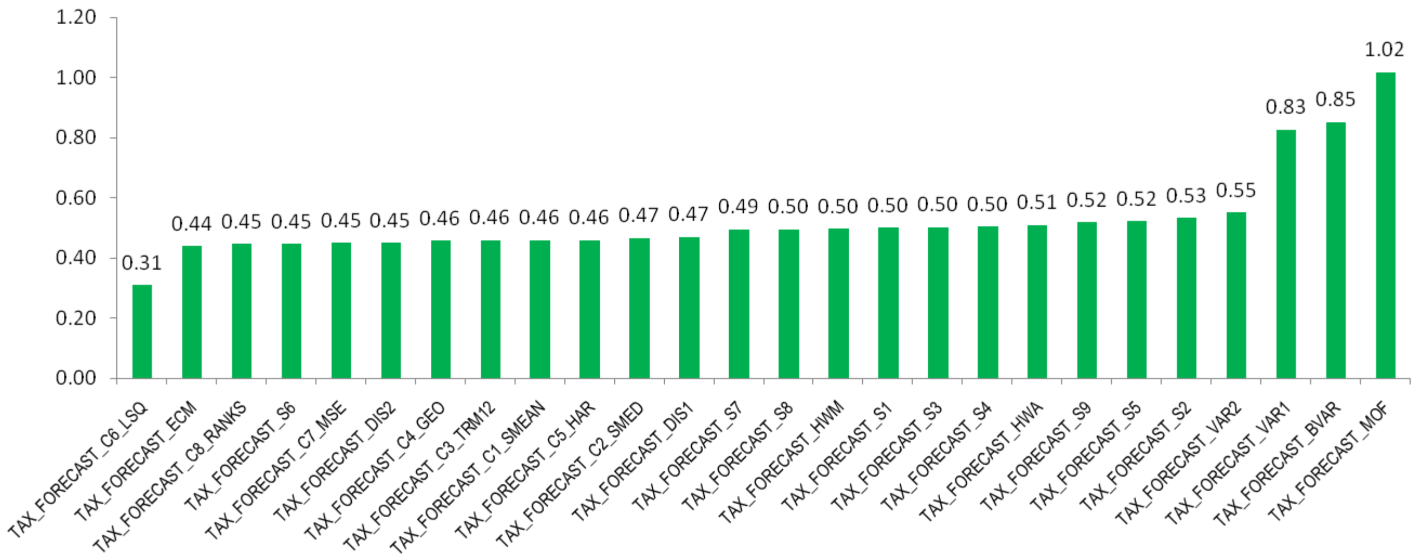


16 Globalization effects

Source: Authors 2016

In Figure 4, as a measure of forecast quality we have presented the Theil's U_2 statistic, where we have compared our forecasts with our benchmark which is chosen to be the Random Walk forecast.

Figure 4: Theil's U2: Forecast quality



Source: Authors 2016

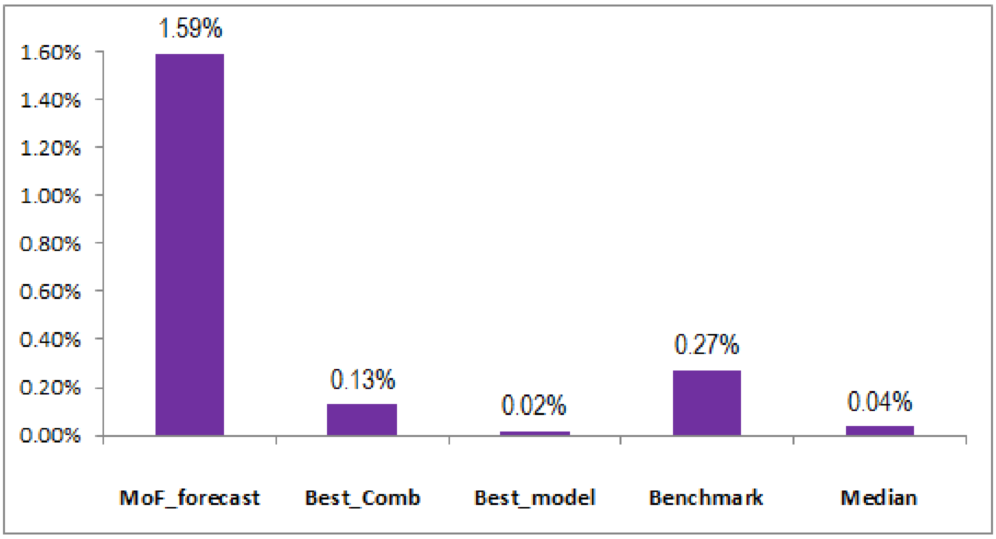
The forecasters that have a statistic $U_2 < 1$, show to be a better forecasting technique than the (naïve) method. All our forecasters except the Ministry of Finance forecast beat the Random Walk forecast, showing a greater forecast quality than the benchmark (naïve) method. Chong and Hendry, (1986) encompassing test given in table 8 in the Annex, emphasis the fact that the composite average of the forecasts outperforms all the single forecasts, where the null hypothesis H_0 that shows: Forecast *i*, includes all information contained in others, is rejected for all the single forecasts taken from our models. The Diebold-Mariano test p-values in table 9, shows us that for a level of significance of $\alpha = 0.05$, all our forecasts methods(models) beat the random walk model except for the Ministry of Finance forecasts (p-value = 0.924>0.05).As final test we can see from tables 10 in the Annex the p-values of the non-parametric test Wilcoxon-signed rank test, where for a level of significance $\alpha = 0.05$, we fail to reject the hypothesis that the forecasts perform not well in capturing the dynamic tax revenue trend for these forecasters: the 2 Holt-Winters methods, trimmed combination forecast, the geometric and the harmonic combinations. The Wilcoxon-signed rank test brings evidence that the combination of forecasters respectively the trimmed combination forecast, the geometric and the harmonic combinations capture better the tax revenue dynamic trend than the other forecasters.

5. Conclusion

This paper examined the issue of tax revenue forecasting, focusing on a small open emerging market such as Albania. Given the role that tax revenue forecasting has in the budget process, tax revenue forecasting has important effects in designing and evaluating future fiscal policies. From the analysis that we have conducted in this paper, we have noticed that Albanian tax revenue forecasts are among the worst in Europe, being highly optimistic. To avoid the problems that arise from biased tax revenue forecasting in emerging economies such as non-sound fiscal policies, we have applied different forecasting models and techniques in the case of Albania. The including of external factors that might affect tax revenues is considered a plus in the literature of tax revenue forecasting. We have applied 18 different models for forecasting tax revenues in Albania, from the benchmark model random walk to more complicated ones such as arima(s) or vector autoregression(s). In additional, we have used 9 types of combinations of this 18 models to see if this technique improves forecasting tax revenues in our case, and if it can be used also for this problem as well.

The quantitative analysis shows that all of our models and combinations perform better than the past ministry of finance forecasts for the Albanian tax revenue forecasts. The general models that take into account external factors such as globalization effects perform much better than the ones that do not take into account such effects; therefore, taking into account of the external factors in forecasting tax revenues has improved our models considerably. Combining models when forecasting tax revenues seem to be more advantageous than using only single models or techniques. The Theil 1 and 2 tests were applied on our models, and combinations show that our results are also consistent in terms of forecasts quality and accuracy. Summing the results up, we can see in figure 5 below best combination (which is also the best forecast), median model, benchmark model (random walk model) which is also our worse model and the ministry of finance for the years from 2011-2015 in % of GDP.

Figure 5: Tax Revenue forecasts errors (average of 2011-2015) in % of quarterly GDP average



Source: Authors 2016

Clearly, our best model, best combination and best median model not only perform better with lower forecasts errors than the ministry of finance forecasts, but also they all beat the benchmark forecast (which is also our worse model). The tax revenue forecast errors of the ministry are 1.59% of GDP for this period, while our forecasters error are all less than 0.3% of GDP, being on average 530% with lower errors in forecasting.

As no papers were found on adding external information in tax revenue forecasting and not much on combining tax revenue forecasts, this working paper comes into hand for other emerging markets institutions that deal with issues in tax revenue forecasting.

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Annex

Table 1: The variables names and explanations regarding them

Variables Used	Explanation
Domestic factors/variables	
economic_sentiment	produced by the central bank to measure the expectations of firms for the current and upcoming quarter
gdp_nominal_sa	nominal gdp seasonally adjusted Lek
imports_goods_total	total imports of goods of Albania in Lek
Imports_fuel_minerals	Imports for fuel and minerals as they are subject to the excise taxes, for Albania in Lek
Imports_food_alcohol	Imports for food and alcohol as they are subject to the excise taxes, for Albania in Lekt
Inflation	Change in CPI index
tax_revenue	tax revenues from tax and custom offices in Lek
Custom_tariffs	Average quarterly tariffs of products taxed in the Custom offices
custom_duties	Revenues from the custom taxes
Excise_tax	Revenues from the excise taxes
national_taxes_others	Here are the revenues from national taxes, and solidarity tax
Payroll	the total amount of money that the employed get in the economy as calculated average of private and public workers
cit_rate	This is the corporate profit tax rate
Profit_tax	Revenues from the profit tax
pit_tax	Revenues from the personal income tax
vat_domestic	Revenues from the Value Added Tax collected by the tax authorities
vat_foreign	Revenues from the Value Added Tax collected by the custom authorities
External factors/variables	
euro5im_gdp_sa	top 5 Albania main EU economic partners GDP (Italy, Germany, Greece, France, Spain), as seasonally adjusted data in Euros
euro_er	euro/ lek exchange rate
oil_prices	international brent oil prices in US dollars

Source: Authors 2016

Table 2: The models used to forecast Albanian tax revenues

Model Name		Forecast name
	Models accounting for domestic information only	
random_walk	Random walk without a constant	tax_forecast_rw
ecm_imf	Error Correction model: f(Taxrevenue; GDP_nominal_sa; seasonal dummies)	tax_forecast_ecm
Var01	VAR model: f(Tax revenue; GDP_nominal_sa)	tax_forecast_var1
Bvar	Bayesian VAR model: Endogenous(Taxrevenue; GDP_nominal_sa)	tax_forecast_bvar
Holt Winter Additive	Holt Winter Additive Smoothing	tax_forecast_hwa
Holt Winter Multiplicative	Holt Winter Multiplicative Smothing	tax_forecast_hwm
Sarima01	SARIMA (2;4) (1;1)	tax_forecast_s1
Sarima02	SARIMA (0;2) (1;1) + GDP_nominal_sa	tax_forecast_s2
Sarima03	SARIMA (0;2) (1;1) + GDP_nominal_sa + Imports_goods_Total	tax_forecast_s3
Sarima04	SARIMA (0;2) (1;1) + GDP_nominal_sa + Imports_goods_Total + Inflation	tax_forecast_s4
	Models accounting also for External factors/variables	
Var02	VAR model: Endogenous_F(Tax revenue; GDP_nominal_sa;) + Exogenous_F(Euro5Im_GDP_sa; Oil_Prices)	tax_forecast_var2
Sarima05	SARIMA (0;2) (1;1) + GDP_nominal_sa + Oil_prices + Euro_ER	tax_forecast_s5
Sarima06	SARIMA (0;2) (2;1) + GDP_nominal_sa + Imports_goods_Total + Oil_prices + Euro_ER + Inflation	tax_forecast_s6
Sarima07	SARIMA (3;3) (1;1) + GDP_nominal_sa + Oil_prices + Euro_ER + Euro5Im_GDP_sa	tax_forecast_s7
Sarima08	SARIMA (1;2) (1;1) + Economic_Sentiment + Oil_prices + Euro_ER + Euro5Im_GDP_sa	tax_forecast_s8
Sarima09	SARIMA (0;2) (1;1) + Economic_Sentiment + Oil_prices + Euro_ER	tax_forecast_s9
Sum of Sarima of disaggregated tax elements 1	SARIMA-s for all 6 tax components (VAT, Custom duties, Excises, National taxes, Personal Income Tax, Profit Tax), version 1	tax_forecast_dis1
Sum of Sarima of disaggregated tax element 2	SARIMA-s for all 6 tax components version 2	tax_forecast_dis1

Source: Authors 2016

Table 3: Sarima model(s)

	Domestic factors models				External factors models				
Eq Name:	sarima01	sarima02	sarima03	sarima04	sarima05	sarima06	sarima07	sarima08	sarima09
Method:	LS	LS	LS	LS	LS	LS	LS	LS	LS
Dep. Var:	DLOG(TAX_REVENUE,2)	DLOG(TAX_REVENUE,2)	DLOG(TAX_REVENUE,2)	DLOG(TAX_REVENUE,2)	DLOG(TAX_REVENUE,2)	DLOG(TAX_REVENUE,2)	DLOG(TAX_REVENUE,2)	DLOG(TAX_REVENUE,2)	DLOG(TAX_REVENUE,2)
C coefficient	-0.001	-0.014	-0.101	-0.103	-0.068	-0.115	-1.13	0.13	0.17
standard error	0	-0.02	0.03	0.03	-0.07	-0.1	-1.24	-0.35	-0.29
t-value	[-1.36]	[-0.69]	[-3.38]	[-3.44]	[-1.00]	[-1.18]	[-0.91]	[0.37]	[0.59]
LOG(GDP_NOMINAL_SA)		0.001	0.033	0.034	0.003	0.038	-0.028		
		0	0.01	0.01	-0.01	-0.03	-0.04		
		[0.67]	[2.99]	[2.93]	[0.29]	[1.11]	[-0.76]		
LOG(IMPORTS_GOODS_TOTAL)			-0.027	-0.028		-0.032			
			0.01	0.01		-0.03			
			[-2.81]	[-2.72]		[-1.28]			
INFLATION				0		-0.001			
				0		0			
				[0.21]		[-0.93]			
LOG(OIL_PRICES)					-0.003	0.002	-0.002	-0.005	-0.001
					-0.01	0	-0.01	0	0
					[-0.52]	[0.56]	[-0.31]	[-1.23]	[-0.46]
LOG(EURO_ER)					0.009	0.001	0.04	-0.048	-0.015
					-0.03	-0.01	-0.05	-0.04	-0.03
					[0.33]	[0.05]	[0.89]	[-1.37]	[-0.46]
LOG(EURO5IM_GDP_SA)							0.09	0.022	
							-0.1	-0.02	
							[0.86]	[1.03]	
LOG(ECONOMIC_SENTIMENT)								-0.043	-0.02
								-0.02	-0.03
								[-1.89]	[-0.69]
AR(01)							-1.610661	0.373469	
							0.175253	0.318532	
							[-9.19]	[1.17]	
AR(02)							-1.505402		
							0.178123		
							[-8.45]		
AR(03)							-0.447949		
							0.168289		
							[-2.66]		
MA(01)	-0.9158	-1.4581	-1.6200	-1.6123	-1.4593	-1.9999	0.2430	-1.9997	-1.5329
	18.37	1.87	1.02	1.05	4.29	0.29	162.28	0.15	3.86
	[-0.05]	[-0.78]	[-1.59]	[-1.54]	[-0.34]	[-6.94]	[0.00]	[-13.18]	[-0.40]
MA(02)	0.7970	0.4581	0.6200	0.6123	0.4593	0.9999	-0.2430	0.9999	0.5329
	50.60	1.02	0.71	0.72	2.35	0.26	195.65	0.18	2.26
	[0.02]	[0.45]	[0.88]	[0.85]	[0.20]	[3.78]	[-0.00]	[5.70]	[0.24]
MA(03)	-1.1862						-0.9999		
	83.32						1472.54		
	[-0.01]						[-0.00]		
MA(04)	0.3049								
	18.01								
	[0.02]								
SAR(04)		0.997	0.998	0.997	0.995	0.712	0.997	0.991	0.996
		-0.010	0.006	0.007	0.007	0.241	0.005	0.010	0.006
		[139.31]	[156.25]	[144.4]	[144.72]	[2.96]	[183.89]	[97.13]	[159.68]
SAR(08)						0.280			
						0.237			
						[1.18]			
SMA(04)	-0.850	-0.870	-0.887	-0.884	-0.813	-0.736	-0.833	-0.762	-0.836
	(-0.15)	-0.14	0.140823	0.148539	0.119916	0.139	[0.17]	0.122971	0.115548
	[-5.54]	[-6.23]	[-6.30]	[-5.95]	[-6.78]	[-5.29]	-5.170	[-6.19]	[-7.29]
Observations:	68	67	67	67	57	57	57	58	58
R-squared:	0.92	0.9	0.92	0.92	0.92	0.95	0.94	0.93	0.92
F-statistic:	75.72	94.53	93.65	80.4	70.12	76.42	47.82	65.47	73.68
Prob(F-stat):	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Authors 2016

Table 4: VAR model(s)

	Domestic factors				External Factors	
Eq Name:	VAR01		BVAR		VAR02	
Method:	Vector Autoregression Estimates		Bayesian VAR Estimates*		Vector Autoregression Estimates	
Sample (adjusted):	1999Q3 2016Q1		2000Q1 2016Q1		2000Q1 2016Q1	
Dep. Var:	L_TAX_REVENUE	L_GDP_NOMINAL_SA	L_TAX_REVENUE	L_GDP_NOMINAL_SA	L_TAX_REVENUE	L_GDP_NOMINAL_SA
L_TAX_REVENUE(-1)	0.187	0.045	0.786	-0.006	0.044	0.061
	-0.135	-0.035	-0.076	-0.018	-0.109	-0.037
	[1.384]	[1.265]	[10.372]	[-0.353]	[0.406]	[1.666]
L_TAX_REVENUE(-2)	-0.052	0.051	0.038	0.003	-0.082	0.064
	-0.126	-0.033	-0.245	-0.059	-0.107	-0.036
	[-0.408]	[1.547]	[0.153]	[0.042]	[-0.763]	[1.787]
L_TAX_REVENUE(-3)			0.047	0.001	-0.068	0.069
			-0.060	-0.014	-0.108	-0.036
			[0.785]	[0.059]	[-0.633]	[1.894]
L_TAX_REVENUE(-4)			0.057	-0.002	0.614	0.031
			-0.205	-0.049	-0.098	-0.033
			[0.275]	[-0.037]	[6.287]	[0.935]
L_GDP_NOMINAL_SA(-1)	1.041	0.579	-0.005	0.916	0.360	0.267
	-0.482	-0.126	-0.044	-0.011	-0.423	-0.142
	[2.159]	[4.609]	[-0.115]	[87.199]	[0.849]	[1.876]
L_GDP_NOMINAL_SA(-2)	-0.071	0.283	-0.016	0.033	-0.238	0.001
	-0.447	-0.116	-0.148	-0.035	-0.414	-0.139
	[-0.158]	[2.433]	[-0.105]	[0.920]	[-0.575]	[0.008]
L_GDP_NOMINAL_SA(-3)			0.035	0.027	0.234	0.215
			-0.034	-0.008	-0.402	-0.135
			[1.011]	[3.352]	[0.582]	[1.594]
L_GDP_NOMINAL_SA(-4)			0.023	0.009	-0.315	0.162
			-0.115	-0.027	-0.369	-0.124
			[0.204]	[0.331]	[-0.855]	[1.304]
C	-2.809	0.717	0.335	0.259	-14.674	-0.178
	-0.743	-0.194	-0.393	-0.094	-4.475	-1.503
	[-3.781]	[3.706]	[0.852]	[2.750]	[-3.279]	[-0.118]
L_EURO5IM_GDP_SA					1.345	0.154
					-0.371	-0.125
					[3.620]	[1.235]
L_OIL_PRICES					0.023	0.002
					-0.024	-0.008
					[0.995]	[0.245]
Observations:	67 after adjustments		65 after adjustments		65 after adjustments	
R-squared	0.967	0.997	0.952	0.996	0.983	0.997
F-statistic	449.4	5034.8	139.3	1757.2	313.8	2090.1

Standard errors in ( ) & t-statistics in [ ] * Prior type: Sims-Zha (normal-Wishart) * Initial residual covariance: Univariate AR

Source: Authors 2016

Table 5: Random walk and ECM model

Eq Name:	random_walk	ecm
Method:	LS	LS
Dep. Var:	LOG(TAX_REVENUE)	D(L_TAX_REVENUE)
LOG(TAX_REVENUE(-1))	1.002	
	0.00	
	[865.10]	
L_TAX_REVENUE(-1)-L_GDP_NOMINAL_SA(-1)		-0.027
		-0.01
		[-3.24]
D(L_GDP_NOMINAL_SA)		0.904
		-0.28
		[3.25]
@SEAS(1)		-0.19
		-0.02
		[-8.34]
@SEAS(2)		0.027
		-0.02
		[1.64]
@SEAS(3)		0.002
		-0.03
		[0.08]
Observations:	69	68
R-squared:	0.95	0.81

Source: Authors 2016

Table 6: Disaggregated model(s)

	Domestic factors								External factors					
Eq Name:	national_taxes1	national_taxes2	pit1	pit2	profit1	profit2	vat_dom1	vat_dom2	vat_for1	vat_for2	custom_duties1	custom_duties2	excises1	excises2
Method:*	LS	LS	LS	LS	LS	LS	LS	LS	LS	LS	LS	LS	LS	LS
Dep. Var:	DLOG(NATIONAL_TAXES_OTHERS)	DLOG(NATIONAL_TAXES_OTHERS)	DLOG(PIT_TAX,2)	DLOG(PIT_TAX,2)	DLOG(PROFIT_TAX)	DLOG(PROFIT_TAX)	DLOG(VAT_DOMESTIC)	DLOG(VAT_DOMESTIC)	DLOG(VAT_FOREIGN)	DLOG(VAT_FOREIGN)	DLOG(CUSTOM_DUTIES)	DLOG(CUSTOM_DUTIES)	DLOG(EXCISE_TAX)	DLOG(EXCISE_TAX)
C	0.057	0.058	-0.526	-0.781	0.107	-0.415	0.837	0.692	0.669	0.520	-4.902	-5.373	0.697	0.783
	-0.200	-0.210	-0.380	-0.550	-0.600	-0.870	-1.110	-1.360	-2.000	-2.100	-2.710	-2.920	-0.220	-0.180
	[0.28]	[0.28]	[-1.40]	[-1.42]	[0.18]	[-0.48]	[0.76]	[0.51]	[0.33]	[0.25]	[-1.81]	[-1.84]	[3.19]	[4.47]
LOG(CUSTOM_TARIFFS)											0.127	0.158		
											-0.100	-0.100		
											[1.28]	[1.60]		
LOG(IMPORTS_GOODS_TOTAL)									-0.020	-0.021	0.209	0.285		
									-0.040	-0.040	-0.200	-0.190		
									[-0.51]	[-0.52]	[1.06]	[1.47]		
LOG(IMPORTS_FUEL_MINERALS)													-0.089	-0.101
													NA	-0.040
													[-1.97]	[-2.78]
LOG(IMPORTS_FOOD_ALCOHOL)													-0.014	-0.017
													NA	NA
													[-0.33]	[-0.47]
LOG(GDP_NOMINAL_SA)	-0.003	-0.003												
	-0.020	-0.020												
	[-0.15]	[-0.16]												
LOG(GDP_NOMINAL_SA(-1))					0.070	0.095								
					-0.030	-0.050								
					[2.19]	[1.95]								
LOG(PAYROL(-1))			0.006	0.015										
			-0.010	-0.020										
			[0.59]	[0.66]										
LOG(ECONOMIC_SENTIMENT)			0.099	0.133	-0.167	-0.113	0.004	0.026						
			-0.070	-0.090	-0.070	-0.110	-0.190	-0.290						
			[1.39]	[1.44]	[-2.54]	[-1.08]	[0.02]	[0.09]						
LOG(CIT_RATE)					0.102	0.119								
					-0.020	-0.040								
					[4.96]	[3.27]								
LOG(CONSUMPTION_HSD)							-0.069	-0.066						
							-0.050	-0.080						
							[-1.39]	[-0.87]						
INFLATION							0.006	0.006						
							-0.020	-0.020						
							[0.32]	[0.27]						
DUM08			-0.136	-0.156										
			-0.090	-0.160										
			[-1.57]	[-0.98]										
DUM14			0.048	0.011										
			-0.150	-0.180										
			[0.33]	[0.06]										
LOG(OIL_PRICES(-1))													0.075	0.089
													-0.030	-0.030
													[2.14]	[3.35]
LOG(EURO_ER)									-0.238	-0.244	0.481	0.394		
									-0.060	-0.060	-0.170	-0.260		
									[-4.26]	[-4.27]	[2.80]	[1.50]		
LOG(EURO5IM_GDP_SA)									0.052	0.065				
									-0.160	-0.170				
									[0.33]	[0.39]				
Observations:	68	68	62	62	62	62	61	61	58	58	58	58	69	69
R-squared:	0.45	0.45	0.9	0.86	0.8	0.76	0.4	0.48	0.93	0.94	0.9	0.88	0.82	0.8
F-statistic:	6.98	6.98	25.22	27.26	20.78	20.73	3.72	3.73	67.78	61.38	40.58	30.32	23.17	26.11
Prob(F-stat):	0	0	0	0	0	0	0	0	0	0	0	0	0	0

*AR, MA, SAR and SMA terms are not shown in the table in order not to overload it but they are taken into account influecning also the above results

Source: Authors 2016

Table 7: Evaluation Forecast Statistics

Forecast	RMSE	MAE	MAPE
TAX_FORECAST_C6_LSQ	1541.6	1151.0	2.1
TAX_FORECAST_S6	2266.7	1756.1	3.2
TAX_FORECAST_ECM	2304.8	1692.8	3.1
TAX_FORECAST_DIS2	2331.9	1739.4	3.2
TAX_FORECAST_C8_RANKS	2359.9	1820.4	3.3
TAX_FORECAST_C7_MSE	2380.3	1837.5	3.3
TAX_FORECAST_C4_GEO	2430.1	1879.8	3.4
TAX_FORECAST_C3_TRM12	2435.6	1880.9	3.4
TAX_FORECAST_C1_SMEAN	2442.0	1881.9	3.4
TAX_FORECAST_C5_HAR	2443.0	1878.3	3.4
TAX_FORECAST_DIS1	2444.4	1895.9	3.5
TAX_FORECAST_C2_SMED	2463.6	1891.0	3.4
TAX_FORECAST_S7	2540.1	1948.2	3.6
TAX_FORECAST_S8	2568.0	1886.3	3.5
TAX_FORECAST_HWM	2597.4	2005.5	3.7
TAX_FORECAST_S3	2639.7	2086.6	3.8
TAX_FORECAST_HWA	2640.3	2097.5	3.9
TAX_FORECAST_S1	2647.8	1976.5	3.6
TAX_FORECAST_S4	2653.4	2095.9	3.8
TAX_FORECAST_S9	2736.1	2122.3	3.9
TAX_FORECAST_S5	2755.5	2119.9	3.9
TAX_FORECAST_S2	2789.4	2186.5	4.0
TAX_FORECAST_VAR2	2900.1	2170.2	4.0
TAX_FORECAST_VAR1	4194.6	3364.6	6.4
TAX_FORECAST_BVAR	4492.0	3697.6	7.2
TAX_FORECAST_RW	5168.0	4242.4	8.3
TAX_FORECAST_MOF	5244.3	4198.4	7.6

Source: Authors 2016

Table 8: The en-compassing test

Forecast	F-stat	F-prob
TAX_FORECAST_DIS1	-0.69	1
TAX_FORECAST_DIS2	-0.69	1
TAX_FORECAST_ECM	-0.69	1
TAX_FORECAST_HWA	-0.69	1
TAX_FORECAST_HWM	-0.69	1
TAX_FORECAST_BVAR	-0.69	1
TAX_FORECAST_RW	-0.69	1
TAX_FORECAST_S1	-0.69	1
TAX_FORECAST_S2	-0.69	1
TAX_FORECAST_S3	-0.69	1
TAX_FORECAST_S4	-0.69	1
TAX_FORECAST_S5	-0.69	1
TAX_FORECAST_S6	-0.69	1
TAX_FORECAST_S7	-0.69	1
TAX_FORECAST_S8	-0.69	1
TAX_FORECAST_S9	-0.69	1
TAX_FORECAST_VAR1	-0.69	1
TAX_FORECAST_VAR2	-0.69	1
TAX_FORECAST_MOF	-0.69	1

Source: Authors 2016

Table 9: DM test

Forecast	p-value
TAX_FORECAST_DIS1	0.0008
TAX_FORECAST_DIS2	0.0006
TAX_FORECAST_ECM	0.0005
TAX_FORECAST_HWA	0.0005
TAX_FORECAST_HWM	0.0014
TAX_FORECAST_BVAR	0.0091
TAX_FORECAST_S1	0.0012
TAX_FORECAST_S2	0.0020
TAX_FORECAST_S3	0.0014
TAX_FORECAST_S4	0.0017
TAX_FORECAST_S5	0.0014
TAX_FORECAST_S6	0.0007
TAX_FORECAST_S7	0.0011
TAX_FORECAST_S8	0.0016
TAX_FORECAST_S9	0.0019
TAX_FORECAST_VAR1	0.0356
TAX_FORECAST_VAR2	0.0026
TAX_FORECAST_C1_SMEAN	0.0004
TAX_FORECAST_C2_SMED	0.0008
TAX_FORECAST_C3_TRM12	0.0004
TAX_FORECAST_C4_GEO	0.0004
TAX_FORECAST_C5_HAR	0.0005
TAX_FORECAST_C6_LSQ	0.0001
TAX_FORECAST_C7_MSE	0.0005
TAX_FORECAST_C8_RANKS	0.0005
TAX_FORECAST_MOF	0.9241

Source: Authors 2016

Table 10: Wilcoxon signed rank test

Forecast	value	p
TAX_FORECAST_DIS1	3.7	0.00
TAX_FORECAST_DIS2	3.7	0.00
TAX_FORECAST_ECM	4.1	0.00
TAX_FORECAST_HWA	1.8	0.07
TAX_FORECAST_HWM	1.8	0.08
TAX_FORECAST_BVAR	4.3	0.00
TAX_FORECAST_RW	4.2	0.00
TAX_FORECAST_S1	4.3	0.00
TAX_FORECAST_S2	4.2	0.00
TAX_FORECAST_S3	4.2	0.00
TAX_FORECAST_S4	4.1	0.00
TAX_FORECAST_S5	4.2	0.00
TAX_FORECAST_S6	4.3	0.00
TAX_FORECAST_S7	4.2	0.00
TAX_FORECAST_S8	4.3	0.00
TAX_FORECAST_S9	4.2	0.00
TAX_FORECAST_VAR1	4.4	0.00
TAX_FORECAST_VAR2	4.3	0.00
TAX_FORECAST_C1_SMEAN	4.2	0.00
TAX_FORECAST_C2_SMED	4.2	0.00
TAX_FORECAST_C3_TRM12	0.4	0.70
TAX_FORECAST_C4_GEO	0.4	0.69
TAX_FORECAST_C5_HAR	0.4	0.69
TAX_FORECAST_C6_LSQ	4.4	0.00
TAX_FORECAST_C7_MSE	4.2	0.00
TAX_FORECAST_C8_RANKS	4.2	0.00

Source: Authors 2016