SIMPLIFY AND IMPROVE: REVISITING BULGARIA'S REVENUE FORECASTING MODELS

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SIMPLIFY AND IMPROVE: REVISITING BULGARIA'S REVENUE FORECASTING MODELS

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Abstract: In the thirty years since the end of real socialism, Bulgaria has gone from having a rather radically 'different' tax system to adopting flat-rate taxation with marginal tax rates falling from figures as high as 40% to 10% for both the corporate and personal income tax. Crucially, the econometric forecasting models in use at the Bulgarian Ministry of Finance hinted at an increase in tax revenue compatible with the so-called 'Laffer curve'. Similarly, many economists held the view that revenues should increase. However, reality fell short of those expectations based on forecasting models and rooted in mainstream economic theory. Thus, this paper asks whether there are better-performing forecasting models for personal and corporate income tax revenues in Bulgaria that are readily implementable and overperform the ones currently in use. After articulating a constructive critique of the current forecasting models, the paper offers readily implementable, transparent alternatives and proves their superiority.

Keywords: tax revenues; revenue forecasting; Bulgaria; econometric modelling

JEL codes: C5; C87; H2

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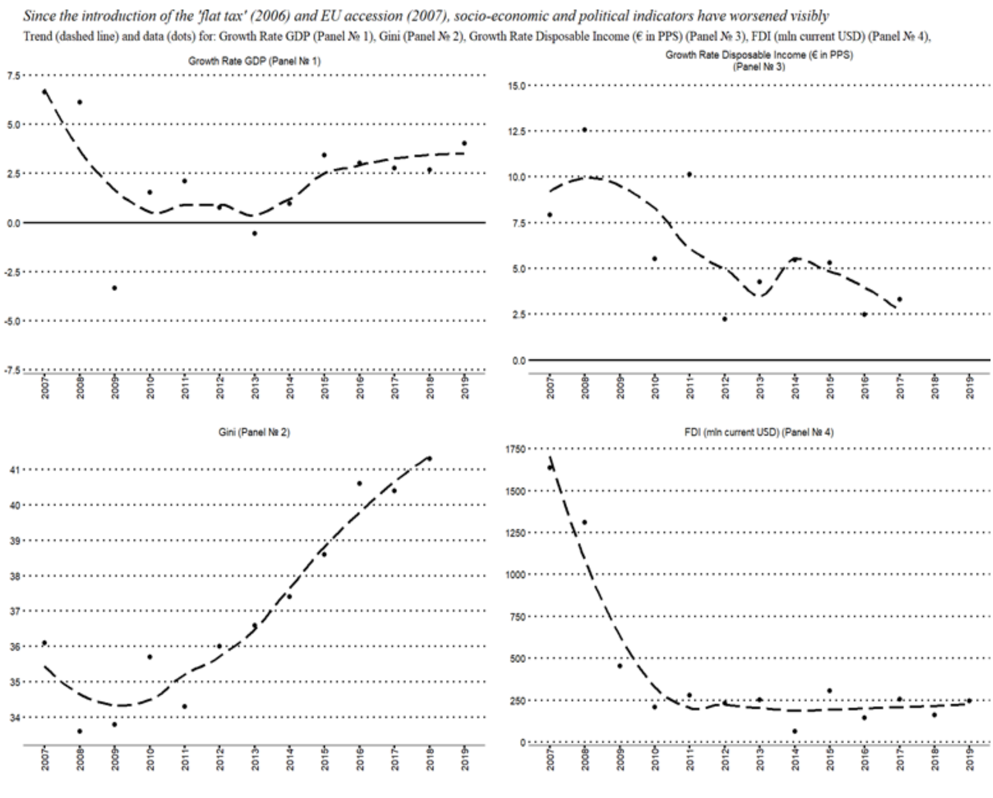
Introduction

In the thirty years since the end of real socialism, Bulgaria has gone from having a rather primitive or radically different tax regime to adopting flat-rate taxation in a manner that is manifestly regressive. By 2006, marginal tax rates which used to be as high as 40% flattened to 10% for both the corporate income tax (CIT) and the personal income tax (PIT). Academicians and policy advisors armed with imported ideas (and funds, as Dostena Lavergne, 2010, discussed) promoted these reforms as a sure way to foster growth, increase competitiveness, and attract foreign capital money (e.g., Ganev, 2016). Eventually, none of these promises was kept (Ninov, 2019). On the contrary, the flat-tax regime accompanied a steadfast deterioration of such macro- and socio-economic indicators as gross domestic product (GDP), disposable income, foreign direct investment (FDI), and income inequality.

Indeed, the literature has already discussed several aspects of the flat-tax regime and its introduction (e.g., Karagyozova-Markova et al., 2013; Tanchev, 2016; Tanchev & Todorov, 2019). However, not many have highlighted the role that the Bulgarian Ministry of Finance's (MF) forecasting models played in this policy's adoption and persistence. In fact, the official models corroborate the view of those Bulgarian economists who fall into the fallacy of the *Laffer curve* and prognosed increasing revenues under a flat-rate regime (Gălăbov, 2009; Nenovski & Hristov, 2001; Angelov, 2016; Nikolova, 2016). However, reality has fallen short of those expectations (Figure 1), as it has happened elsewhere after similar reforms (cf. Alvord, 2020). Official models remain severely ineffective even over short-term periods of relative economic stability and despite the absence of major policy change (see Chabin et al. 2020, pp. 18–19). Thus, it is high time to shed light on the failure of these forecasting models rooted in mainstream economic theory.



Data source by panel: № 1, EUROSTAT, 2021, № 2, 2020; № 3, WB, 2020, № 4, 2021.

Figure 1. Key socio-economic indicators in Bulgaria, 2007–2020.

Data and methodology

Data

This paper uses data for both actual and forecasted tax revenues from PIT and CIT for the years 2005–2020. All figures are publicly available in ministerial and parliamentary acts connected with each year's budgetary processes. Intuitively, actual revenues offer a benchmark to assess the efficiency of both the proposed and current forecasting models by estimating the appropriate measures of statistical error.

Additionally, several macroeconomic variables are used as proxies representing the entire tax base (the regression models' *predictors*) in the proposed models. Specifically, according to the National Statistical Institute (NSI), just three variables make up over 90% of gross personal income: employment income, pensions (which are tax-exempt), and other social transfers. On the corporate side, the key variables are corporate profits for different categories of companies (non-/financial companies, pension funds, investment firms, insurers) and gross insurance premiums.

Literature review on econometric modelling

According to a literature review by the US Federal Reserve (Fukac & Pagan, 2010, p. 2), the '*interpretative* models' that emerge from economic theory are the basis on which forecasting models are built. Each of the former (e.g., Keynesianism, neo-classical synthesis, etc.) roughly corresponds to a 'generation' of the latter. Predictably, electronic calculators' capabilities at a given point in time posited an objective limit to each generation's specific techniques. Hence, it is unsurprising that surveys of the methodological literature agree on the main macro-econometric forecasting techniques (Jenkins et al., 2000, pp. 35-47, 48-63, 64-181). Yet the few endeavours at sketching a typology of these methods lack systematicity (e.g., Bayer, 2013).

Both the current and proposed models belong to the 'third generation' of forecasting models. Indeed, this class is rather heterogeneous in terms of methods, ranging from differential equations and tax elasticity/buoyancy (for a Bulgarian example, see Tanchev & Todorov, 2019) to various autoregressive moving average (ARMA, ARIMA, ARIMAX) models (on Bulgaria: Telarico, 2021) and many others.

Essentially, the choice of proposing third-generation models is practically and methodologically motivated. On the one hand, it allows a more straightforward comparison with the current ones and makes it easier for forecasting authors to implement them immediately. After all, they provide just a 'small number of simple rules' that can easily be communicated to an auditorium of non-experts (Cairney & Kwiatkowski, 2017, p. 4). On the other, this class of models is preferable to fourth-generation ones from a purely econometric standpoint, too. In fact, comparative analyses and methodological studies show that third-generation models outperform more complex alternatives in terms of sheer efficiency and parsimony (Keene & Thomson, 2007).

An econometric overview of the proposed models

Like any 'multiple' or 'multivariable' regression model (MLR), the proposed forecasting models aspire at predicting an independent variable (y) by leveraging its relation with some independent variables ($X_1, X_2, \dots, X_p$) whose value is known.[1] An MLR model is commonly specified using vectors, as in this paper; but matrix notation is perfectly equipollent. The models have been fit to the training data by using ordinary least-squares (OLS) regression to estimate the values of the regression coefficients $\left(\beta_{X_1}, \beta_{X_2}, \dots, \beta_{X_p}\right)$. In addition, the models allow for the dynamic forecasting of revenues thanks to the replacement of the randomly distributed error ε of OLS regression with the error term ϵ, which is distributed as an autoregressive, moving-average (ARIMA) process. Essentially the introduction of ϵ allows for historical information about the predicted time series ($y_{t'}\ \forall\, t' \leq t-1$) to be incorporated. Hence the model's equation for each time period is: $y_{\mathrm{t}} = \beta_{X_1} x_{1_{\mathrm{t}}} + \beta_{X_2} x_{2_{\mathrm{t}}} + \dots + \beta_{X_p} x_{p_t} + \epsilon_t$.

Given that OLS works best in the presence of 'stationary' time series, several stationarity tests have been employed: augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Comparing their results helps to identify distortions due to small sample sizes.

The correction of trends takes place through differencing (for stochastic trends). In fact, the available literature on Bulgaria suggests that differencing once is usually sufficient (Tanchev, 2016; Tanchev & Todorov, 2019; Telarico, 2021). For determinist trends, natural or base-10 logarithms are not preferable because the transformed series are only covariance-stationary (Kirchgässner et al., 2013, p. 156). Thus, this paper also considers the appropriateness of filters that decompose each time series in a trending (non-stationary) component and a stationary one. The literature has made wide use of two such tools: the Beverdige-Nelson (BN) and the Hodrick-Prescott (HP) filters. Notably, the HP filter has yielded appreciable results in the study of fiscal (Todorov, 2021) and monetary policy (Telarico, 2022) in Bulgaria. However, comparing the two filters' results is indispensable, owing to a number of complimentary weaknesses: 'artificial short-run cycles due to overdifferencing' (Kirchgässner et al., 2013, p. 161), assumptions forcing the cyclical component's mean to be null, lack of a unique solution for the BN filter, and incorrect selection of the smoothing parameter's value (Baxter & King, 1999) and endpoints' suboptimality (King & Rebelo, 1993, p. 219) for the HP filter.

This paper alternatively acknowledges recent advancements in macro-econometrics arguing that OLS regressions of non-stationary variables are consistent as long as the latter are cointegrated (Kirchgässner et al., 2013, p. 209). Practically, such cointegration is assessed quantitatively when there are qualitative reasons to suppose it (e.g., between the tax base and tax revenues) by carrying out the eigenvalue version of Johansen's test. Practically, an OLS has been attempted for cointegrated, non-stationary variables even if a stationary timeseries could be obtained by differencing or filtering.

Forecasting error

The efficiency of the proposed and current models has been assessed using testing data which were not used to train the model and consisting of the last three years' observations. Namely, all the most frequently used forecasting-error's measures have been considered (Kirchgässner et al., 2013, pp. 87–88; Chabin et al., 2020, p. 10): the mean error (ME), the sign of which informs about biases; the mean absolute error (MAE), which corrects for cancelling-out errors but overemphasises underestimations; symmetric absolute errors (sMAE), which correct the MAE's tendency to overweight underestimations; the root mean square error (RMSE), providing information on the size of the errors on the mean; and Theil's U_1, which quantifies the distance between actual and forecasted time series.

Specification of the predictors

The predictor variables have been selected on both macroeconomic and econometric criteria: (1) their macroeconomic relevance, with the variables representing a large part of the tax base as defined in the relevant legal act; (2) their strength; and (3) significant correlations between them and tax revenues.

The first criterium manifests a macroeconomic rationale rooted in the tax base's higher predictability in comparison to other revenue determinants. Simplistically, tax revenues under a flat-rate regime depend on the effective tax rate (r_e) – which, in turn, is a function of the policy rate (r_p) – and the scope of the tax base (TB) according to the formula $T = f(r_e, TB)$. Clearly, the effective and policy rates can shift quite dramatically due to policy changes and are often unobservable variables dependent on the tax regime's complexity as well as the tax base's composition. Moreover, there are ongoing policy and theoretical debates regarding the sign of the relation between tax rates and the tax base; whereas there is a certain continuity and predictability in the tax base's legal definition due to the need for preserving the tax regime's logicalness and, especially within the EU, ensuring international harmonisation (Barrios et al., 2020).

The second criterium provides econometric backing to the previous argument. In fact, statistical indexes of correlation indicate how strong/weak the relation is between the evolution of revenues and that of the selected predictors. In this case, besides Pearson (r), two other coefficients have been calculated: Kendall (τ) and Spearman (ρ). Practically, the latter two are better 'at dealing with violations of standard assumptions' (Wilcox et al., 2013, pp. 328-329, 319), with τ being more robust and slightly more efficient than ρ.

The third criterium strengthens the econometric value of the preceding argument by testing the significance of the correlation between predictors and the dependent variable. Thus. Student's t-test, Pearson's χ^2, the Wilcoxon signed-rank test, and the Mann–Whitney rank-sum test, were used to ensure that correlations are all significant and ensure robustness against violations of one or another assumption (cf. Wilcox et al., 2013, p. 323).

Current forecasting models

Common remarks about the PIT and CIT forecasting models

Ultimately, the Bulgarian tax forecasts' opacity helps to explain the difficulty in assessing their effectiveness. It is undeniable considering that the MF has not conducted a methodological review since the Great Recession, even though much more established forecasting institutions have done so (ARA-PE, 2019; RTMRF Advisory Panel, 2012). For this paper, the author obtained more detailed information on the current models by filing several requests for the disclosure of public information not already published in accordance with Bulgarian law.

As a result, it appears that the forecasting models for PIT and CIT revenues are comprised of two parts: one strictly mathematical; the other somewhat more 'discretionary'. The following paragraphs better detail the implementation of the model and its discretionary adjustments for each tax. Yet there is a general disclaimer that must be made.

Crucially, despite being directly questioned, the Ministry's documents fail to spell out any details about the method used. By reading between the lines of the Ministry's documents, it is reasonable to infer that adjustments related to policy changes were integrated in the models' results only ex-post (cf. Angelov & Bogdanov, 2006, p. 13), as was concluded more than a decade ago. Hence, one can infer that the MF's backward forecasting is based on tax-base specific elasticities. Furthermore, the MF has allowed significant room for discretionary interventions deriving from enacted and/or planned changes in tax legislation and the administrative regulation of the labour market. The only hint as to how these estimates are conducted consists of a vague mention of reporting data from the National Revenue Agency [NAP] the National Statistical Institute, the Employment Agency, the Bulgarian National Bank [BNB], and other statistical and administrative sources.

Current forecasting model for PIT revenues

The MF stated in an answer to the author's request for the disclosure of public information that its PIT model takes into account 'the relevant indicators from the official macroeconomic forecast of the Ministry of Finance'. Namely, the model considers five independent variables: number of persons employed (EMP); unemployment rate (U); average wage (AWG); compensation of employees (CE); and gross domestic product at current prices (BVP). Summarily, the model is based on the sensitivity of PIT revenues to the percentage change in the selected components of its tax base, as follows:

$$PIT_t = \eta_{EMP}EMP_t + \eta_U U_t + \eta_{AWG}AWG_t + \eta_{CE}CE_t + \eta_{BVP}BVP_t$$
$$where: \left| \begin{array}{l} PIT_t \text{ are personal income tax renevues at the time } t \\ \eta_X \text{ is the elasticity of renevues to the predictor } X \end{array} \right. \quad (1)$$

Unfortunately, historical estimates of elasticity (η) are obtained using an undisclosed methodology. It is thus impossible to reproduce official forecasts even if these five components of the PIT tax base were known.

Current forecasting model for CIT revenues

As regards CIT, the methodology used over the years has been neither clear nor stable. For instance, in 2021 the MF stated that its econometric model forecasts the three main streams: corporate taxes (KD), the tax on dividends (DDD), and that on insurance premiums (DZP), through a single, backward-looking model considering:

the tax rate, the nominal growth of the gross operating surplus[, ...] the declared taxable profit/loss for the [previous] financial year [...], as well as the data declared by taxable persons with the annual tax returns for losses that are deductible in subsequent reporting periods. (Reshenie № 963 na Ministerskia savet, 2020, pp. 76-77)

This model looks similar to the one employed in 2019 and 2020 (Reshenie № 928 na Ministerskia savet, 2018, pp. 59–60; Reshenie № 815 na Ministerskia savet, 2019, p. 58). However, in 2018 the description was visibly different (Reshenie № 808 na Ministerskia savet, 2017, p. 86). And it changed again in 2022, albeit the legislation remained almost unvaried (Reshenie № 43 na Ministerskia savet, 2022, p. 77 [e-version: 207]).

Overall, the CIT-revenue forecasting model for 2022 is very similar to the PIT one. However, the tax base in this case is much more complex, as it includes: declared profits (π); advance payments on the KD in accordance with applicable legislation for companies with over 300,000 leva in yearly turnover (ADV); equalisation contributions paid by sole traders (EQC); amounts refunded due to overpayment in the previous year (REF); and the losses carried forward for tax purposes (TLS). Thus, the model is based on the sensitivity of PIT revenues to the percentage change in the components of its tax base. Additionally, the DZP and most minor corporate taxes are not estimated directly, whilst the DDD is forecasted separately through simpler first-order autoregressive (AR) models.

$$CIT_t = \begin{cases} CIT_t = (KD_t + DZP_t) + DDD_t \\ KD_t + DZP_t = \eta_\pi \pi_t + \eta_{ADV} ADV_t + \eta_{EQC} EQC_t + \eta_{REF} REF_t + \eta_{TLS} TLS_t \\ DDD_t = AR(1) = \varphi_0 DDD_{t-1} + \varepsilon_t \end{cases} \tag{2}$$

$$where: \left[\begin{array}{c} CIT_t \text{ are corporate income tax renevues at the time } t \\ \eta_X \text{ is the elasticity of renevues to the predictor } X \\ \varepsilon_t \text{ are the errors of the autoregressive model} \end{array} \right.$$

Pros and cons of the current models

This clarifying overview provides the basis to argue these models' outdatedness and inadequacy. Schematically, the current models offer (1) some practical advantages, essentially related to the limited need for periodical revision. But they suffer from evident drawbacks related to (2) the selection of variables, (3) excessive arbitrariness and lack of transparency, and (4) their underlying econometric functioning.

1. Pros – Practical advantages

The advantages of the current models are mostly related to a certain assessment of their econometric implementation. In fact, without requiring frequent updates, the 'frequently-used method of forecasting revenue by applying an aggregate tax buoyancy to GDP forecasts is usually reasonably reliable' (IMF FAD, 2020, p. 2). In fact, according to some estimates, '90% of the explained forecast error' of CIT and PIT 'can be attributed to wrong macroeconomic assumptions' rather than wrong elasticity estimations (Göttert & Lehmann, 2021, p. 20).

Moreover, assuming that elasticity is a long-run relation, its value is stable unless there is some structural shock (Jenkins et al., 2000, p. 39).

2. Cons – Variable selection

As regards variable selection, different problematic aspects emerge for PIT and CIT forecasts. Generally, neither models is not transparent enough to allow anyone to reproduce the estimates. Moreover, the choice of the current predictors does not seem econometrically sound.

It is essentially difficult to find either a reasonable macroeconomic or econometric explanation for these choices. In macroeconomic terms, it is hard to see why CE and U should be highly determining for PIT revenues. It is not even so useful as the MF argues to use unemployment as a proxy for social transfers. In fact, the nominal expenditure for taxable social transfers is directly available in advance and can be forecasted by the National Insurance Institute (NOI). Meanwhile, CE is almost completely irrelevant, given that it represents 0.008% of Gross National Income. Additionally, EMP and AWG can be considered to be duplicates, as both stand as proxies for taxes on salaries and employment relations more generally.

As regards CIT, the selection of variables is neither clear nor stable through the years. Despite the complete lack of clarity in the MF's documents, the KD model looks econometrically quite similar to the PIT one. However, the tax base here is much more complex, including between five and seven variables. Again, it is difficult to find a reasonable technical explanation for these choices. In macroeconomic terms, it is hard to see why the model would need to consider so many other variables (ADV, EQC, TLS, ADT) when the KD is a tax on profits. Even assuming that more variables would increase precision, other indicators should be more relevant since they are more closely related to business cycles (e.g., GDP). In addition, it makes little sense to consider the aggregated profits for all companies given the differences in various sectors' performances (IMF FAD, 2020, p. 3) and in the applicable tax regimes.

3. Cons – Econometric weakness

All in all, the current models' underlying predictive power rests on the correct estimation of tax elasticity to model the long-term relation between the tax base and revenues. But many scholars have had second thoughts about the use of such techniques in forecasting tax revenues. Namely, there is a convincing econometric argument based on cases of 'false predictions of the elasticities' in developed countries (Göttert & Lehmann, 2021, p. 20). Others have built strong cases noting the difficulty of estimating elasticity correctly (Sen, 2006) or the forecasts' scarce precision (Botrić & Vizek, 2012). Moreover, Bulgarian forecasters seem to treat tax-related elasticities as a structural factor. But this assumption has been disproven time and again (Saez et al., 2009, pp. 43-46).

The new forecasting model for tax revenues

The methodology disclosed by the MF shows that recommendations to scrap elasticity-based models have had hardly any effect. Crucially, 'unrealistic forecasts' play a key role in the spreading of anti-Keynesian, trickle-down economics 'on the political left and right' and justifying the adoption of RTRs and 'fiscal profligacy' (Frankel, 2008, p. 13).

Hence, it is opportune to verify whether alternative forecasting models can be more effective than the current ones.

Selection of variables for PIT forecasts

The proposed model improves the MF's choice of proxies for the estimation of the PIT tax base in both macroeconomic and econometric terms. The MLR regression coefficients have been estimated using revenue data from the yearly budget and administrative data for the selected explanatory variables. Namely, the model looks as follows:

$$PIT_t = \beta_{WAGE} WAGE_t + \eta_{SOC} SOC_t + \epsilon_t$$
$$where: \left| \begin{array}{c} PIT_t \text{ are personal income tax renevues at the time } t \\ \beta_X \text{ is the regression coefficient of the predictor } X \\ \epsilon_t \text{ is the error term, distributed as an } ARIMA\ (p,d,q) \text{process} \end{array} \right. \quad (3)$$

As shown below, the choice of these predictors is econometrically sound. Namely, all predictors are strongly and significantly correlated with revenues, proving a strong statistical rationale to an economically sensible selection.

1..Representativity of the tax base

First, selecting average employment income (WAGE) and taxable social transfers (SOC, which notably exclude pensions) allows for over 90% of total (monetary and in-kind) taxable average income to be accounted. Moreover, these variables are much easier to measure and forecast than non-labour income, financial, or other sorts of rents. Unfortunately, the NSI's *Infostat* platform only provides data going back to 2004.

2. Strong and significant correlation with PIT revenues

Besides their macro-economic relevance, these two variables are also statistically corelated with revenues. In fact, the aggregate of the considered variables' correlation with PIT revenues is larger than $.95$, except for Pearson's r and Kendall's τ for SOC.

These results are also highly significant, given that both Student's t and Whitney's U_1 paired tests allow for the null hypothesis of independence to be rejected with 99% confidence for all the considered variables (including their aggregate).

Selection of variables for CIT forecasts

The proposed model improves the MF's choice of proxies for the estimation of the CIT tax base in both macroeconomic and econometric terms. The MLR regression coefficients have been estimated by combining all the available data for the period 2006 – 2017 (training data set); the following three observations were kept as testing data.

1. Representativity of the tax base

The corporate tax regime in Bulgaria is rather fragmented, with ad-hoc taxes weighing on specific sectors and their activities to different extents. However, the KD on corporations' profits accounted for about 90% of corporate tax revenues in 2002–20. Only DZP are estimated separately, given gross insurance premiums (PRM), using a simple linear regression model. Thus, the KD tax base, non-financial, and financial corporations' profits ($\pi = \pi_{NF} + \pi_F$) may be a good proxy for the CIT base. Namely, given that there are no data on the value of dividends distributed in Bulgaria, total corporate profits have been tested for correlation and causation with both KD revenues and the sum of KD and DDD revenues. Hence, the general model for CIT revenues is:

$$CIT_t = \begin{cases} CIT_t = (KD_t + DDD_t) + DZP_t \\ KD_t + DZP_t = \beta_{\pi_{NF}} \pi_{NF\,t} + \beta_{\pi_F} \pi_{F\,t} + \epsilon_t \\ DZP_t = \beta_{PRM} PRM_t + \epsilon_t \end{cases} \tag{4}$$

$$where: \left| \begin{array}{c} CIT_t \text{ are corporate income tax renevues at the time } t \\ \beta_X \text{ is the elasticity of renevues to the predictor } X \\ \epsilon_t \text{ is the error term, distributed as an } ARIMA\,(p,d,q) \text{ process} \end{array} \right.$$

Overall, these variables are not only representative of the corporate tax base, but also easier to measure and forecast than the ones currently in use. Unfortunately, however, determining the total amount of corporate profits is made somewhat difficult by a lack of clear data.

As regards financial institutions, the NSI provides data for three categories of companies: 'pension funds', 'investment firms', and 'insurance companies'. Thus, financial sector profits equal the sum of these three sectors' profits $\pi_F = \pi_{Insurance} + \pi_{Investment} + \pi_{Pension}$. Profit figures are available only for the first two.

Insurers' profits ($\pi_{Insurance}$) are calculated on the basis of the Key Economic Indicators for Insurance Enterprises dataset, by diminishing the turnover (TNR) of gross claims incurred (CLM) and purchases of goods and services (PUR), so that: $\pi_{Insurance} = TNR_{Insurance} - (CLM + PUR_{Insurance})$.

Estimating non-financial corporations' profits is somewhat less straightforward. In fact, besides PUR, the available datasets contain two similar variables for expenses: 'Remuneration expenses' (RXP) and 'Staff expenses' (SXP). In an official document trying to clarify this distinction, the MF stated that: 'There is no legal definition of "staff expenses" in any law, including tax and accounting legislation' (Karayvanova, 2016, p. 1). Rather, it is the equivalent of employees', 'Staff income', or 'Employee benefits' in the employers' accounts (MS-RB, 2005, pp. 76-84). So, RXP is a broader concept than SXP. Given the special tax treatment reserved for 'compulsory social security contributions' in Bulgaria (see DOPK, 2005/2021; and ZKBO, 2006/2022, art. 41.3, 5-8), it is impossible to a-priori choose between the two. Hence, the following calculations test two definition of non-financial firms' profits and, coherently, profits overall:

$$\begin{matrix} \pi_{NF_1} = TNR_{NF} - (RXP_{NF} + PUR_{NF}) & \Rightarrow & \pi_1 = \pi_F + \pi_{NF_1} \\ \pi_{NF_2} = TNR_{NF} - (SXP_{NF} + PUR_{NF}) & \Rightarrow & \pi_2 = \pi_F + \pi_{NF_2} \end{matrix} \quad (5)$$

As shown below, the choice of these determinants is econometrically sound, since there is a strong and significant correlation between predictors and revenues.

2. Strong and significant correlation with CIT revenues

Besides their macro-economic relevance, the selected variables are also statistically related to total revenues. First, it is the first definition of non-financial corporation's profits (π_{NF_1}, which uses RXP in the cost component) is slightly more strongly correlated to KD and KD+DDD revenues than the alternative formulation (π_{NF_2}, which uses SXP). Importantly, the considered variables' correlation with the corresponding tax's revenues is very strong no matter what measure is used (on average: $r = 0.913$; $\tau = 0.785$, $\rho = 0.879$). Moreover, there is little difference between the correlation indexes for KD and KD+DDD across tax bases (on average: $\Delta r_\mu = 2.1\%$; $\Delta\tau_\mu = 1.6\%$, $\Delta\rho_\mu = 0.45\%$).

These results are also highly significant given that both Student's t and Whitney's U paired tests allow independence to be rejected with 99% confidence, excluding $\pi_2 \therefore KD$ ($t = 0.124; U = 0.01245$).

PIT model estimation

1. Multivariate linear regression

The ADF, PP, and KPSS tests' discordant results impede the identification of a set stationary time series for OLS, hinting at both HP-filtered and first-difference ($I(1)$) data. Moreover, Johansen's test shows significant cointegration at level (I(0)). Thus, OLS has been run for each, as shown in Table 1.[2]

Table 1. Estimations of the proposed PIT models

Variables	log likelihood	AIC	AICc	BIC	R^2
I(1)	-85.38	176.76	179.42	178.45	.01
HP	-51.81	117.61	136.28	122.08	.99
I(0)	-91.90	189.79	192.19	191.71	.93

Clearly, the OLS MLR using HP-filtered variables is the most effective. Its R^2 is very close to the unit: approximately 99% of the resulting variability is explained by the proposed model. Moreover, it also has the largest log-likelihood and the most favourable (smallest) information criteria.

2. PIT revenue forecasting error

Using the testing dataset for WAGE and SOC, the proposed PIT model appears superior to the current one regardless of metrics (Table 2). Despite training on HP-filtered data, the proposed model is also particularly more efficient when the results are compared with at-level revenues.

Table 2. Forecasting errors for the current and proposed models (HP-filtered).

Error:	ME	MAE	sMAE	RMSE	U_1
Actual Forecasts	98.18	204.69	0.05	214.55	0.03
Proposed model	89.67	89.67	0.02	95.87	0.01
Accuracy gain	8.51	115.02	0.03	118.68	0.02

Clearly, the proposed model is more efficient in predicting the mean (much smaller RMSE) and virtually perfect on average – even though overestimations do not cancel out underestimations as often (smaller MAE). As suggested by the smaller U_1, the proposed model would have overestimated yearly revenues by an average 3.55mln in 2017–20 with a 67% relative increase in efficiency.

CIT model estimation

1. Multivariate linear regression

The ADF, PP, KPSS, and DF-GLS tests' discordant results impede the identification of a set stationary time series for the dependent variables KD + DDD, DZP, hinting at I(1) and HP-filtered data for the former (π_{NF_1}, π_F) and the natural logarithm for the latter (PRM). However, Johansen's test shows significant cointegration for both sets of predictors at level. Thus, OLS has been run for these combinations.

Table 3. Estimations of the proposed KD+DDD model at I(0), I(1), and HP filtered.

Variables	log likelihood	AIC	AICc	BIC	R^2
I(1)	-64.38	134.76	137.16	136.67	.70
HP	-59.41	130.81	141.31	135.06	.95
I(0)	-38.06	82.13	84.79	83.82	.80

Clearly, the OLS MLR using HP-filtered variables is the most effective. Both its R^2 and all the information criteria favour it over the alternatives.

When it comes to DZP revenues, the model of the natural logarithm of predictors is decidedly effective, with $R^2 = .9$, the favour of all information criteria, and the highest log likelihood.

Table 4. Estimations of the proposed DZP model at I(0) and following the natural logarithm

Variables	log likelihood	AIC	AICc	BIC	R^2
I(1)	-13.81	31.62	34.62	31.51	0.86
ln	8.83	-11.67	-3.67	-11.83	0.90

2. CIT revenue forecasting error

Using the testing dataset for π_{NF_1} and π_F built as mentioned above, the proposed model appears superior to the current one regardless of forecasting KD and DDD revenues. In particular, despite training on HP-filtered data, the proposed model is also more efficient when the results are compared with at-level revenues (Table 5).

Table 5. Forecasting errors for the current and proposed KD+DDD models (HP-filtered)

Error:	ME	MAE	sMAE	RMSE	U_1
Actual Forecasts	6.53	73.33	0.03	82.69	0.02
Proposed model	5.66	69.66	0.02	76.52	0.01
Accuracy gain	0.87	3.67	0.01	10.17	0.01

Clearly, the proposed model is more efficient in predicting the mean (smaller RMSE), albeit similarly imprecise (comparable ME) and a bit more upwardly biased (slightly smaller MAE). Yet the proposed model is relatively more efficient overall (smaller U_1).

Table 6. Forecasting errors for the current and proposed DZP models compared to at-level data.

Error:	ME	MAE	sMAE	RMSE	U_1
Actual Forecasts	39.47	39.47	1.69	39.66	0.85
Proposed model	36.63	36.63	0.07	3.24	0.04
Accuracy gain	2.83	2.83	1.62	36.41	0.81

As regards the simple linear regression model for DZP revenues, the proposed model is clearly more efficient. Namely, it better approximates the mean (smaller RMSE) and only has a large ME because its errors do not cancel each other out as often (smaller MAE and sMAE). Finally, Theil's U_1 shows an appreciable improvement in accuracy – albeit not a massive one.

Reasons to adopt the proposed models

Schematically, the proposed models offer: (1) significant practical advantages related to more transparent and simpler underlying econometric functioning; (2) a better selection of variables; (3) increased precisions; (4) and adaptability to different tax regimes. Still, they would not necessarily remove all arbitrary adjustments, leaving some degree of flexibility. Yet (5) the authorities would need to forecast variables with which they have little experience.

1. Econometric simplicity and transparency

The main econometric strength of the proposed models lies in their being extremely transparent: the MF would not even need to publish the regression coefficients estimated for the MLR. Instead, publishing the predictors' forecasts would allow anyone who has access to statistical tools (e.g., R, Stata, or even Excel) to verify their correctness. This is essential in today's political climate because transparency is antagonistic to policy-based modelling, as transparent models cannot be used to preserve and rationalise biased, partisan opinions by cherry-picking favoured results.

In addition, the proposed models are quite simple, which is often associated with efficiency and parsimony, whereas 'overelaboration and overparameterization is often the mark of mediocrity' (Box, 1976, p. 796).

2. Improved selection of variables

The proposed model improves upon the MF's choice of predictors for the estimation of the PIT and CIT revenue bases in both macroeconomic and econometric terms.

In fact, the variables chosen to forecast PIT revenues are much easier to measure and forecast than non-labour income, financial, or other sorts of rents. Additionally, this choice forces the data sources to be diversified, as the data is forecasted separately by the MF (WAGE) and the NOI (SOC), while the NSI operates an ex-post revision. Thus, the proposed model would increase public scrutiny. In addition, these variables are also statistically correlated to total revenues. The relation is very strong and highly significant no matter what measure is used.

3. Increased precision

The proposed model would result in a 67% relative increase in precision. Namely, the proposed PIT model is more efficient at predicting mean revenues over a period of time (smaller RMSE) and virtually perfect on average ($ME \approx 0$), even though overestimations do not cancel out underestimations as often (smaller MAE). Meanwhile, the proposed CIT model is more efficient in predicting the mean (smaller RMSE), although it is similarly imprecise on the long term (comparable ME) because overestimations do not cancel out underestimations as often (slightly smaller MAE). Yet there is a perceptible increase in relative efficiency (smaller U_1), suggesting that its simplicity and transparency are not alternative, but complementary, to its precision.

Conclusion

Building on previous, more limited studies, this paper showed that using complex, opaque, and inefficient models for predicting revenues is the prevailing economic practice in official Bulgarian forecasts.

Practically, this paper offers the first systematic overview and attempt at formalising the current forecasting models used by the Bulgarian Ministry of Finance. In addition, it provides three alternative MLR models to predict PIT, KD+DDD, and DZP revenues in a transparent and parsimonious way using a limited number of variables as proxies for the respective tax bases. Crucially, this class of models are comparatively easier to implement than the one already provided in the literature (e.g., Telarico, 2021's ARIMA model). Using established measures of forecasting error and testing data, the proposed models have been shown to be more efficient than the current ones in forecasting revenues in many regards.

In terms of limitations, it is worth underlining that this paper does not argue that MLR models are the *most* efficient for forecasting revenues in Bulgaria, but rather that they are *more* efficient than the current ones. Thus, more studies are needed to find out how different techniques (e.g., non/Bayesian VAR, pure ARIMA, generalised linear regression, etc., as well as fourth-generation dynamic stochastic general equilibrium modelling) compare to the proposed MLR. Contextually, arguments can be made as to the best tools to measure these models' precision and econometric soundness (e.g., error measures, the Granger test, the Toda-Yamamoto test, etc.). However, something strikingly undeniable emerges here. Despite the absence of massive policy changes and exogenous shocks, the current models are actually less effective than simpler alternatives using easily forecastable predictors. Thus, it seems apparent that the bulk of the current forecasts' imprecision stems from their poor design rather than substantial unpredictability.

Hence, the findings presented above add weight to some respected Bulgarian economists' remarks (e.g., Angelov & Bogdanov, 2006; Gechev, 2010; Tanchev, 2016) encouraging the MF to update its methodologies. The economic profession will undoubtedly have a role to play in discontinuing the current models. However, doing so will require an improved understanding of the unspoken assumptions and implicit ideology that underpin them (see Nikolov, 2008, p. 100ff). Hence, it is necessary to underline the role that these models have had in supporting 'irresponsible, socially unjust and technically ineffective' (Nikolov, 2008, p. 99) economic policies in Bulgaria. After all, unrealistic forecasts have played a key role in justifying the adoption of fiscal profligacy elsewhere in the past. And forecasting models similar to the ones currently in use in Bulgaria 'have been used by various countries' to justify regressive tax regimes (Jenkins et al., 2000, p. 40). Hence, they are crucial in spreading trickle-down economics across the political spectrum (Frankel, 2008, p. 13) and in academia. For better or worse, much is still to be written on this.

Endnotes

[1] One must notice that sometimes MLR is improperly labelled *multivariate* regression by behavioural and social scientists, making the words almost synonyms (cf. Arminger et al., 1995, pp. 97-99; Charles, 2012, fol. 1,4 for examples of such an improper use).

[2] AIC, AICc, and BIC are information criteria (Akaike's, Akaike's corrected for small samples, and Bayesian) that quantify two or more models' efficiency in relative terms.

Conflict of interest

The author declares no conflict of interest.

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