FORECASTING THE QUARTERLY EVOLUTION OF BUDGET REVENUES IN MOLDOVA UTILIZING A TIME SERIES MODEL

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SUMMARY

The aim of the paper is to develop a time series model fitted on the quarterly evolution of total budget revenues in Moldova for monitoring and forecasting purposes. While the developed model is specific to Moldova it may be of interest to use the methodology discussed in the paper in order to develop similar time series models in other countries to serve as a benchmark for monitoring and forecasting budget revenues. Following a brief analysis of the properties and estimation of time series models, the paper presents the data set to be used for the estimation exercise, as well as analyse the data's stationarity and the correlogram of the stationary series to be modelled. The data sample comprises the quarterly evolution of total budget revenues in Moldova from the first quarter of 2016 to the first quarter of 2023. The paper proceeds to provide the econometric estimates of the preferred time series model, as well as use the estimated model to generate the forecast of the quarterly evolution of budget revenues from the second quarter of 2023 to the fourth quarter of 2024. The model's annual forecast of budget revenues for 2023 is slightly more optimistic than the Ministry of Finance's estimate for 2023 contained in the recently approved Medium Term Budget Framework document and is almost identical with the projection of the International Monetary Fund contained in its latest country report for Moldova. The paper concludes by summarising the uses and limitations of time series models for monitoring and forecasting purposes and suggesting areas for further work.

Keywords: *time series econometrics, auto-regressive integrated moving average models, budget revenues, Moldova*

Scopul acestui studiu este dezvoltarea unui model de serie temporală adaptat pentru analiza evoluţiei trimestriale a veniturilor bugetare totale din Moldova, cu scopul de monitorizare și și prognozare. Chiar dacă modelul dezvoltat este specific Moldovei, metodologia discutată în articol prezintă interes pentru dezvoltarea unor modele de serie temporală similare în alte ţări, care pot servi drept referinţă pentru monitorizarea și prognozarea veniturilor bugetare.

După o analiză concisă a proprietăţilor şi estimărilor modelelor de serie temporală, studiul prezintă setul de date utilizat pentru procesul de estimare, precum și analiza staţionarităţii datelor și corelograma seriei staţionare, care urmează să fie modelată. Eşantionul de date cuprinde evoluţia trimestrială a veniturilor bugetare totale în Moldova, începând din primul trimestru al anului 2016 și până în primul trimestru al anului 2023.

Articolul furnizează estimările econometrice ale modelului de serie temporală, precum și este utilizat modelul estimat pentru a genera o prognoză a evoluţiei trimestriale a veniturilor bugetare din al doilea trimestru al anului 2023 până în al patrulea trimestru al anului 2024. Prognoza anuală a veniturilor bugetare, conform modelului pentru anul 2023, este puţin mai optimistă decât estimarea Ministerului Finanţelor pentru acelaşi an, conform Cadrului Bugetar pe Termen Mediu recent aprobat, și este aproape identică cu proiecţia Fondului Monetar Internaţional prezentată în ultimul său raport de ţară pentru Moldova.

Studiul se încheie prin rezumarea posibilităţilor de utilizare şi a limitărilor modelelor de serie temporală în contextul monitorizării și prognozării, precum și prin formularea domeniilor pentru cercetări viitoare.

Cuvinte cheie: *econometrie în serii cronologice, modelul medie mobilă integrată autoregresivă, venituri bugetare, Moldova*

Цель данной статьи заключается в разработке модели временных рядов, специализированной для анализа квартальной динамики общих доходов бюджета Молдовы с целью мониторинга и прогнозирования. Несмотря на то, что данная модель специфична для Молдовы, описанная методология может быть полезной при разработке аналогичных моделей временных рядов в других странах, которые также будут использоваться для мониторинга и прогнозирования доходов бюджета.

После краткого анализа свойств и оценки моделей временных рядов в статье представлен набор данных, использованный для прогноза. Также проводится анализ стационарности данных и коррелограмма стационарного ряда, который подлежит моделированию. Этот набор данных включает в себя квартальную динамику общих доходов бюджета Молдовы с первого квартала 2016 года по первый квартал 2023 года.

В статье представлены результаты эконометрических оценок предпочтительной модели временных рядов, а также используется оценочная модель для формирования прогноза квартальной динамики доходов бюджета с второго квартала 2023 года по четвертый квартал 2024 года. Годовой прогноз доходов бюджета на 2023 год, полученный с использованием данной модели, немного более оптимистичен, чем официальный прогноз Министерства финансов на 2023 год, представленный в недавно утвержденном документе "Среднесрочные бюджетные рамки", и практически идентичен прогнозу Международного валютного фонда, представленному в последнем страновом отчете по Молдове.В заключение статьи обобщаются возможности использования и ограничения моделей временных рядов для целей мониторинга и прогнозирования. Также предлагаются области для дальнейших исследований.

Ключевые слова: *эконометрика временных рядов, интегрированная модель авторегрессии скользящего среднего, доходы бюджета, Молдова*

INTRODUCTION

The actual and future evolution of total budget revenues in an economy is a critical variable for the design and conduct of economic policy and the maintenance of fiscal and debt sustainability. The aim of this paper is to develop and estimate a time series model fitted on the quarterly evolution of total budget revenues in Moldova and use the estimated model to generate short to medium-term forecasts. While the model developed in this article is specific to the case of the Moldovan economy, it may be of interest to use the methodology described in this article in order to develop similar time series models for other countries. These models could serve as a benchmark to assist analysts and forecasters in monitoring and forecasting the evolution of budget revenues.

The paper is organised as follows: Following a brief analysis of the characteristics and estimation of time series models, the paper presents the data set to be used for the estimation and the data's stationarity and the correlogram of the stationary series to be modelled. This is followed by a section which includes the econometric analysis and the estimates of the preferred time series model, as well as the forecast of the quarterly evolution of budget revenues in Moldova from the second quarter of 2023 to the fourth quarter of 2024. A table therein compares the forecasted annual budget revenues for 2023 and 2024 of the model with the forecasts by the Ministry of Finance contained in the recently approved Medium-Term Budget Framework document and the forecasts contained in the latest International Monetary Fund country report for Moldova. The paper concludes by summarising the uses and limitations of time series models and suggesting areas for further work.

A NOTE ON TIME SERIES MODELS

The origin of time series econometrics is the seminal work of Box and Jenkins (1970). The current section provides an overview of the properties of time series models focusing on the methodology of analysing and estimating the so-called Auto-Regressive Integrated Moving Average (ARIMA) models.

It is well-known that ARIMA models are widely used in empirical work for analytical and forecasting purposes. Even though ARIMA models are typically a-theoretical they have proved to be very useful instruments in order:

1. To provide insight and analyse the underlying data-generating process of the particular time series under investigation; and/or

2. To generate forecasts of the analysed time series. As a rule the forecasts generated by ARIMA models are frequently used as benchmarks: the ARIMA- generated forecasts are taken into account and are combined with other economic indicators, analysis and professional judgement on the combined effect of a number of economic variables and the structural characteristics of the economy under consideration and its external environment in order to arrive at a reliable forecast of the time series in question.

ARIMA models are linear models which incorporate an autoregressive dynamic process and a moving average dynamic process. Given any time series variable, yt:

1. An Auto-Regressive (AR) process is a process where the current value of yt is a function of its own past values and an error term, ut:

2. $y_t = f\,(y_{t-1}, y_{t-2}, \ldots) + u_t$.

3. A Moving Average (MA) process is a process where the contemporaneous value of yt is a function of the past as well as contemporaneous values of the error term, ut

4. $y_t = g\,(u_{t-1}, u_{t-2}, \ldots) + u_t$.

We now turn to the issue of the stationarity of the time series under analysis. The initial step in developing an ARIMA model is to ensure that the time series that will be modelled is stationary or, in other words, that the series to be fitted by an ARIMA model does not contain a unit root. This is because it is well-known that a non-stationary time-series may give rise to spurious (i.e false) regressions. A time-series that follows a stationary process has the property that its mean, variance and autocorrelation structure is finite and constant over time.

The stationarity of a time series is tested through the use of a number of statistical tests. If the time series under scrutiny is not stationary then, following the Box and Jenkins (1970) methodology, the first difference of the time series under consideration is taken and the resulting time series is subsequently tested for stationarity. This differencing process is repeated until the resulting time series is stationary. The number of times the time series under analysis has to be differenced in order to arrive at a stationary time series determines the so-called order of integration of the ARIMA model.

In general any ARIMA model could be characterised by a vector of three numbers (p,d,q), where:

- p refers to the number of lags in the AR process in the estimated model;
- d refers to the order of integration (i.e. the number of times the time-series under analysis needs to be differenced in order to eventually obtain a stationary series); and
- q is the number of lags in the MA process in the estimated model.

At the identification stage of the ARIMA model's specification, the researcher seeks also to analyse briefly the property of the time series under investigation. The model's identification process requires the exercise of informed judgement supplemented by a number of diagnostic tools and tests to assist in the analysis. Graphs of the autocorrelation and partial autocorrelation functions of the time series are frequently employed in order to facilitate the determination of the number of lags in modelling the AR and/or the MA process in the specified ARIMA model. Both the autocorrelation and partial autocorrelation functions are summarised in the correlogram of the time series under investigation, which displays the autocorrelation and partial autocorrelation functions up to the specified number of lags. In particular:

- the autocorrelation function displays the coefficients of correlation between a time series and time lags of the same series, while.
- by partial autocorrelation we refer to the correlation between a variable and a lag of itself that is not explained by the correlations of all lower-order-lags.

It is notable that:

- The typical correlogram of a pure AR process is characterised by a geometrically decaying autocorrelation function, while the partial auto-correlation function drops to zero after a number of time lags. The spikes in the partial autocorrelation function are indicative of the AR order to be introduced in the ARIMA model's specification;
- In a typical pure MA process the number of spikes in the autocorrelation function is indicative of the MA order to be introduced in the ARIMA specification. The correlogram of a typical MA process is characterised by a geometrically decaying partial autocorrelation function and an autocorrelation function that drops to zero after a few lags.
- Finally, if the correlogram of the time series under investigation is characterised by geometrically decaying autocorrelation and partial auto-correlation functions, this may be indicative that a mixed AR and MA process may be the appropriate specification.

In general the aim of the ARIMA model identification and selection process is to arrive at a specified ARIMA model that:

- Is parsimonious, or, in other words, as simple as possible; and
- Passes the diagnostic tests that are used to assess the overall fit of the specified regression equation.

Now a parsimonious ARIMA model is desirable because:

- Including irrelevant time-lags in the model's specification increases the coefficient standard errors (and therefore reduces their t-statistics and their statistical relevance).
- Regression models that incorporate large numbers of time-lags, tend not to forecast very well. This is because such models are likely to over-fit data-specific features of the data under estimation (by explaining much of the random features in the data set under investigation rather than providing a more efficient reflection of the underlying data generating process).

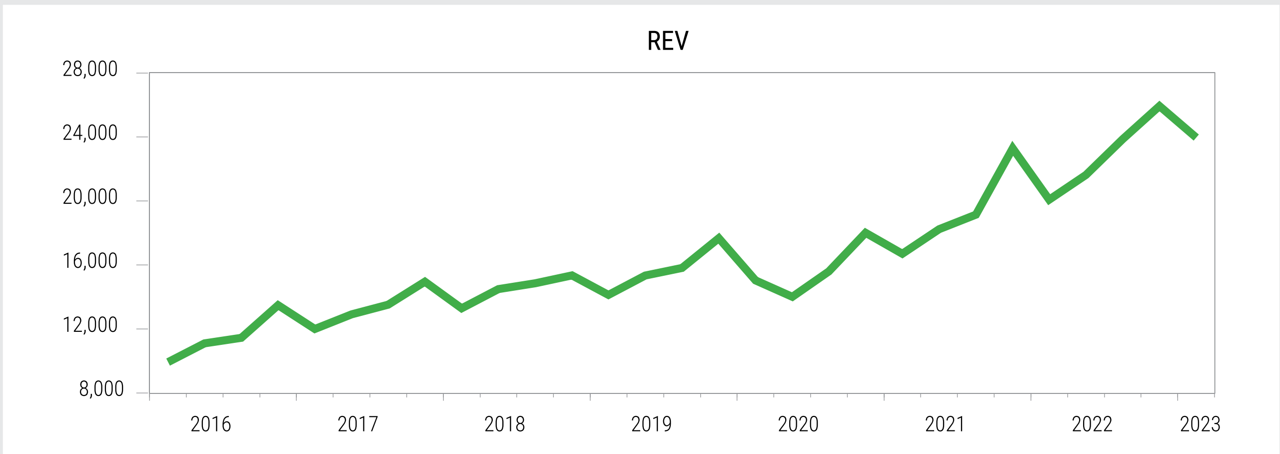
It is notable that in the estimation and testing steps of the ARIMA's model development a number of descriptive statistics and statistical tests are used to assist the analysis, the ARIMA model selection and its validation. These tests include also information criteria (such as the Akaike information criterion and the Schwarz criterion) that are used to compare different alternative regression specifications and balance: (1) the goodness of fit requirement of the specified regression; with (2) the need for a parsimonious (i.e. simple) specification.

DATA, STATIONARITY AND THE CORRELOGRAM

The data to be used for the econometric analysis in the paper is the quarterly evolution of total budget revenues in Moldova from the first quarter of 2016 to the first quarter of 2023. The data are reproduced in the paper's appendix. Graph 1 below provides a visual representation of the evolution of budget revenues over the period.

Graph 1:

Graph of the quarterly evolution of budget revenues from the first quarter of 2016 to the first quarter of 2023



Source: Ministry of Finance.
Note: The numbers are in millions of Moldovan lei.

Tables 1 and 2 below report the stationarity tests of the budget revenues time series itself and its first difference respectively. Both series are nonstationary.

Table 1.

Stationarity test of the time series
Null Hypothesis: REV has a unit root

Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=6)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.132553	0.9966
Test critical values:	1% level	-3.737853	
	5% level	-2.991878	
	10% level	-2.635542	

**MacKinnon (1996) one-sided p-values.*
Source: EViews-generated estimates

Table 2.
Stationarity test of the first difference of the time series
Null Hypothesis: D(REV) has a unit root

Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=6)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.575736	0.4791
Test critical values:	1% level	-3.737853	
	5% level	-2.991878	
	10% level	-2.635542	

**MacKinnon (1996) one-sided p-values..*
Source: EViews-generated estimates

On the other hand table 3 below provides firm evidence that the second difference of the budget revenues time series is stationary.

Table 3.
Stationarity test of the second difference of the time series
Null Hypothesis: D(REV,2) has a unit root

Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=6)

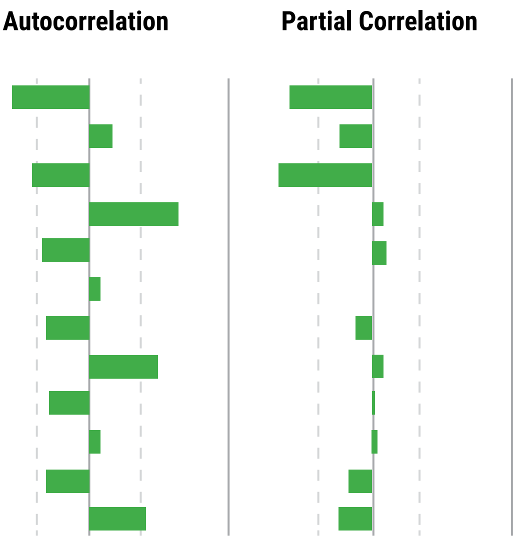
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.98663	0.0000
Test critical values:	1% level	-3.737853	
	5% level	-2.991878	
	10% level	-2.635542	

**MacKinnon (1996) one-sided p-values..*
Source: EViews-generated estimates

Table 4 below reproduces the correlogram of the second difference of the budget revenues time series.

Table 4.
Correlogram of the second difference of the time series.

Sample: 2016Q1 2027Q4
Included observation: 27



	AC	PAC	Q-Stat	Prob
1	-0.563	-0.563	9.5486	0.002
2	0.161	-0.228	10.364	0.006
3	-0.417	-0.671	16.051	0.001
4	0.648	0.083	30.349	0.000
5	-0.349	0.114	34.694	0.000
6	0.095	-0.003	35.032	0.000
7	-0.313	-0.114	38.877	0.000
8	0.507	0.089	49.484	0.000
9	-0.283	0.024	52.977	0.000
10	0.092	0.027	53.365	0.000
11	-0.311	-0.155	58.092	0.000
12	0.403	-0.209	66.561	0.000

Source: EViews-generated estimates

The partial correlation function depicted in table 4 is characterised by three spikes in the first three lags, with the spikes from the fourth lag onwards being much less significant. This indicates that a possible ARIMA model specification to be estimated may include the first three ar lags.

The autocorrelation function in table 4 is more difficult to characterise. There are spikes in the first, third and fourth lag, but it is not apparent how to succinctly characterise the general evolution of the function besides noting that the spikes seem to slowly decrease from the fifth lag onwards (albeit it with a significant spike in lag 8). As the previous section of the paper indicated the spikes in the autocorrelation function may be indicative of the possible inclusion of ma terms in the regression model to be estimated. The possible inclusion of ma terms in the ARIMA model's specification is further analysed through statistical tests which are reported in the following section.

ECONOMETRIC ESTIMATES AND FORECASTS

The above-mentioned analysis of the partial correlation function suggests that the (3,2,0) model may be a good starting point for the econometric investigation. Table 5 below reproduces the regression results of the (3,2,0) model.

Table 5.
Regression results of the (3,2,0) model

Dependent Variable: D(REV,2)
Method: Least Squares
Sample (adjusted): 2017Q2 2023Q1
Included observations: 24 after adjustments
Convergence achieved after 4 iterations

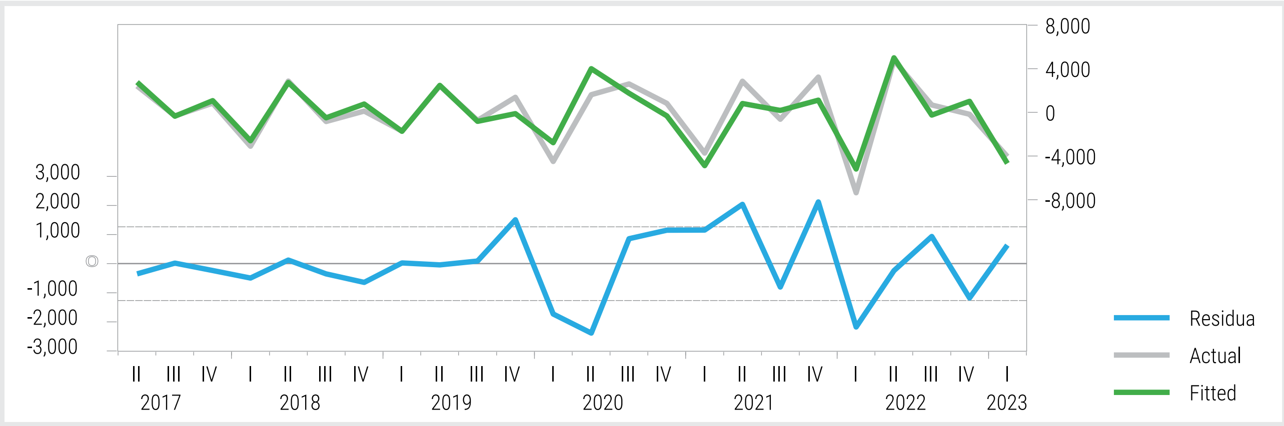
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	19.22616	65.51823	0.293447	0.7722
AR(1)	-1.043593	0.122095	-8.547416	0.0000
AR(2)	-1.021039	0.151022	-6.760861	0.0000
AR(3)	-0.884974	0.121355	-7.292440	0.0000
R-squared	0.834282	Mean dependent var		-19.96250
Adjusted R-squared	0.809425	S.D. dependent var		2902.713
S.E. of regression	1267.178	Akaike info criterion		17.27798
Sum squared resid	32114778	Schwarz criterion		17.47433
Log likelihood	-203.3358	Hannan-Quinn criter.		17.33007
F-statistic	33.56239	Durbin-Watson stat		2.297964
Prob(F-statistic)	0.000000			

Source: EViews-generated estimates

Despite the relatively small sample size the overall fit of the regression reported in table 5 is quite good with the model explaining more than 83% of the total variation of the dependent variable, and with all three ar regression terms being highly statistically significant. On the other hand, the regression's constant term is not significant.

Graph 2 below depicts the actual, fitted and residuals graph of the regression of the (3,2,0) model. It is notable that the largest deviation between the actual and fitted values occurred in the second quarter of 2020 reflecting the adverse impact of the COVID-19 pandemic on the economy in general and Moldova's fiscal aggregates including its budget revenues in particular.

Graph 2:
Actual, fitted and residuals graph of the regression reported in table 5



Source: EViews-generated estimates

The advantage of the estimated (3,2,0) model is its good overall fit and its simplicity. Furthermore, it is notable that the addition of ma terms in the regression does not improve the estimation results. More specifically the addition of a ma (1) term in the regression reported in table 5 gives rise to a regression outcome where the ma (1) term is not statistically significant, while the overall fit of the resulting (3,2,1) model deteriorates when compared with the original (3,2,0) model, which has also the additional advantage of being simpler[2]. The regression results of both the (3,2,2) and (3,23) models report that the estimated ar process is nonstationary.

We proceed to generate short to medium term forecasts of the estimated (3,2,0) model. Table 6 below contains the estimated model's dynamic forecasts of the quarterly evolution of budget revenues from the second quarter of 2023 to the fourth quarter of 2024.

Table 6.
Forecasts of the quarterly evolution of budget revenues from the second quarter of 2023 to the fourth quarter of 2024 generated by the (3,2,0) model

2023Q2	25854.21
2023Q3	28065.80
2023Q4	29653.40
2024Q1	28224.37
2024Q2	30368.40
2024Q3	32491.86
2024Q4	33734.12

Source: EViews-generated estimates

Now it is well known that the short-term forecasts of a time series model are more reliable than its forecasts over longer periods (which become increasingly uncertain as the forecast horizon expands). It follows that the quarterly estimates for 2023 in table 6 above are more reliable than the quarterly estimates for 2024. I shall return to this point at the end of the current section.

A natural question which arises concerns the comparison of the budget forecasts generated by the estimated (3,2,0) time series model with other forecasts by national and/or international institutions.

Of particular importance for the design and conduct of fiscal policy in Moldova are the forecasts of the Ministry of Finance of Moldova. With regard to the methodology used by the Ministry of Finance, it is notable that it uses the effective rate methodology and relies heavily on a professional judgement which takes into account all the relevant variables and the available information, as well as the impact of the changes in economic policy and the structural reform programme over the forecasting period. Moldova's fiscal policy in the medium-term is analysed in the recently approved Medium-Term Budget Framework for 2024-2026 (Ministry of Finance, 2023b). At the same time Moldova's reform programme in the area of Public Financial Management is analysed in the Public Financial Management Strategy 2023-2030 document (Ministry of Finance of Moldova, 2023a).

[2] *The regression results of the (3,2,1) model are included in the paper's appendix. When compared with the simpler (3,2,0) model, the (3,2,1) model fits the data less well as indicated by a comparison of the adjusted R-squared, the Akaike information criterion and the Schwarz criterion.*

[2] *According to the International Monetary Fund's Manual on Fiscal Transparency under the effective rate approach "the forecast for each tax is made by multiplying a forecast of the tax base by the corresponding effective tax rate. The effective tax rate is calculated by dividing the tax collected for the most recently available period by the estimated tax base. For transparency, it is necessary to disclose the way in which the effective tax rate is calculated, the economic assumptions underlying the tax base forecast, and any adjustments that are made to reflect any of the aforementioned changes" (International Monetary Fund, 2007, p. 38).*

Table 7 below reports the recent annual forecasts of the Ministry of Finance of Moldova, the recent forecasts of the International Monetary Fund, as well as the forecasts of the estimated (3,2,0) time series model for the years 2023 and 2024.

Table 7.
Selected forecasts of budget revenues in Moldova for 2023 and 2024

Source: Ministry of Finance, International Monetary Fund and own calculations

	2023	2024
Ministry of Finance	100659	105398
International Monetary Fund	106886	111518
Forecasts from the estimated (3,2,0) model	107542	124819

Note: The numbers in the table are in millions of Moldovan lei. The Ministry of Finance numbers are contained in the recently approved Medium-Term Budget Framework for 2024-2026 and comprise the latest budget amendment for 2023 and the Ministry's forecast for 2024 (Ministry of Finance, 2023b). The International Monetary Fund numbers are taken from the latest country report for Moldova and comprise the projection of revenues and grants for 2023 and the forecast for 2024 (International Monetary Fund, 2023, p. 33). The forecasts from the estimated (3,2,0) model are rounded estimates based on the actual budget revenues for the first quarter of 2023 and the quarterly forecasts contained in table 6 above.

The forecasts of the estimated (3,2,0) model are more optimistic, especially for 2024. One possible reason may be that, over the forecasting period to the end of 2024, inflation in Moldova is expected to decelerate significantly as indicated by the latest Inflation Report of the National Bank (National Bank of Moldova, 2023). And while the expected inflationary process is taken into account in the forecasts of the two institutions, it is exogenous to the forecast generated by the time series model (which relies exclusively upon the actual historical path of the data).

My second comment brings us back to the above-mentioned property of the time series model regarding the short term forecast being more reliable than the forecast over a longer time period. Focusing upon 2023, the forecast generated by the estimated time series model is only slightly more optimistic that the forecast of the Ministry of Finance and almost identical with the projection of the International Monetary Fund.

CONCLUSION AND SUGGESTIONS FOR FURTHER WORK

As the paper has emphasised the forecasts of time series models are, at best, only useful as benchmarks and an additional tool in the forecasting process. The forecast of any time series model cannot (and should not) replace the need for the exercise of professional judgement and the prudent assessment of all the available information by the forecasters.

A natural area for further work would be to expand the data sample by including earlier observations. This may well increase the efficiency of the econometric analysis and the generated econometric estimates and forecasts.

A straightforward extension would be to include in the regression equation three seasonal dummy variables to capture the inherent seasonality of the Moldovan economy. The expanded data set would allow a more efficient assessment of the extended model's forecasting ability in comparison with the original specification. It is notable that, with the existing data set, the inclusion of the three seasonal dummy variables improves the regression's fit as captured by the adjusted R-squared, the Akaike information criterion and the Schwarz criterion. Furthermore it should also be noted that the annual forecasts for 2023 and 2024 of budget revenues of the extended model are very close to those generated by the simple (3,2,0) model reported in table 7 above. The results of the estimation of the extended model with the three seasonal dummy variables appear at the end of the paper's appendix which also includes the out-of-sample forecasts of the extended model to the end of 2024.

Looking forward another closely related area for further work would be to update the analysis, econometric estimates and forecasts of the estimated model as new data become available through time. This will render the time series model a useful instrument for monitoring and forecasting purposes.

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APPENDIX

Data set

Data set					
2016Q1	9925.000	**2018Q3**	14858.60	**2021Q1**	16698.80
2016Q2	11103.00	**2018Q4**	15350.10	**2021Q2**	18234.40
2016Q3	11443.10	**2019Q1**	14128.30	**2021Q3**	19143.60
2016Q4	13482.80	**2019Q2**	15338.90	**2021Q4**	23296.20
2017Q1	11993.20	**2019Q3**	15811.40	**2022Q1**	20075.90
2017Q2	12916.00	**2019Q4**	17670.60	**2022Q2**	21627.40
2017Q3	13516.30	**2020Q1**	15029.60	**2022Q3**	23865.20
2017Q4	14953.90	**2020Q2**	14008.10	**2022Q4**	25936.90
2018Q1	13291.60	**2020Q3**	15597.60	**2023Q1**	23968.20
2018Q2	14495.60	**2020Q4**	18014.70		

Source: Ministry of Finance.
Note: The estimates are in millions of Moldovan lei.

Regression results of the (3,2,1) model

Dependent Variable: D(REV,2)
Method: Least Squares
Sample (adjusted): 2017Q2 2023Q1
Included observations: 24 after adjustments
Convergence achieved after 7 iterations
MA Backcast: 2017Q1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	18.69594	51.24176	0.364857	0.7192
AR(1)	-0.964616	0.150725	-6.399818	0.0000
AR(2)	-0.957388	0.167202	-5.725918	0.0000
AR(3)	-0.859721	0.136927	-6.278693	0.0000
MA(1)	-0.266968	0.255714	-1.044010	0.3096

R-squared	0.841190	**Mean dependent var**	-19.96250
Adjusted R-squared	0.807756	**S.D. dependent var**	2902.713
S.E. of regression	1272.714	**Akaike info criterion**	17.31874
Sum squared resid	30776194	**Schwarz criterion**	17.56417
Log likelihood	-202.8249	**Hannan-Quinn criter.**	17.38385
F-statistic	25.15988	**Durbin-Watson stat**	1.975773
Prob(F-statistic)	0.000000		

Source: EViews-generated estimates.

Regression results of the (3,2,0) model with the addition of seasonal dummy variables

In the regression below the variable q2 takes the value of 1 in the second quarter and of 0 in the other three quarters. Similarly, the variable q3 takes the value of 1 in the third quarter and of 0 in the other three quarters and the variable q4 takes the value of 1 in the fourth quarter and of 0 in the other three quarters.

Dependent Variable: D(REV,2)
Method: Least Squares
Sample (adjusted): 2017Q2 2023Q1
Included observations: 24 after adjustments
Convergence achieved after 9 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-608.7553	500.3477	-1.216665	0.2404
Q2	370.1220	718.7205	0.514974	0.6132
Q3	4074.718	1092.984	3.728066	0.0017
Q4	-1887.787	1247.761	-1.512939	0.1487
AR(1)	-1.199017	0.206965	-5.793344	0.0000
AR(2)	-0.801234	0.308065	-2.600862	0.0186
AR(3)	-0.571511	0.205040	-2.787315	0.0126

R-squared	0.872097	Mean dependent var	-19.96250
Adjusted R-squared	0.826955	S.D. dependent var	2902.713
S.E. of regression	1207.492	Akaike info criterion	17.26897
Sum squared resid	24786625	Schwarz criterion	17.61257
Log likelihood	-200.2277	Hannan-Quinn criter.	17.36013
F-statistic	19.31884	Durbin-Watson stat	2.029049
Prob(F-statistic)	0.000001		

Inverted AR Roots -.11-.76i -.11+.76i -.98

Source: EViews-generated estimates.

As noted in the paper's section on areas for further work the inclusion of the three seasonal dummy variables improves the regression's overall fit as captured by the adjusted R-squared, the Akaike information criterion and the Schwarz criterion. However only the seasonal dummy variable for the third quarter is highly statistically significant.

The table below contains out-of-sample forecasts of the quarterly evolution of budget revenues from the second quarter of 2023 to the fourth quarter of 2024 generated by the extended (3,2,0) model with the incorporation of seasonal dummy variables.

2023Q2	25596.84
2023Q3	27509.73
2023Q4	29628.71
2024Q1	28255.43
2024Q2	29753.83
2024Q3	31754.65
2024Q4	33968.14

Source: EViews-generated estimates.

Finally the table below reproduces table 7 in the main text and adds another raw containing the forecast of the annual revenues estimated by the extended (3,2,0) model with the incorporation of seasonal dummy variables rounded to the first integer.

	2023	2024
Ministry of Finance	100659	105398
International Monetary Fund	106886	111518
Forecasts from the estimated (3,2,0) model	107542	124819
Forecasts from the estimated (3,2,0) model with seasonal dummy variables	106704	123732

Source: EMinistry of Finance, International Monetary Fund and own calculations

The annual forecasts of the extended (3,2,0) model with the incorporation of seasonal dummy variables are very close to the forecasts generated by the simple (3,2,0) model (which remain the highest in the table).

It should be stressed that a more complete analysis of the efficiency of the econometric estimates and the extended model's forecasting ability will require a larger data set and will become possible when earlier data are included in the data set.