Does Money Matter for Predicting Overall Prices in Albania? An Analysis with Recurrent Neural Network

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Abstract: - The purpose of this article is to assess the information content of monetary aggregates in predicting overall prices in Albania. The relevance of money is evaluated by comparing forecasts derived from no-money versus money-based models. Rather than employing traditional econometric models, an important innovation in our analysis is to use the Long Short-Term Memory (LSTM) technique of recurrent neural networks. These powerful tools allow higher flexibility than conventional functional forms for achieving the desired degree of forecast accuracy. After estimating the neural network parameters on quarterly data from 1993 to 2016, the forecast performance is then evaluated in a pseudo-out-of-sample exercise for horizons varying from one to twelve quarters ahead during the period 2017-2022. Preliminary results indicate that narrow monetary aggregates, particularly base money that is controlled by the central bank, have an important role in predicting prices at all horizons up to around two years. Contrary to expectations, the contribution of broader monetary aggregates M2 and M3 is found unstable across time horizons. The LSTM model results also uncover time-varying effects of monetary aggregates. We find evidence that the impact of money growth on overall price developments was weaker in the years before the pandemic, and it increased considerably during the accelerating inflation in the post-coronavirus and energy shock period. As it is the more recent period that matters for monetary policy, it is argued that money matters in the case of Albania (at least in particular economic circumstances) and due diligence should be dedicated to money-based price models.

Key-Words: - Albania, monetary aggregates, prices, nonlinearity, recurrent neural network, LSTM method.

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1 Introduction

The Bank of Albania used to assign an important role to broad money in its monetary policy strategies up to the middle of the 2000s. There was a sense of neglecting money thereafter as the central bank gradually shifted from a monetary targeting regime to a full-fledged inflation-targeting framework in early 2015. Nevertheless, recent economic developments have instigated the monetary authority to broaden the scope of attention in its monetary policy medium-term strategy reports since 2019 by stimulating empirical studies that re-assess the information content in the monetary indicators. The Bank of Albania has continually maintained in its official documents that domestic prices are substantially influenced by several factors and money is linked to inflation, especially in the long run, [1] and [2]. Therefore, the questions we ask in this article are rather *to what extent it matters* and at what horizons.

The quantity theory of money (QTM) predicts that money and price movements have a long-term one-to-one relationship. This hinges on the presumption that demand for real money balances is stable in the long run, owing to limited shifts in trend real income and little variations in the opportunity cost of holding money. However, the current generation of dynamic general equilibrium models that are based on the New Keynesian framework provide little or no role for money, claiming that output gap or inflation does not react to monetary developments in the short run, [3]. In search for empirical evidence, recent works have provided strong support in favor of the one-to-one link of money and prices as predicted by the QTM, but the link seems to weaken in countries and periods of low inflation, [4], [5] and [6].

Following the outbreak of the Covid-19 pandemic, money supply increased dramatically throughout the world economy. In Albania, the central bank money (monetary base) and narrow money M1 (consisting of currency in circulation and demand deposits) experienced a cumulative increase of over 37 percent in 2020-2022. Similarly, broad money M2 and M3 rose by more than 23 percent. The rise in monetary aggregates is manifold higher than their developments in the three years before the pandemic, 2017-2019. By comparison, overall prices (GDP deflator) witnessed a cumulative increase of 14 percent over the same period after the pandemic or more than threefold of its cumulative rise in the three preceding years. The concurrence of these movements has generated a renewed debate on the money-price nexus. This article attempts, therefore, to shed light on the relevance of money in explaining price movements in the recent period, while also referring to the distinctive features during the modest and accelerating inflation regimes about the pre-, and post-coronavirus years.

The irregular patterns that are often evidenced in the Albanian economic indicators might negatively affect the stability of model parameters with linear estimation methods. Nonlinear techniques – led by artificial neural networks – can be useful in capturing a better fit of Albanian time series data, [7]. As these methods may commonly use a huge number of parameters that could affect in-sample model explanation, we derive inferences on the relevance of money by comparing the out-of-sample forecast ability of the cashless versus money-based models during the period 2017-2022. The method that we use could perhaps be understood in the argument that "In economics, one often starts with a model and tests what the data can say about the model. The physics approach to this field differs in that it starts in the spirit of experimental physics where one tries to uncover the empirical laws which one later models", [8]. Moreover, econometricians have always held the belief that a good out-of-sample forecast performance conveys strong support for an empirical model and the economic theory on which it is based, [9]. Therefore, our empirical findings can also contribute to the literature on the usefulness of computational intelligence and related nonparametric statistical methods as analytical tools to support economic policy decisions.

The rest of the paper is organized as follows. Section 2 briefly reviews the existing theoretical and empirical debate on the money-price relationship. Section 3 describes the long short-term memory neural network that is employed in this study, the data characteristics, and the modeling and forecasting procedure. Section 4 presents the forecast evaluation results and discusses the contribution of monetary aggregates both to the forecast performance of univariate price models and to the trivariate model that consists of prices, gross domestic product, and the monetary policy base rate. Section 6 provides a summary of the results and some concluding remarks.

2 Related Literature

The role of money in monetary policy discussions has been much debated in the last decades on both, theoretical and empirical bases. After being a central tool of macroeconomic teaching for over half a century, the IS-LM-AS model was losing its charm in offering satisfying explanations for the changing macroeconomic issues and environment in the 1990s. By that time, the U.S. Federal Reserve and many other central banks were paying little attention to the information content of monetary aggregates, even though money supply targeting was one of the basic assumptions in the IS-LM framework. Joining many other critics on the weaknesses in the IS-LM model, [10] showed how they can be avoided in his modeling approach if the central bank's money targeting assumption in the LM curve is replaced with a real interest rate rule equation. In the standard New Keynesian models, the interest rate channel has become the primary mechanism for monetary policy analysis.

On the other side, monetarists criticize the New Keynesian theoretical framework without money as oversimplifying the economic structure and, at best, incomplete. Despite being still not able to provide a generally accepted toolbox that includes money, the literature of New Monetarists contends that money is important to forward certain transactions that would otherwise be difficult to accomplish [11] and when changes in short-term interest rates are incapable to exert all the power of monetary policy operations [12].

As it is argued, policy analysis in (i) "models without monetary aggregates do not imply that inflation is a non-monetary phenomenon and are not necessarily non-monetary models," and ii) "…theoretical considerations suggest that such models are misspecified, but the quantitative significance of this misspecification is very small", [13]. Although the notion that models based on interest rate 'policy rules are fundamentally misguided' is dismissed in the paper, the author admits that they are not necessarily preferable to models that include monetary indicators, such as reserves or the monetary base. Testing for the quantity theory of money in a sample of about 160 countries over 30 years, it is found that the relationship between money growth and long-run inflation is strong in high-inflation economies and weak in countries with an annual inflation of less than 10 percent on average, [14]. In short, the debate about the long-run neutrality of money is rather empirical, whereas its role in the short-run is disagreed among the various economic schools concerning both, the transmission mechanisms and the magnitude of monetary effects, [15].

Monetary indicators are found to be useful in predicting Euro Area inflation at medium-term horizons, [16]. Using direct and iterated forecasting models, including standard bivariate models, factor models as well as trivariate two-pillar Phillips Curve models, the author assesses the role of several monetary indicators in forecasting HICP inflation for 1 to 12 quarters ahead over the period 1999Q1 to 2005Q4. The results suggest that the information content of broad money M3 has decreased since 2003, yet further analysis reveals that monetary indicators are still useful for future inflation and should not be neglected, particularly at forecast horizons longer than two years.

Other studies, such as [17] and [18], have investigated whether money growth matters for inflation in the Euro Area and the United States. Using Bayesian VAR estimation techniques, the authors evidence that money improves inflation forecast accuracy, but its contribution appears quantitatively limited and has smaller predictive power in the recent sub-period. In a recent analysis of the Euro Area and the U.S., the authors conclude that monetary developments can only be "relevant for inflation in unsettled monetary and inflationary conditions," but not so when inflation is relatively low and stable, [19]. Nevertheless, exploration of the link between money and inflation reveals that the relationship is sensitive to the selected model class. For instance, one finds that the inclusion of money provides relevant information in predicting the Euro Area inflation with New Keynesian DSGE models and VARs, but it adds little news to dynamic factor models and performs worse in partial equilibrium models. Moreover, the cashless models outperform monetary models in an all-out comparison, [20].

In a similar vein, some authors have studied the predictive power of monetary indicators for future inflation in selected Central European countries (the Czech Rep., Hungary, Poland, and Slovakia), [21]. The results show that M2 growth, as well as the constructed monetary indicators, such as monetary overhang, and nominal and real money gap, were unable to systematically outperform the benchmark univariate inflation forecasts. Instead, money-related forecasts of up to two years were found to be quite heterogeneous and suggested that the relevance of money for anticipating inflation could be to the same degree as past inflation.

Regarding the empirical evidence for Albania, some authors have estimated a structural VAR model to investigate the importance of various monetary transmission channels, [22]. Their findings indicate that money and expectations are the most important channel, while the once effective strength of the exchange rate channel has considerably declined. Other authors have found it useful to include M1 and M3 monetary aggregates beside other economic indicators to improve their set of inflation forecasting models, [23]. Also, money serves as an important monetary policy instrument for anchoring inflation expectations, as is concluded by another study that first finds a stable money demand function and then uses a P-star model framework, [24]. Finally, others have inquired into the conventional view that monetary developments should not be incorporated to model the monetary policy stance once the interest rate is already included, [25]. They find that entering both, the policy rate and broad money M2 could help in improving the VAR analysis to be in line with theory and eliminate the exchange rate and liquidity puzzles that result in model estimations without money.

Estimations with non-linear techniques, such as parametric threshold VAR or the non-parametric recurrent neural networks and kernel recursive least squares regression, have opened up new avenues for assessing the usefulness of monetary aggregates, in spite of finding marginal improvements in predicting U.S. inflation when including money growth. Certain authors conclude that it is worthy to account for possible nonlinear functional forms and monitor the behavior of monetary indicators, [26] and [27]. To our knowledge, the nonlinear functional methods have not yet been explored for the money-inflation link in Albania. Even though linear methods are generally used with success in the analysis of the monetary policy of the Bank of Albania, they are inherently limited in the case of the presence of non-linearity in the statistical series. As mentioned above, there is evidence of the usefulness of non-linear methods in forecasting important macroeconomic indicators in Albania, it gives us another incentive for using the recurrent neural network in this exercise.

3 Empirical Methodology

Macroeconomists have widely believed in the long-run link between money supply and prices, yet the mechanism that explains their relationship remains essentially complex and, almost surely, not linear. Short-run dynamics related to several factors including productivity and economic conditions abroad may disguise the money-price co-movements, as well as increase the possibility of a time-varying and nonlinear relationship. The paper that compares linear and nonlinear univariate models in forecasting the main economic indicators in Albania finds that nonlinear methods – led by feed-forward artificial neural networks – rank on top for more than three-fourths of out-of-sample forecasts. Consequently, to explain the structure of the money-price link in our analysis we have relied on recurrent neural network modeling, which is a nonlinear fashion within the discipline of deep-learning methods that are increasingly being applied as additional tools to help improve economic and forecast analyses in central banks.

3.1 Long Short-Term Memory Networks

The Long Short-Term Memory (LSTM) network is currently one of the most popular approaches within the artificial neural network (ANN) method, which is extensively used in the context of nonlinear nonparametric Machine Learning (ML) models. While the latter could also boil down to a parametric method if the estimated function is identified (or assumed) to be linear in coefficients, the nonlinear methods are more appealing due to their ability to usually provide more reliable predictions if they are done correctly. Before describing the LSTM model in detail, we make a brief overview of the earlier stages of neural networks and disclose some of its advantages as opposed to other techniques.

The Artificial Intelligence technique of neural networks provides a completely flexible mapping of economic variables and, unlike conventional econometric techniques, is not constrained to model selection and parameter specification in advance. Of course, choosing the number of hidden layers and nodes to establish the architecture for the neural network resembles the process of choosing the right order of a polynomial to obtain a good curve fitting as well as satisfactory predictions for new data. However, the process of training the network does not necessarily require having an exact understanding of the rules as knowing empirical regularities can allow it to ignore excess input variables. Furthermore, neural networks can approximate linear and nonlinear data transformations; therefore, the explanatory variables can be of differing orders of integration without having to determine it in advance.

A simple connected neural network can take the following form [28]:

$$\hat{y}_{t|t-1} = b^o + \sum_{n=1}^{N} w_n \cdot \sigma\left(b^n + \sum_{\tau=1}^{P} w_\tau^n \, x_{t-\tau}\right) \quad (1)$$

where y_t -hat is the current predicted value of our variable of interest based on the information at time $t–1$; b^o and b^n are the biases of output and the hidden units n, respectively; w_n denotes the weight from the hidden unit n to the output, while w^n_τ represents the weight of input x from the time lag τ to the hidden unit n. The input vector x can be viewed as a set of explanatory variables, which may include past values of the dependent variable and other regressors. The hidden layer, on the other hand, has no parallel in econometrics and helps process the information from units in the input layer to units in the hidden layer and the output by using a nonlinear “activation” function, σ. There are various activation functions, such as the logistic functions, the Sigmoid function, the hyperbolic tangent activation functions, or the Rectified Linear Unit (ReLU) function. We use the latter based on its computational efficiency, [29].

The architecture of traditional feed-forward neural networks (FF-NN) has been extended to include recurrent connections that allow output layer activations to feedback as inputs to units within the same or preceding network layer(s). Units that receive feedback values in the recurrent neural network (RNN) are referred to as the “state” unit, and are used as additional inputs at the next step. A basic RNN is defined by the following set of equations:

$$s_t = \sigma(x_t w + s_{t-1} u + b) \quad (2)$$

where x_t represents the model's layer of input units at time t; s_t denotes the output (prediction) results; and b, w, and u are the model's weights. Equation 2 shows how a basic RNN model improves upon the FF-NN technique by including the previous model prediction s_{t-1} as a supplementary input in conjunction with the current explanatory variables x_t. Moreover, contrary to traditional NNs that treat all the lags equally, the distance and sequence of input lags in RNNs can have important implications for the final prediction. In our case, the state a.k.a. the context of the RNN can inform us about any potential trend, cycle, or seasonality in the data series.

Nevertheless, the heavy reliance on recent data to generate future forecasts reduces the ability of basic RNNs to capture relevant information from the same period in previous years, hence exposing them to the "short-term memory" problem. The development of long short-term memory (LSTM) networks paved the way to extenuate the basic RNN deficiency by introducing the so-called "gates", which are special internal structures that enable the preservation of relevant "long-term memory". An LSTM unit can decide which input information and part of the network state are worth "memorize" or "forget" on the next iteration. The following set of equations describe a LSTM network:

$$\begin{aligned} i &= \sigma(x_t w^i + s_{t-1} u^i + b^i), \\ f &= \sigma(x_t w^f + s_{t-1} u^f + b^f), \\ o &= \sigma(x_t w^o + s_{t-1} u^o + b^o), \\ \hat{c} &= \tanh(x_t w^c + s_{t-1} u^c + b^c), \\ c_t &= f \times c_{t-1} + i \times \hat{c}, \\ s_t &= o \times \tanh(c_t), \end{aligned} \tag{3}$$

where i, f, and o are the input gate, forget gate, and output gate, respectively; while w, u, and b are the learned weights that control them. Expression $\sigma(x) = \frac{1}{1+e^{-x}}$ is a sigmoid or logistic function that activates the three gates. c_t denotes the state unit that represents its memory about the past; it is regulated and updated through a linear combination of the gates together with the new candidate activation $\hat{c}$ and its own previous value c_{t-1}. In the cell state c_t equation, the $i \times \hat{c}$ term indicates how much information in the candidate $\hat{c}$ is decided by the input gate i to be added to the state, whereas the $f \times c_{t-1}$ term shows how the forget gate f determines what part of the previous state memory c_{t-1} should be forgotten. The last equation presents the updated state c_t that is "compressed" by a nonlinear hyperbolic tangent and how much of it should be adjusted by the output gate o to be presented in the output (prediction) s_t.

3.2 Data Characteristics

Although the central bank of Albania monitors and is committed to maintaining headline CPI, the price measure in our analysis is represented by the price deflator for gross domestic product, which may be a more suitable indicator of the total price behavior that captures all economic sectors, not just prices in the household consumption basket. Next, we consider four money supply indicators, namely the monetary base, M1, M2, and M3 aggregates. The first indicator is essentially controlled by the monetary authority and consists of currency in circulation and reserves (deposits) held by depository corporations at the central bank. The narrow money M1 consists of cash plus transferable and non-term lek deposits of residents. The broad M2 aggregate comprises M1 plus lek-denominated term deposits up to two years (excluding banks and central government). At the same time, M3 aggregate consists of M2 plus all demand and time deposits in foreign currency.

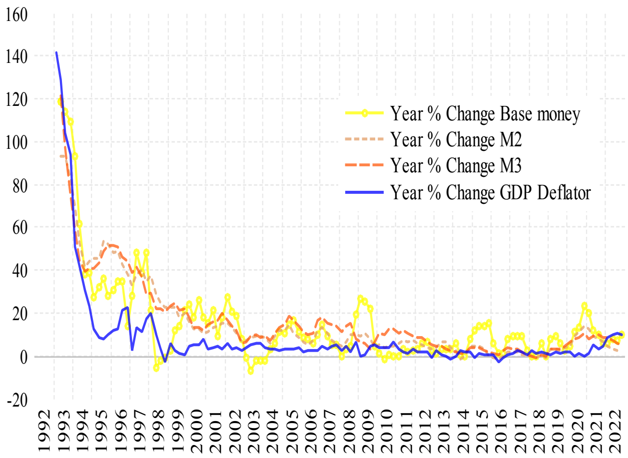

Fig. 1: Annual percent growth of money and output deflator

Figure 1 reports the annual percent growth of monetary indicators and the GDP deflator. Money appears to have grown more rapidly than prices for most of the sample period. All variables show high instability in the early years of the transition, as the country experienced many structural reforms to a market-based economic framework and underwent a series of necessary stabilization policies. Although the overall price behavior has settled to a relatively modest annual growth rate since 1999, monetary variables have continued to grow faster and with greater volatility till the end of the period under investigation. Recent years have witnessed, however, a return of high price growth (5.6 percent on average), as the domestic economy is coping with unprecedented economic and financial stability measures to mitigate the adverse COVID-19 effects as well as disruptions in global supply chains.

Table 1. Descriptive Statistics

	Base Money	M1	M2	M3	GDP Deflator	Real GDP	Pol. Rate
	Average annual percent growth (except policy rate)						
Whole Sample	16.1	15.3	15.7	17.4	8.9	5.2	7.4
1993q1:1999q4	41.4	33.1	45.9	47.4	28.8	8.6	18.3
2000q1:2009q4	11.4	12.9	10.0	12.2	3.8	6.0	6.4
2010q1:2019q4	4.6	6.2	2.9	4.5	1.4	2.6	2.7
2020q1:2022q4	10.9	12.4	7.4	8.0	4.6	3.6	1.2
	Standard deviation						
Whole Sample	23.6	18.4	20.1	22.1	21.8	10.1	7.1
1993q1:1999q4	37.2	26.8	21.9	29.2	39.3	19.8	6.3
2000q1:2009q4	9.1	13.2	3.1	4.1	1.6	2.8	1.1
2010q1:2019q4	4.4	6.1	2.7	3.9	1.6	1.9	1.6
2020q1:2022q4	5.7	5.9	4.0	1.6	4.1	7.1	1.1
	Normality test#) (Jarque-Bera probability)						
Whole sample	0.00	0.00	0.00	0.00	0.00	0.00	0.00

#) Normality tests are rejected even if tried on variables in levels.

The descriptive statistics in Table 1 indicate that the behavior of economic variables has not been constant throughout the sample. The average annual growth and standard deviations in different sub-samples, together with the Jarque-Bera probabilities for normal distribution, exhibit that variables do not have stable mean and variance and are not Gaussian. If the money and price relationship has changed from the early transition years to the "great moderation" period and the changing role of supply chains, it is necessary to examine their link using nonlinear techniques.

3.3 Modeling and Forecasting Procedure

We assess the information content of money in predicting inflation in Albania based on the out-of-sample forecast evaluation. While the in-sample tests generally infer causality from the impulse response functions, [30], the out-of-sample tests are closer to the notion of Granger causality, [31]. In that vein, we initially attempt to find out whether the bivariate LSTM network can produce better price growth forecasts than the univariate network and then, whether a fourvariate model forecasts perform better than those of a trivariate model without money. Consequently, the explanatory input units consist of between one to three variables representing combinations of previous GDP deflator growth rates, one of the monetary indicators, the policy rate, and the real GDP growth. Because of their capability of "remembering" information over a long interval, modeling with the LSTM neural networks does not require determining the integration order of time series in advance. The nonlinear ANNs should also be adept at sorting out the seasonal patterns in data series; therefore, it is not necessary to eliminate seasonality from our model variables. Nevertheless, seasonal effects are subdued in our analysis since we use annual growth rates.

As there is no theoretical basis for selecting the network, the number of units in the input layer and the hidden layer(s) could be chosen based on certain information criteria, such as Akaike (AIC) and Schwarz (SIC), or through a process of trial and error. A study that conducts a broad sensitivity analysis on their models for forecasting US CPI inflation concludes that in setting up an LSTM network the researcher "…should not include too few hidden units or allow too few lags;" and ought to "…train the model for a sufficient amount of time" [32]. In line with these recommendations, we allow our neural network to select the number of input units from a maximum lag length of 8 quarters. Next, the network includes five hidden layers where the number of hidden units halves successively from 1024 in the first hidden layer to 64 in the last one. Finally, the model is trained by backpropagation with the Adam optimizer algorithm, which is a computationally efficient gradient-descent learning algorithm [33] and has become very popular for training deep learning models, such as RNNs. To facilitate convergent learning, the initial learning rate for the Adam optimizer is set to the default configuration parameter 0.001 in the Keras deep learning library, which is documented to perform well on most problems.

In short, the forecasting procedure involves two steps. Initially, the above-mentioned LSTM model is trained by using the fixed number of units and determining the biases and weights through the Adam optimizer until a global minimum value is achieved. The initial training (or model fitting) period covers 84 quarters starting from 1993Q1 to 2013Q4. We try 150 epochs of parameters and single out the setup with the weights and biases that deliver the lowest forecast error in the subsequent validation period with 12 data points (2014Q1:2016Q4). Once the LSTM structures are trained and validated for the *n*-variate models, they are used in the final testing (or forecast evaluation) period that stretches over the last 24 quarters (2017Q1:2022Q4). We compute and retain the RMSE of every model's forecasts for 1 to 12 quarters ahead of the testing period. By shifting the selection horizon forward by 1 quarter in the forecast evaluation period, the process is repeated 24 times for the one-step-ahead predictions and consecutively down to 13 times for the 12-step-ahead forecast horizons, resulting in a total of 222 repetitions for each model.

4 Empirical Results

We apply the LSTM technique on the quarterly data series that have been transformed into annual (q_t/q_{t-4}) percent changes, except the policy interest rate that enters the model in levels. As we mentioned above, the relevance of information carried in money should be manifested if the prediction of no-money models is improved when they are augmented with monetary indicators. The analysis below presents the results of adding money aggregates initially to the univariate price model and afterward to a trivariate model that consists of prices, gross domestic product, and the monetary policy base rate. Furthermore, we examine the forecast performance in two subsamples, which allow us to discern between the modest price growth (averaging 1.4%) in the pre-Covid period (2017q1:2020q1) and accelerating price growth (averaging 5.4%) in the post-Covid period (2020q3:2022q4).

4.1 Univariate and Bivariate Models

Figure 2 presents the forecast evaluation for the univariate and bivariate LSTM networks, which is here expressed as the difference between their respective root mean square errors (RMSE). They are shown for 1 to 12 forecasting horizons for the full out-of-sample period as well as the two subsamples. Base money appears the only monetary aggregate to provide consistent and persistent relevant information on future price growth. Its full-sample line is above zero up to nine quarters, indicating that the central-bank-controlled money exerts influence over price developments for around two years or so.

The forecast accuracy for the bivariate model with money is improved on average by 21.4 basis points during the first 8 quarters while reaching the best results in the second and fourth quarters (37.3 and 32.4 basis points, respectively). This favorable outcome does not hold in the longer run, however, as the monetary base information loses its strength and changes position into the negative territory.

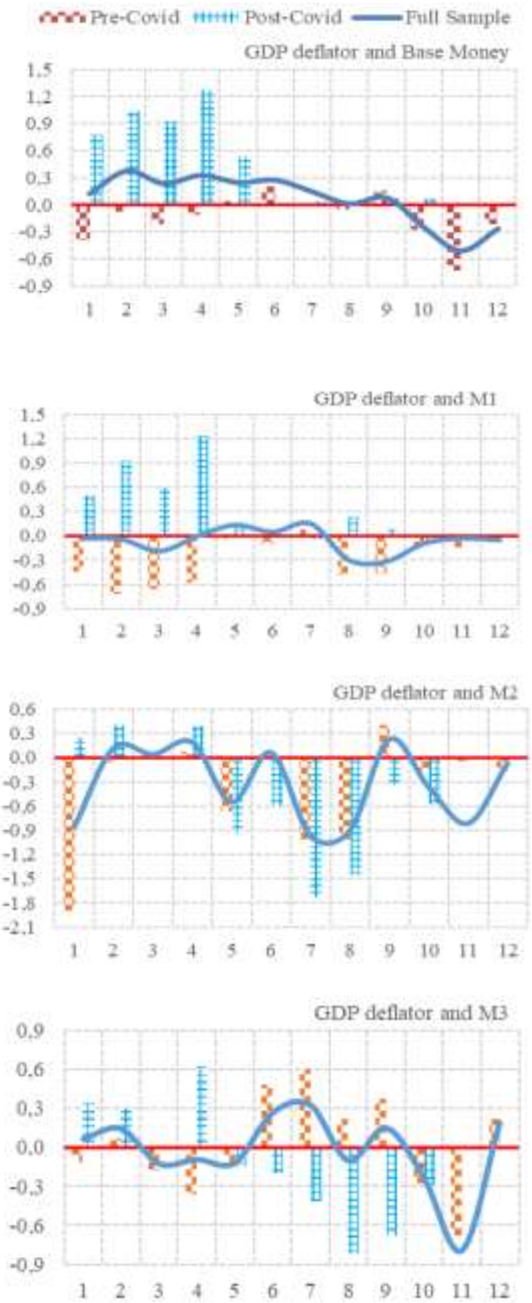

Fig. 2: RMSE difference between Univariate vs. Bivariate LSTM networks

Note: difference in RMSE is calculated as the univariate network ($x_t = \Delta p_t$) minus the bivariate network ($x_t = \Delta p_t$; Δm_t). Thus, any data point below zero (the horizontal red line) suggests no role for money in predicting inflation.

On the other hand, the narrow and broad money aggregates only provide temporal contributions (or at irregular intervals) in improving the GDP deflator forecasts. A glimpse at the graphs suggests us that M2 and M1, which capture domestic currency aggregates, increase the predictive ability of future prices mainly from 2 to 4, and 5 to 7 quarters, respectively. The broadest M3 aggregate, which includes foreign-currency-denominated deposits, seems relevant for the first couple of quarters and particularly in the medium term, with considerable improvements tending to occur at 6 and up to 9 forecasting horizons.

A comparison of results between the two subsamples before and after the COVID-19 shocks reveals certain new findings that are worthwhile pointing out. The positive contribution of base money in predicting price changes appears to be significantly influenced by its good performance in the post-Covid period, especially in the first 5 quarters where RMSE improvement averages 91 basis points. In the relatively modest price growth period of 2017q1:2020q1, the so-called central bank money is found only sporadically helpful during the forecast interval of 5 to 9 quarters ahead. In the same fashion, narrow money M1 seems to have been useful for future price predictions during the accelerating inflation period after Covid-19. Again, its larger improvements appear in the first five forecast horizons with an average of 67.4 basis points, or about three-fourths of the base money impact.

By the same token, the information content in broad money M2 and M3 is not uniform in the two subsamples. In the post-coronavirus period, they both become more informative in horizons up to 4-steps ahead (yet their contribution is computed around one-fourth or one-third of that of base money). Whereas during the modest inflation years before the coronavirus, it can be said that M3 aggregate is shown more important, particularly in the medium-term predictions of 6 to 9 quarters ahead.

The forecast evaluation on the bivariate relation suggests us that the current neglect of money growth in formulating monetary policy may not be generally consistent with the data. The empirical results for the 2017-22 period demonstrate that base money might be considerably informative in the short term, while broad money M3 is more relevant in the medium term. Furthermore, the relationship between money and price growth in Albania ought not to be considered simple, or time-invariant. The results reveal that M3 used to be relatively informative before the coronavirus, which is in line with assertions in the Bank of Albania's development plan over 2006-08 and its monetary policy document for the period 2012-14. However, its role as an indicator of longer-term inflationary pressures seems to have changed in the post-Covid period, as M3 is only found indicative in the short run, while narrow money seems to have taken a more important role.

4.2 Trivariate and Fourvariate Models

Until most of the 2000s, the Bank of Albania's monetary policy relied officially on a monetary targeting regime to control domestic inflation. This regime has been agreed with the IMF in the January 2006 PRGF/EEF agreement, according to which the quantitative objectives of the monetary base would serve as a determinant of the monetary supply in the economy, M3. Attaining the inflation objective under this regime required the balancing of money supply with real economic growth, [34]. Although the money-targeting regime remained as the official monetary policy framework until the middle of the last decade, the Bank of Albania has for long discerned in its reports – such as the Medium-Term Development Plan 2003-05 – that inflation in the country "is not primarily a monetary phenomenon and in certain situations is significantly influenced by other factors". For these reasons, the operational framework has generally functioned similarly to that of the European Central Bank, where the base interest rate (repo) has been used as the main indirect instrument for the implementation of monetary policy. Meanwhile, as attention to monetary aggregates gradually faded away – and especially after the transition to the de-jure inflation-targeting regime in 2015 – broad money M3 was afterward only referred to as a "complementary indicator for the assessment of inflationary pressures," pointing out that "inflation is a monetary phenomenon in the long run", [35].

If movements in monetary aggregates are influenced by developments in other economic indicators, the results derived from the bivariate models above may be biased in the upper direction.

Therefore, the analysis below attempts to shed light on the informative role of money in predicting future prices once we extend the models with output and interest rate indicators in line with a small monetary policy, two-pillar Phillips curve framework. More specifically, we first estimate a trivariate LSTM model without money where annual price changes, Δp, are a function of its lags, $_{t-p}$; lags of annual output changes, Δy_{t-p}; and lags of the policy interest rate, i $[\Delta p_{t+h} = (\Delta p_{t-p}; \Delta y_{t-p}; i_{t-p})]$. Next, in the fourvariate case, we augment the model with lags of annual monetary changes, Δm_{t-p} $[\Delta p_{t+h} = (\Delta p_{t-p}; \Delta m_{t-p}; \Delta y_{t-p}; i_{t-p})]$.

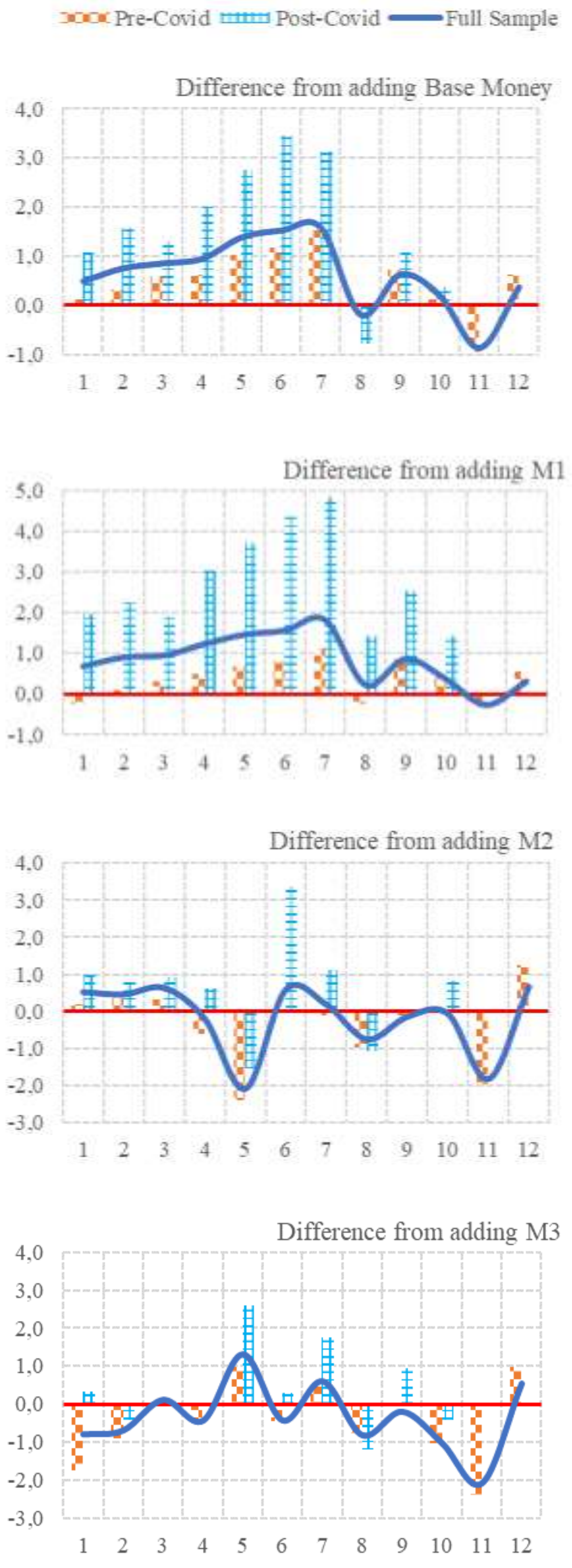

Fig. 3: RMSE difference between Trivariate and Fourvariate LSTM networks

Note: Difference in RMSEs is calculated as the trivariate network (x_t = Δp_t; Δy_t; Δi_t) minus the fourvariate network (x_t = Δp_t; Δy_t; Δi_t; Δm_t). Thus, any data point below zero (the horizontal red line) suggests no role for money in predicting inflation

Figure 3 displays the difference between the RMSE produced by the trivariate prediction models and the RMSE produced by the respective fourvariate forecasts. Generally speaking, the extended models show considerable improvements in favor of models with money. The new results re-emphasize the central role of narrow money in predicting overall prices. Including it in the price models appears now to substantially reduce the forecast error size, clearly outperforming the no-money model in almost all of the 1-12 quarter horizons that we tried out. The RMSE in models with narrow money M1 (base money) becomes lower in magnitude as we move from the first quarter horizon to the seventh, gradually improving from 0.69 (0.51) to about 1.84 (1.59); the amelioration starts losing momentum in the third year, yet evidencing a salient difference from the model-without-money RMSE. Finally, the results with narrow money are robust across virtually all forecast horizons even when we get a load at the two subsamples. However, the information content in narrow money is more profound in the ability to predict prices during the post-pandemic period of mounting inflationary pressures.

Contrary to expectations, the impact of broad money on prices as based on forecast evaluation is again shown as unstable across time horizons for both, M2 and M3 aggregates. Although the differences in their RMSEs concerning the model without money have enlarged for good or ill in comparison to the bivariate results, the discontinuous forecast improvements make it difficult to draw any sound or inferred conclusion, particularly for the M3 aggregate. Despite that, a close examination of the two subsamples suggests that our results are heavily influenced by the time interval before the coronavirus. M2 aggregate, for instance, seems to matter in the first three forecast horizons in the pre-COVID period, but its forecast ability has considerably improved in both size and continuity after the coronavirus, being presently comparable with the effects of base money. The M3 aggregate, too, shows signs of improving forecast performance, clearly increasing its contribution to price predictions particularly at a horizon of two years.

5 Concluding Remarks

Do developments in monetary aggregates matter for predicting overall prices in the Albanian economy? We investigate this issue empirically by applying the long short-term memory (LSTM) recurrent neural network. Because of their flexible architecture and potential to capture data nonlinearities, LSTM networks are becoming popular in the literature on forecasting financial time series with neural networks. Estimating the models with quarterly data from 1993 to 2016, we derive inferences on the role of money by comparing the forecast performance between models with and without money during the period 2017-2022.

Narrow monetary aggregates, particularly the "outside" base money, provided clear evidence of the usefulness of money as an indicator of future inflation even after controlling for output and the policy interest rate. Comparing no-money models with multivariate money-based models at forecast horizons of up to 12 quarters ahead revealed that the central-bank-controlled monetary aggregate consistently improves the ability to forecast price developments for around two years or so. On the other hand, the broader "inside" money aggregates only provided temporal improvements, as indicated by the unstable relation across time horizons for both, M2 and M3.

Furthermore, it seems that the money-price relationship depends on the existing inflation regime. Separating the testing set between the modest price growth in the years before the coronavirus and the accelerating inflation period afterward demonstrates that the aforementioned results hold in general, but the size of money contribution is a question of the sample period (and forecast horizon in certain cases). Our findings appear to be substantially influenced by the quantitative improvements in the predictive power from including money in the post-Covid subsample. As it is the more recent periods that matter mostly for monetary policy purposes, the current neglect of monetary developments in Albania might be arguably incoherent, and due emphasis ought to be given to money-based price models, particularly for monetary policy horizons of up to two years.

Future research could focus on the predictive ability of money within a more structural or integrated framework that brings together economic and monetary pillars. This may need to introduce financial frictions or adjustment costs that are often included in money demand models. Moreover, several different money indicators could be constructed to represent various versions of the general-equilibrium-inspired analytical models. Similarly, in the context of using quantitative easing tools for long in the aftermath of the global financial crisis, it would be interesting to review theoretical arguments and explore whether money and credit developments contain useful information for future real sector movements beyond the influence of interest rates.

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