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The benefits of the Velvet Revolution in Armenia: Estimation of the short-term economic gains using deep neural networks

Abstract
This article primarily aims to estimate the impact of the Armenian revolution and test the hypothesis, that is, the benefits of revolution and establishment of democracy can be seen even in the first year after the political change. To calculate the short-term net surplus of the revolution, we estimated the difference between the projection of Armenian economic activity for the four quarters after the revolution, using only pre-revolutionary (assuming there was no revolution) and real data for the same period after the revolution. Using deep neural network models, such as recurrent neural networks and convolutional neural networks (CNN), we compared prediction accuracy with structural econometrics, such as autoregressive integrated moving average and error correction model, using pre-revolutionary data (2000Q1–2018Q1) for Armenia and combinations of models using an ensembling mechanism. As a result, CNN overperformed the rest of the models. The CNN simulation on post-revolutionary data indicates that during the period 2018-Q2–2019-Q1, Armenia gained approximately 850 million EUR in terms of GDP, thanks to the revolution and the new government. Moreover, out of seven models, the five best models in terms of accuracy indicated that the revolution had no negative impact on the Armenian economy, as the actual values were within or above the 95% confidence interval of the prediction.

Keywords
Armenia | revolution | GDP | neural networks | ensembling mechanism

JEL Codes
C45, E02, P16

1 Introduction

In March 2018, Armenia entered a new era of democracy after a non-violent revolution occurred on the streets of Yerevan. Locals called the revolution ‘velvet’, as, during the governmental transition, there were neither deaths nor violence. According to many prominent scholars, democracy comes with many benefits for the economy in the long run; however, in the first period immediately after the revolution, the economy also faced many challenges and risks. However, it may also be true that any revolution and rapid political change may lead to a short-term economic downturn, due to uncertainty, devastation or the destruction of public goods as well as a tendency on the part of investors to avoid conflict and areas of risk.

In this article, both the short-term costs and gains of the non-violent revolution on the economic situation in Armenia are analysed. The main hypothesis is that in the first year after the revolution in Armenia, the economic benefits outweigh the costs.

Three key elements have changed positively in Armenia since the revolution:
1. the level of democracy has increased;
2. the level of corruption and the volume of the shadow economy have decreased and
3. people have become more optimistic about the future.

All the three factors will have many positive effects on economic growth in the long term. Yet, conversely, two elements resulted in short-term costs for the economy:

1. the damage of public goods and labour inactivity during the revolutionary process and
2. uncertainty due to the political changes and organisation of new elections after the revolution, which affected foreign investment.

In addition, according to some scholars, democracy may lead to an increase in consumption, thus decreasing savings and investment levels, also resulting in a negative impact in the long term.

This article primarily aims to analyse the short-term economic impact of the non-violent revolution in Armenia. Since this revolution raised the level of direct democracy in Armenia, this study shows the short-term economic impact of democracy. Even though there are many publications about the impact of democracy on the economy in general (for the long-term) or the impact of the revolution on the geopolitical situation in the country, there are hardly any articles discussing the short-term economic costs or benefits of the revolution or establishment of democracy. This article tries to fill this gap by estimating the short-term net economic effects of the revolution, taking the example of Armenia and using advanced methodologies such as machine learning (ML) and deep neural networks (DNNs).

In addition, this article compares the DNN and ensembling model prognosis with more standard, classic model approaches, such as autoregressive integrated moving average (ARIMA) or error correction model (ECM), using the example of the Armenian economy. The growing number of articles using the DNN models in macroeconomic estimations indicates the potential of these methods and creates a new opportunity for projections and forecasts in macroeconomics. Moreover, some articles indicate that the DNN models for developing economies are better at capturing non-linear links between the potential influences of external factors and GDP. This study measures the accuracy of forecasting for all the aforementioned models and uses the most accurate models to measure the net cost/benefit of the revolution, based on the 95% confidence interval of the prognosis.

In this article, the quarterly data of GDP and 18 explanatory variables from the official webpage of the Statistical Committee of the Republic of Armenia (SCRA) and International Monetary Fund (IMF) are used for the years 2000–2018. Data are transformed into time series (TS) and seasonal autoregressive integrated moving average (SARIMA), ECM, recurrent neural networks (RNN), convolutional neural networks (CNN) as well as ensembling models [simple average, least absolute shrinkage and selection operator (LASSO) and linear stacking] are implemented to forecast the period 2018-Q2–2019-Q1. Later, it is compared with real data, and the difference will indicate either a net surplus or the cost of the revolution.

Section 1 is dedicated to a short, historical background of Armenia and its political and economic situations. It also discusses the main drivers of the Armenian economy and its dependency on its strategic partner, Russia. Section 2 discusses the political and economic events that led to the national revolution, highlighting the motives behind the movements and the main benefits, based on public opinion surveys and different international ratings. The attitude of the people towards the new government and its tendencies is also considered as well as the key changes made by the new government immediately after the revolution. Finally, in this section, the impact of democracy on economic performance is discussed by analysing various studies regarding this topic.

Taking Armenia as an example, Section 2 is devoted to the analysis of short-term economic growth after the revolution and its comparison with predictions of economic activity during the same period, using pre-revolutionary data. Economic activity has been measured by GDP, which was predicted using the historical data of GDP, commodity prices, interest rates, inflation rates, foreign direct investments (FDI), unemployment, debt to GDP ratio and other factors, discussed in Section 2. Both classical (SARIMA, ECM) and non-linear DNN models (RNN, CNN) as well as the ensembling of all models were used to analyse 53 quarters of data (2000-Q1–2013-Q1), then data for the next 4-year period (2013-Q2–2018-Q1) were analysed. Afterwards, using those models, the GDP of Armenia was forecasted quarterly for the period 2018-Q2–2019-Q1. Finally, the prediction of 95% confidence intervals was estimated and compared to actual, post-revolutionary values. Since predictions are generated by using pre-revolutionary data relating to internal factors, which are a consequence of the previous regime and external factors (commodity prices, which are independent of Armenian political change), prediction estimates will represent what would have been the economic growth had there been no revolution, and the difference will indicate the approximate effect of the revolution on the economy.

As no papers are analysing the economic situation in Armenia after the revolution and few articles are analysing the economic impacts of the political revolution, this article tries to bridge the gap, providing econometric evidence using neural networks and ensembling models.

2 The challenges and opportunities of the Armenian economy

As one of the oldest civilisations in the world, Armenian history dates back to the twelfth century BC. Since then, the Armenian kingdoms and dynasties have been known for their wealth and power; however, after the invasion of the Arabic, Mongolic and Turkish tribes in the thirteenth century, Armenia lost its sovereignty until the twentieth century. In 1918, Armenia gained its independence but became part of the Soviet Union 3 years later as an Armenian Soviet Socialist Republic (Yeghiazaryan, 2014, p. 42).

The sectoral structure of the current Armenian economy has been modelled on the structure of the economy of the Armenian Soviet Socialist Republic. Since the economy of landlocked Soviet Armenia was relying heavily on the network of other member states of the Soviet Union, especially in the industrial sector after the collapse of the USSR and the integration of the capitalistic system, not all sectors of the economy continued to exist and the economy went into recession.

Due to the collapse of the USSR, Armenia overcame an economic crisis in the energy sector. During the years 1990–1993, the GDP of Armenia almost decreased twice with GDP in 1993 is only 46.9% of that of 1990. Power generation also dropped by 46%, due to the blockade of transportation, decrease in fuel imports as well as the closure of nuclear power plants. During these years, most of the regions did not have access to electricity and natural gas (Tagharyan, 2018, p. 96). In 1994, the recession phase was replaced by recovery and except for the year 2009, GDP has experienced positive growth ever since; however, the structural quality of the economy has not improved. During the 1990s, the emigration rate from Armenia reached its peak due to the difficult economic situation and ever since, more people have left the country than have arrived (CIA, 2019). However, the situation has changed since the revolution, as during 2018-Q2–2019-Q1, more Armenians returned home than left (Pashinyan, 2019).

2.1 Main drivers of the Armenian economy

Some of the main factors of growth during the late 1990s and early 2000s were international grants, loans and investments in strategic sectors of the economy (energetics, transportation and telecommunications) and the increasing volume of private transfers. The latter mostly came from the growing Armenian diaspora (EV RC, 2005). During this period, the share of agriculture in the GDP grew, while the share of the industry dropped significantly (Yeghiazaryan, 2014, p. 49).

Figure 1 represents the quarterly Armenian GDP for the period 2000–2019. The data from 2003 to 2008 indicate that the economy moved into an expansion phase, as during that time, the GDP growth rate reached two digits. However, as the economy depended heavily on investment and transfers from outside the country and had an imbalance within its sectors, the global financial crisis had a very negative impact in 2009, when Armenia experienced a 14.1% decrease in economic activity, and since then, recovery has been very slow. In recent years, two of the main contributors to economic growth have been agriculture and the metallurgical industry. The growth of the metallurgical industry could be explained by increasing exports and the growing prices of commodities. Even now, the Armenian economy is heavily dependent on FDI and private transfers from abroad, which, in the long run, make the economy volatile.

2.1.1 Agriculture

The main attributes of agriculture in Armenia are low productivity and a very high dependency on natural factors. During the years 1993–1994, 90% of agricultural land had been privatised, resulting in the number of people engaged in that sector doubling, yet productivity during the recession decreased. With limited access to basic resources, such as electricity and natural gas, people were generally using their

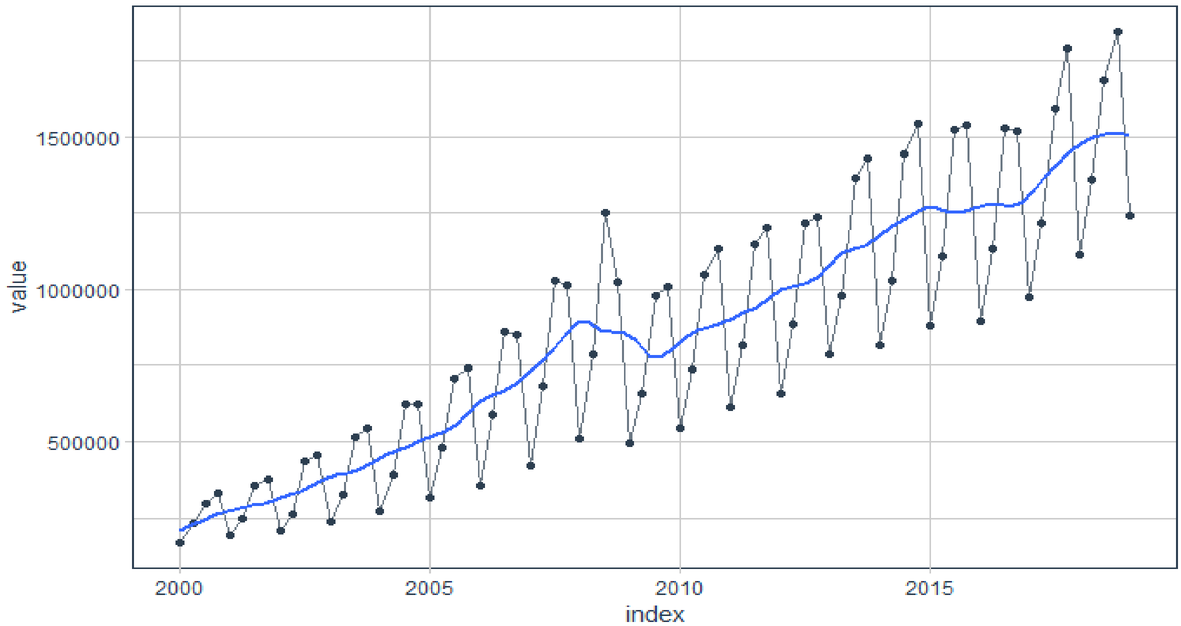

Fig. 1. Quarterly GDP of Armenia.

land as a means of survival and primarily for personal use. However, after the recession, the situation did not change a great deal, as agricultural land was still divided into very small pieces with 96.7% of the land belonging to small private farms and only 3.3% to middle and big agricultural trade organisations. According to data from 2012, the average size of farms was 13,700 m^2, whereas the total area of arable land was 20,500 km^2. Eighty-eight per cent of the farms were smaller than 20,000 m^2 and they made up 77% of the total arable land (Yeghiazaryan, 2014, p. 47). Another problem was the lack of any insurance system to protect against natural disasters and the influences of climate, which was only partially subsidised by the treasury of the government. This has led to more instability in the agricultural sector and the total economy as a whole (as it was one of the main contributors to economic growth). For instance, during the financial crisis, agricultural activity only dropped by 0.1%; yet, in the following year, it dropped by 16%, primarily due to the severity of the climate.

2.1.2 Industry

The mining and metallurgical industries are among the fastest growing industries and are the main contributors to economic growth. In Figure 2, the first pie chart represents the structure of the industry in Armenia and the second pie chart illustrates the composition of process manufacturing. In 2017, according to the Statistical Committee of Armenia, more than a quarter of the industrial volume was derived from those two sectors, both of which have a large share of exports.

Another important sector is the food industry, which comprises 18% of the total industrial volume. However, most food produced are consumed in the local market, and this sector heavily depends on agriculture.

2.1.3 Energy sector

The energy sector is mainly dependent on Russian companies and investors. Most of the oil imports come from Russia. The supply of natural gas is controlled by ArmGazProm, an Armenian–Russian joint venture, 20% of which was owned by the Armenian government and 80% by Gazprom (Russia) until 2013, after which time Gazprom took ownership of 100% (Arzumanyan & Abovyan, 2014, p. 4). Even though a third of natural gas imports come from Iran, the operation is fully controlled by a company majority owned by the Russian government (Gazprom, 2018). In addition, the Metsamor nuclear power plant is fuelled and has been controlled by the Russian company Rosenergoatom since 2003. Full control was given by the government to pay off debts raised by nuclear fuel

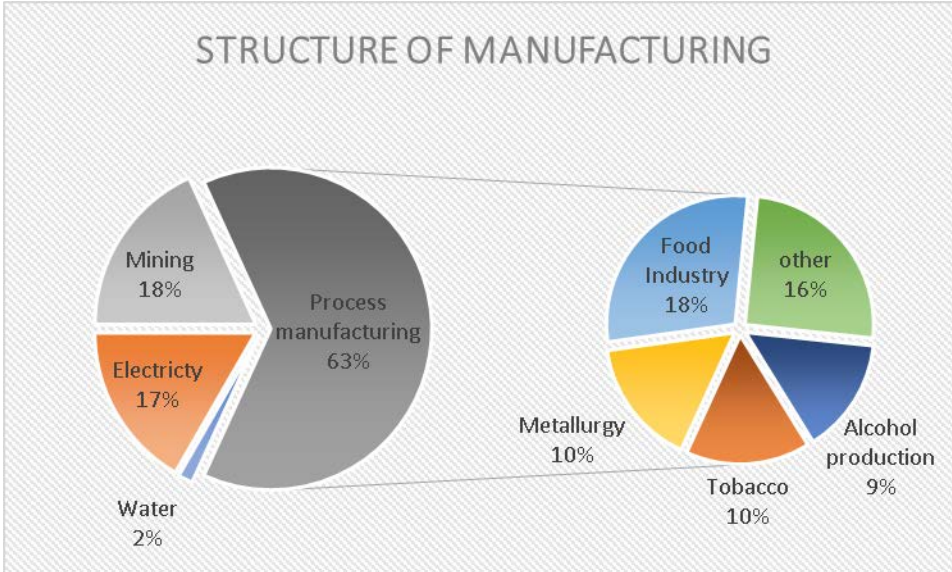

Fig. 2. Structure of manufacturing in 2017.

imports (WNA, 2019). Therefore, the whole sector is controlled by Russia, making the Armenian economy heavily dependent on Russia.

2.2 New era of democracy

After the Velvet revolution in 2018, the Armenian political system embarked upon a new era of democracy. The new government aimed to fight corruption, ensure equal rights for everyone and free the country from the old oligarchic system. Lanskoy and Suthers (2019), in their article 'Armenian's Velvet Revolution', chronicle all the events of this revolution by also making parallels with other post-soviet revolutions (such as in Georgia and Ukraine) and indicating the differences between them. According to some authors, contrary to the other 'colour revolutions', the Armenian revolutionists, led by Nikol Pashinyan, did not wish to engage in geopolitical changes. They only had one clear demand: to overthrow Serzh Sarkisian, the previous president and newly elected Prime Minister of Armenia at that time. The authors also claim that the beginnings of this revolution were in evidence 10 years earlier, when people took to the streets following electoral fraud in support of the runner up of the election, the first President of Armenia, Levon Ter-Petrosian. At that time, they did not succeed, as the protests led to violence; however, protesters learned from their experience over the next 10 years and sought to achieve their goals in a non-violent way.

Many authors, such as Abrahamian and Shagoyan (2012), Lorusso (2013), Ishkanian (2017) and even Human Rights Watch (HRW, 2018), claim that all elections before 2018 were rigged, and there were many incidents of bribery and vote-buying (Giragosian, 2017). Some authors also assumed that most Armenians have gradually started to accept this semi-authoritarian, corrupt regime with less and less involvement in politics. However, as indicated in Abrahamian and Shagoyan's recent article (2018), events at the end of 2018 proved that the Armenian population did not forget the lessons of the past and were able to oppose the old regime, by coming out into the squares and streets of the cities, proving that there is no alternative to freedom and democracy for Armenia.

According to the press conference given by the newly elected Prime Minister, Nikol Pashinyan on 8 May 2019, one of the main objectives of his newly elected government was to increase budget revenue by 25% for the first quarter to fight the shadow economy. This economy was worth around 129 million dollars. Among other changes, mentioned during the press-conference entitled '100 Facts about New Armenia', was the payment of debts to entrepreneurs, the establishment of new businesses, the increase of tourism by 10%, the reduction of the 2.3% debt to GDP rate in comparison with the previous year and the elimination of monopolies, and so on. In addition, according to Prime Minister Pashinyan, for the first time in 12 years, the number of people who arrived in Armenia exceeded the number of people leaving by 15,313 (Pashinyan, 2019).

Based on Freedom House International Organization's 'Freedom on the Net' report, in 2018 Armenia improved its position on the Human Freedom Index by 19 points compared to 2017 and progressed from the list of 'partially free' countries to 'free'. According to the organisation, this index is one of the main fundamentals of democracy (Freedom House, 2018). The Economist chose Armenia as the country of the year 2018, thanks to its non-violent revolution and democratic parliamentary elections (*The Economist*, 2018). In the report 'Doing Business 2019, Training for Reform', published by the World Bank Organization, Armenia improved its position in the rankings, rising from 47th in 2018 to 41st in 2019 (World Bank Organization, 2018, 5). Based on two public opinion surveys, carried out in the same year, the International Republican Institute (IRI) found that the vast majority of Armenian residents were more optimistic about the future, and they believed that the country was heading in the right direction (IRI, 2018).

Scholars, organisations and even the local population were in agreement that in 2018, Armenia transitioned in a non-violent manner into a democratic country, with fair elections and with a parliament legitimately elected by the citizens. This process opened up new opportunities for the Armenian citizens and the country; however, it was not so obvious how the new government would use those opportunities and whether they would result in a positive outcome.

2.3 Impact of democracy on the economy

According to many prominent scholars such as Wittman (1989), Friedman and Wittman (1995), Blondel, Sinnott, and Svensson (1998) and many others, political competition is key to efficient, economic growth. Some of these authors (Blondel et al., 1998; Lizzeri & Persico, 2000) even provide analytical evidence of how weak political competition may lead to an inefficient provision of government services, with consequences on the economy. For instance, using the US historical data, Besley, Persson, and Strum (2010) found that a lack of political competition led to anti-growth policies, which in turn led to low-income growth.

North (1981), Nobel Prize winner, stated, that there is a strong relationship between property rights and long-term economic growth. Hence, institutions that can secure those rights are critical for growth. Even though Douglas did not mention in his study which political 'regimes' can secure property rights, thus fostering economic growth, Acemoglu (2008), a prominent scholar in political economy, claims that democratic countries create significant entry barriers, ensuring better property rights for future potential producers, while authoritarian countries and the principle of oligarchy violate property rights and perpetuate a monopolistic position. Acemoglu constructed a model analysing a trade-off between a democratic and an oligarchic society by featuring two policy distortions: entry barriers and taxation. He found that '... of two otherwise identical societies, the one with an oligarchic organisation will first become richer but will later fall behind the democratic society'.

Yet, some authors (Pempel, 1990; McGuire & Olson, 1994) believe that countries with dominant-party systems such as Japan, Mexico, South Africa or Germany have been successful for decades as they focus more on their political effects. Other authors (Przeworski & Limongi, 1993; Barro, 2000) even argue that democracy does not always influence economic growth and in the case of countries with a weak institutional system, a strong democracy will not help. Two global superpowers—China and Russia—are governed by semi-authoritarian regimes, yet that did not stop them from developing two of the most advanced economies in the world.

There are also many articles claiming that democracy may retard economic growth. One of the first modern statements about the negative impact of democracy on economic growth was made by Galenson (1959). He argued that democracy fosters more consumption, thus undermining investment and hence also economic growth. This argument was later widely accepted by certain prominent scholars such as Huntington and Dominguez (1975), who argue that democracy accelerates demand for current consumption and the demand, in turn, threatens profits, hence reducing investment and consequently growth. Moreover, some advocates of this view conclude that authoritarian regimes foster savings and therefore stimulate economic growth (Rao, 1984).

In 1993, Przeworski and Limongi summarised certain statistical studies in which economic growth is determined by the political regime. According to these authors, the main argument against authoritarian regimes is that their rulers are not interested in maximising total output; in the case of democracies, these stimulate consumption, which, in turn, decreases savings and investment, leading to a decrease in economic growth (Przeworski & Limongi, 1993, 51–55). However, Przeworski and Limongi concluded that 'politics does matter, but "regimes" do not capture relevant differences'. Hence, there is no certain answer as to whether democracy has a positive or a negative impact on the economy.

Nonetheless, one thing is certain: political instability, protests and revolutions have their footprints on economic growth. Acemoglu, Cantoni, Johnson, and Robinson (2011) have found that the French revolution of 1789 had a momentous impact on France and all its neighbouring countries by establishing the principle of equality before the law and removing the barriers protecting oligarchies. These authors provide evidence that institutional reforms and democratisation only had a positive impact on long-term economic growth. However, several studies conducted by professors from leading universities of the world (Edwards & Tabellini, 1991; Ozler & Tabellini, 1991; Alesina, Ozler, Roubini, & Swagel, 1992) outline that any political uncertainty or instability may have a direct negative impact on short-term economic activities.

Using statistical evidence and advanced econometric methods, this article examines the impact of revolution and the establishment of democracy on economic growth in Armenia.

3 Research methodology and data

As indicated in the introduction, the main hypothesis of this article is that the positive impacts of the revolution in Armenia can even be seen within the first year. To validate this hypothesis, the article uses an econometric model, which measures the cost (benefits) of revolution in terms of GDP for the first year after the revolution (Q2-2018–Q1-2019) by forecasting this period using only pre-revolutionary data (until Q1 2018), simulating the scenario as if there were no revolution. Afterwards, the outcome is compared to real, post-revolutionary data. The difference between the simulation and real data indicates the net impact of the revolution on the Armenian economy for the first four quarters. The effect of the revolution is measured as a difference in the changes in the sum of GDP after the revolution and the corresponding sum for the counterfactual state.

To avoid overparameterisation, the pre-revolutionary dataset is divided between training and testing datasets: the model is trained based on 53 observations (Q1 2000–Q1 2013), later validated according to 19 pre-revolutionary observations (Q2-2013–Q1-2018). All assessments of validity and quality of the prediction methods are based on the validated set of observations.

To calculate the prognosis of GDP, this article uses seven models: two DNN models (long short-term memory recurrent NN and convolutional NN), ECM, SARIMA and three ensembling models (simple average, stacking linear and LASSO).

3.1 Dataset

For this model, quarterly data for the period Q1 2000–Q1 2019 are used. To predict GDP growth in addition to quarterly GDP data itself, the following data have been used: debt to GDP rate, inflation rate, FDI assets, monthly average unemployment, REPO and deposit interest rates and commodity prices (copper, gold, molybdenum, zinc and gas). Among many other parameters, these have been selected as predictors because they all were statistically significant in basic linear models. In addition, the main drivers of the Armenian economy discussed earlier are heavily dependent on certain non-domestic factors. Commodity prices and FDI are the main external influences on the metallurgical and energy sectors of the industry. Yet, agriculture in Armenia, as previously mentioned, is heavily dependent on natural factors, which are not controlled by external variables. However, agriculture is also dependent on new investments in capital and technology, which are partially explained by FDI.

The dataset of commodity prices has been downloaded from the official webpage of the International Monetary Fund (IMF). The remainder of the data come from the Statistical Committee of the Republic of Armenia (SCRA). Unfortunately, there was no quarterly data of GDP and other features in SCRA for the period before 2000, consequently, the model is limited to just 77 quarters. The data are divided into three areas: 53 quarters for training, 20 quarters for testing and four quarters to predict and compare with post-revolutionary data.

GDP of Armenia is expressed in millions of Armenian Dram (AMD), monthly average unemployment is measured in thousands of people. The data of FDI assets are the stock indicator, calculated according to the Balance of Payments (BOP) manual, 6th edition (IMF, 2009). The debt to GDP, inflation, REPO and deposit interest rates are shown as percentage points. Data relating to commodity prices are given in terms of percentage change by comparison with the previous period.

According to ADF and Breusch–Godfrey, the Phillips-Perron unit root tests show that Armenian quarterly GDP data have the first order of integration, *GDP ~ I(1)*, while the rest of the data are non-integrated (stationary), demonstrating why first differences in GDP are calculated and in all further research DGDP is used as a dependent variable.

3.2 DNN models: CNN and long short-term memory

In recent years, some scholars have been using unsupervised learning models, like DNNs, to predict or forecast GDP. Tkacz (2001) found that while using quarterly basis data, NN models do not outperform linear models, yet in the long term (using yearly basis data) unsupervised models are superior to linear models. He showed that the non-linear influence of monetary variables seems to be more relevant over a longer period. Qi (2001) and Jahn (2018) confirm this view for developed countries. Chuku, Odour, and Simpasa (2017), using the example of frontier economies in Africa, show that NN models also perform better than the ARIMA and other structural econometric models for developing countries. The authors draw three main conclusions:

I. Neural network models can be used to predict GDP growth in countries with developing economies 'that are exposed to potential chaotic influences from commodity prices, external factors and even political economy factors because this class of model is better able to learn the system and capture the nonlinearities inherent in the input variables'.
II. It is recommended to revalidate NN predictions with structural economic models, as in some cases it can produce outliers in certain data points.
III. In their paper, structural econometric models underperformed in the case of developing African countries mainly 'because of the sudden changes and chaotic patterns of macroeconomic variables in developing economies'.

Cook and Hall (2017) forecasted the US unemployment rate using four different types of NN methods: FC network, CNN, RNN and encoder-decoder network. In the last two models, they use long short-term memory (LSTM) as an architecture. The authors exhaustively explain the theory behind all these models and as a comparison, use the VAR model. As a result, all deep learning models perform better than benchmark models in the short term (one or two-quarters prognosis), yet, for the longer term (three or four quarters prognosis), only encoder-decoder network outperforms the others. Using the same US unemployment data, Stasinakis et al. (2015) carried out another comparison of NN models with linear models. They discovered that the radial basis function neural network performed statistically better than the rest of their models. However, in both of these articles, a univariate TS was investigated, while in contrast to some linear TS models, such as VAR or ARIMA, NN models can also 'learn' from numerous features using multivariate TS data.

There are various types of Neural Networks, however, only a few of them suited the multivariate TS models. More advanced networks are called DNNs. Compared to simple shallow NN models, DNN has more than two layers and uses specific mathematical modelling in each layer to process data. Both CNN and RNN (LSTM) that have been used in this study are part of that 'family'. Both models have been created in Python by using the 'keras' library. All parameters were selected to minimise the mean absolute error (MAE) of the outcome.

3.2.1 Convolutional neural network

CNNs have received a lot of attention in the ML community over the last few years, due to various successful applications in areas such as object detection, speech recognition and TS prediction. The original goal of CNN was to form the best possible representation of visual images to recognise them. The CNN solution needs to detect and classify and be sufficiently robust. Unlike the fully connected setting in other NN models, in the convolutional layer of this network, each input is connected in the layer to a few computational nodes. Each node receives input from a smaller clustered set of input nodes. Later, all weights of input in the layer are shared across all computational

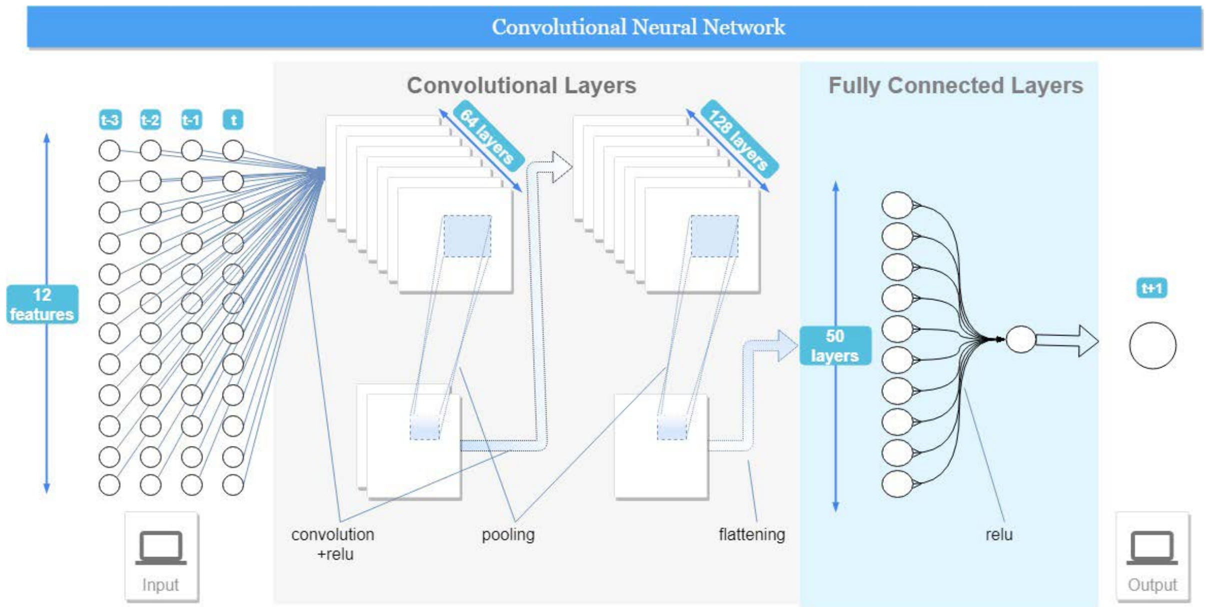

Fig. 3. Convolutional neural network architecture.

nodes, identifying patterns that increase predictive accuracy (Cook & Hall, 2011).

Figure 3 represents the architecture of CNN implemented in this article. An input model takes a 12x4 matrix with 12 features (also including the GDP growth rate) for the periods t-3, t-2, t-1 and t and returns an output of GDP growth rate for period t+1. As the dataset is not very big (having only 76 quarters) including more time steps would have reduced the training set. To get the best results, two convolutional layers are stacked together. To reduce the layers of each stack, max pool filter (sample-based discretisation process, reducing the dimensionality) is applied, and then it is flattened into a one-dimensional layer for the fully connected layers. The output of the final phase gives the prediction of the target variable for the t+1 period.

3.2.2 Recurrent neural network (LSTM)

The traditional neural network takes each input as an individual data point, assuming the data are non-sequential and each data point is independent of the others. In contrast, RNN is designed with loops that take not only one new input at a time but also the output from a previous data point that was fed into the network. Therefore, at a specific period of k, to predict GDP_{k+1} as an input model, it not only takes x_k (including lagged values) but also the output of the previous state weight matrix W_{k-1} between the input and the hidden unit (for period t - 1). As a result, RNN can remember the analysis that was carried out up to a given point, by maintaining a state as a memory. That state transfers back into the neural network with each new input to predict the output.

The LSTM model is a type of a recurrent NN model, which, in comparison with the vanilla RNN model, is capable of maintaining a strong gradient over many time steps. This means that the model can be trained with relatively long sequences, along with the short-term memory of the most recent network outputs. The architecture of the LSTM unit consists of the following elements—memory cell and three logistic gates: input, forget and output. The gates are logistic functions of weighted sums, where the weights might be learned during iterations. The input and forget gates manage the state of the cell or so-called long-term memory. The output gate produces the hidden state or the output vector. (Petneházi, 2018, pp. 2–3).

Figure 4 represents the architecture of the model used in this study. Once again, the model has a 12x4 matrix as an input (12 features for four previous periods). The first part of the model is an LSTM network, consisting of four units, (as input data have four-time steps) and 800 nodes. Twelve features from the t-3 time step are passed to the first unit of the network, which uses the random initialised hidden state and output to produce the new hidden state and first step output. The next unit takes three inputs: the output and hidden layer from the previous unit and the features from the next time step. The second part

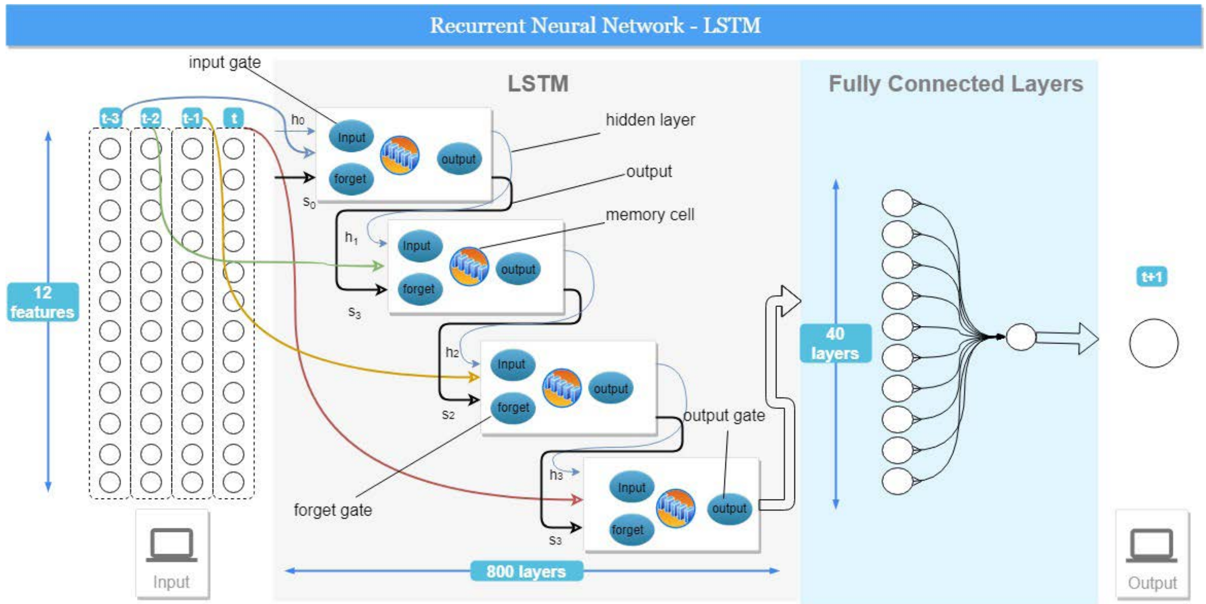

Fig. 4. LSTM recurrent neural network architecture.

of the model consists of fully connected layers with 50 nodes of the hidden layer and output layer.

3.3 Validation models: SARIMA and ECM

To compare and validate the DNN models, two structural econometric models are included in this article. Both are widely used in literature for prediction purposes.

3.3.1 Error correction mechanism

First is the linear approach using error correction mechanism (ECM). To build the model, Engle-Granger's two-step method (Engle & Granger, 1987) has been implemented. At the start, the integration level of all variables is checked, and then the linear model with lagged variables is made to check co-integration between variables of the same integration level. The model has been transformed from general to specific, leaving only statistically significant variables with their time lags. Afterwards, the residuals from the OLS regression are calculated from the model, and the fourth lag of the last residual is included in the final model. The residual is taken from 1 year ago (fourth lag) so that it is possible to predict four periods using only pre-revolutionary data. The final model has the following formula:

$$\Delta \mathrm{GDP}_t = \beta_1 \Delta \mathrm{GPD}_{t-4} + \beta_2 \mathrm{Inf}_{t-4} + \beta_3 \mathrm{Inf}_{t-5} + \beta_4 \mathrm{Go}_{t-2} + \\ + \beta_5 \mathrm{Co}_{t-2} + \beta_6 \mathrm{Mo}_{t-1} + \beta_7 \hat{\varepsilon}_{t-4} + v_t$$

where *ΔGDP* is the differentiated *GDP*, *Inf* is inflation, *Go, Co* and *Mo* are gold, copper and molybdenum commodity prices, respectively. If commodity prices have external parameters and the Armenian revolution has no impact on them, there is no need to restrict them to have fourth lag or higher to predict post-revolutionary quarters.

3.3.2 Seasonal autoregressive integrated moving average

Due to the seasonality of the data, another favourable method is capturing the trend line by using SARIMA. The SARIMA TS approach to forecasting is one of the most popular approaches, due to its ability to use past values without any requirement for economic fundamentals and theory (De Gooijer & Hyndman, 2006).

To create an appropriate ARIMA model, ACF and PACF graphs are built as a ground point and are

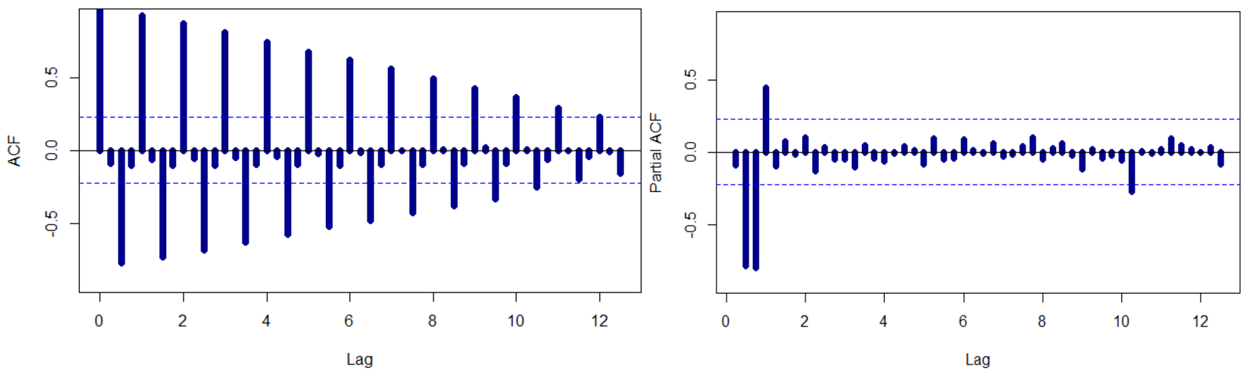

Fig. 5. ACF and PACF graphs for the SARIMA model.

represented in Figure 5. According to the graphs, the model has some AR and seasonal effects.

The final model has been built in *R* using 'auto. arima' function from the package 'function', which uses the algorithm of Hyndman and Khandakar, which minimises selected information criteria and MLE matches the best ARIMA model (Hyndman & Khandakar, 2008). According to the algorithm, the best structure was SARIMA$(0,0,1)(0,1,1)_4$. After fitting the model, the Ljung-Box test on residuals was checked. As the test p-value is greater than 0.05, the residuals are independent of the model. In addition, this model has the lowest MAE on the training dataset compared with other ARIMA models tested during this study.

3.4 Ensembling models: simple average, stacking linear and LASSO

Taking into consideration that all four aforementioned models have completely different architecture and use different sets of information, it is also beneficial to ensemble these models to obtain better predictive performance. Ensembling methodology uses multiple learning algorithms to form a new model. In this study, there are three types of ensembling models used: simple average, stacking linear and LASSO.

3.4.1 Simple average

For this model, the mean of the predictions of the input models are taken, which are the four models discussed earlier (ECM, SARIMA, CNN and LSTM). This model is especially useful in predicting the accuracy of the models from the bottom layer which are close to each other.

3.4.2 Stacking linear

Stacking is one of the most popular ensembling methods (Wolpert, 1992; Ozay & Vural, 2013). The idea behind forecast combination methods is to take the outputs of some models (bottom layer) as an input and make new regression (top layer). Depending on the top layer model, there can be different types of models. Most often, logistic regression is implemented as a top-layer model. By giving parameters to each input from the bottom-layer models, this model is able to give more weight to models having higher predictive accuracy.

3.4.3 Stacking LASSO

The last model implemented in this article is also a stacking model, using LASSO as a top-layer model. The advantage of this method is that LASSO minimises the residual squared error by adding a coefficient constant, which creates a penalisation balance on each estimate (Wang, Li, & Jiang, 2007). By doing so, it leads some coefficients to 0 or close to 0, which is why this model is more adaptive than a simple regression (Stasinakis et al., 2015).

Tab. 1: Model error statistics

	RMSE	MAE	MedAE	R²	SD
CNN	58266.74	46161.45	34190.78	0.9778	13733.60
Stacking linear	58119.65	46434.29	48105.92	0.9780	13698.93
SARIMA	66447.39	47783.78	36712.05	0.9712	15661.80
Stacking LASSO	59349.38	47907.44	48731.62	0.9770	13988.78
Simple average	70968.70	57434.54	48855.18	0.9671	16727.48
LSTM	102526.21	77680.84	56860.31	0.9314	24165.66
ECM	128851.99	109558.86	101529.37	0.8917	30370.71

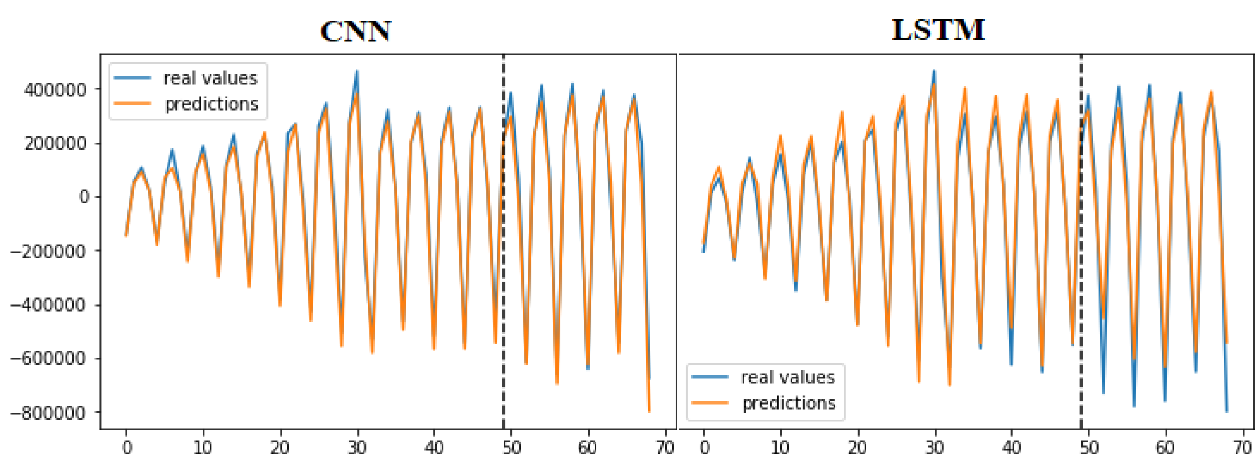

Fig. 6. CNN and LSTM real versus predicted values.

4 Empirical results

To statistically evaluate the forecasts from all models, the root mean squared error (RMSE), mean absolute error (MAE), median absolute error (MedAE), standard deviation (SD) and R^2 of each testing set are compared. For the first three statistics, the smaller the outcome, the better the performance of the model and vice versa R^2. Apart from R^2, all values are shown in millions of AMD.

Table 1 represents the outcome of the statistics mentioned above arranged in terms of MAE results. According to the results, CNN outperforms the rest of the models, except for the stacking linear model that shows a slight difference. Those two models have similar prediction accuracy because, in the training dataset, CNN also outperforms the rest of the models, hence recording the biggest parameter for the stacking model. The LSTM and ECM models had worse prediction accuracies, which is why the simple average model also underperformed compared with the other ensembling LASSO and CNN models. According to this outcome, CNN is the superior model regarding most of the statistical criteria. The ensembling models did not significantly improve the accuracy of the individual performances; however, they were more accurate compared to LASSO and ECM and to a certain extent SARIMA.

By comparing both the training and test prognosis on both neural networks, results showed that they performed in quite a similar way on the training dataset, yet on the test set, the LSTM model overpredicted the lowest values (Figure 6). The bad performance of the LSTM model was mostly due to the data frame size, as it was very small in comparison with certain big data TS analyses, where it overperformed.

Figures 7–9 are graphical representations of forecast on the test set as well as the post-revolutionary year (shaded in grey). To consider the variability of the

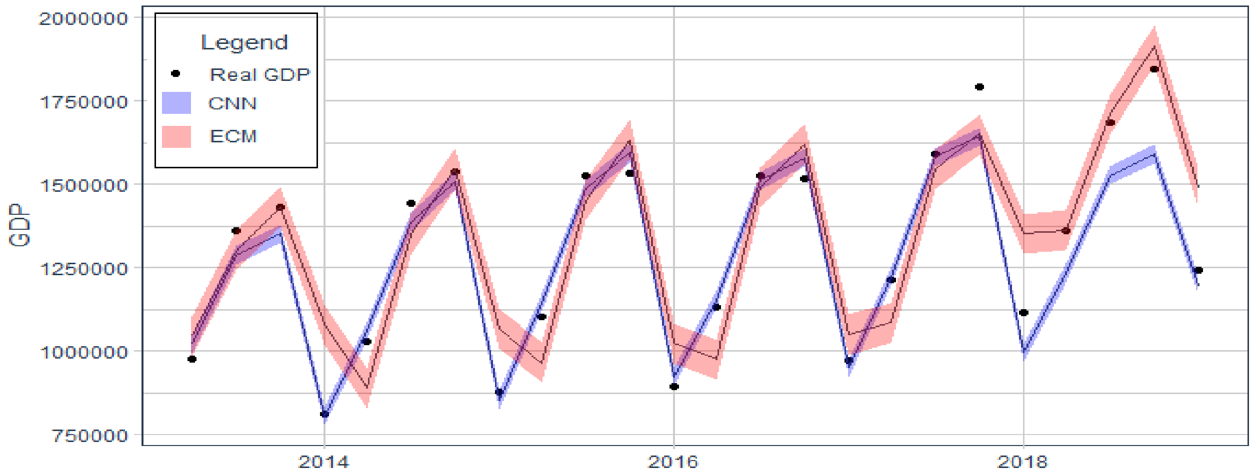

Fig. 7. CNN and ECM test predictions including post-revolutionary data.

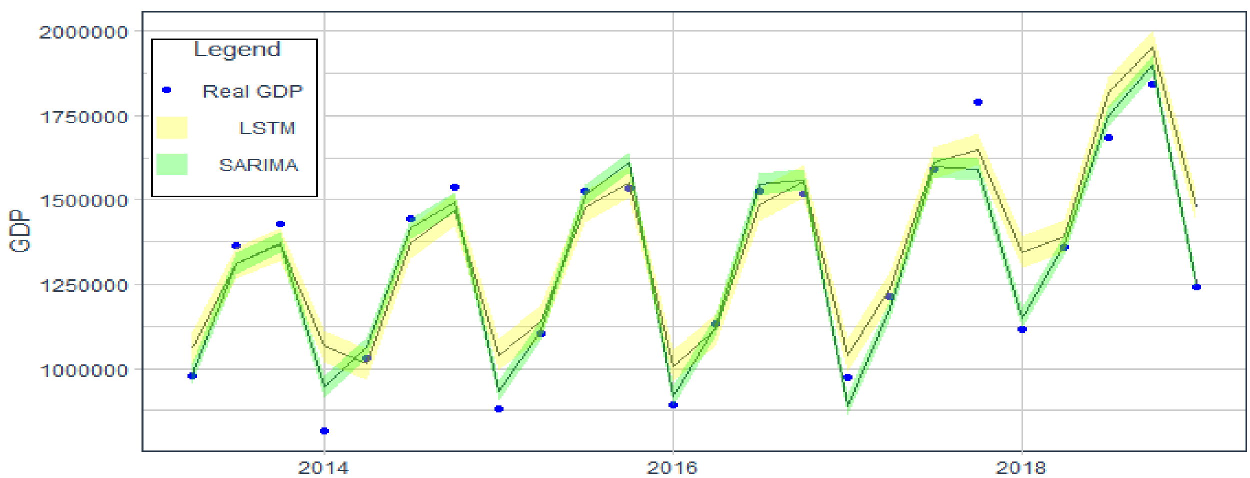

Fig. 8. LSTM and SARIMA test predictions including post-revolutionary data.

predictions, the prediction interval is introduced on those figures. A 95% confidence interval of each model prediction is shaded in a different colour to see how accurate they are and how they differ from one other. The confidence interval of prediction is calculated by the following formula:

$$\Delta\widehat{GDP}_t \pm z * \sigma$$

where $\Delta\widehat{GDP}_t$ is the predicted value for time *t*, z is the critical value from Gaussian distribution (which is 1.96 for the 95% confidence interval) and *s* is the standard deviation of the model based on the test set results (Table 1).

From the graphs alone, even without any calculations, the overperformance of CNN over ECM (Figure 7) and SARIMA over LSTM (Figure 8) can be seen in the test set, yet the ensembling models have very similar performance, and it is even hard to distinguish between them in Figure 9. However, in the grey area, since 2018, Q2, there has not been any obvious dominance or similar pattern between models. CNN, LSTM and linear stacking models have predicted the real GDP to be lower, yet for the other models, almost all observations are within the prediction confidence interval.

If converted to Euros (the exchange rate is taken from SCRA as of 31 December 2018), the sum of the difference between real and forecasted values, considering the confidence intervals of prediction, reveals the value of 856.7 million EUR, based on the CNN model difference. Similarly, for linear and LASSO stacking, it is slightly lower (around 440.2 and 523.5 million EUR, respectively), with the SARIMA

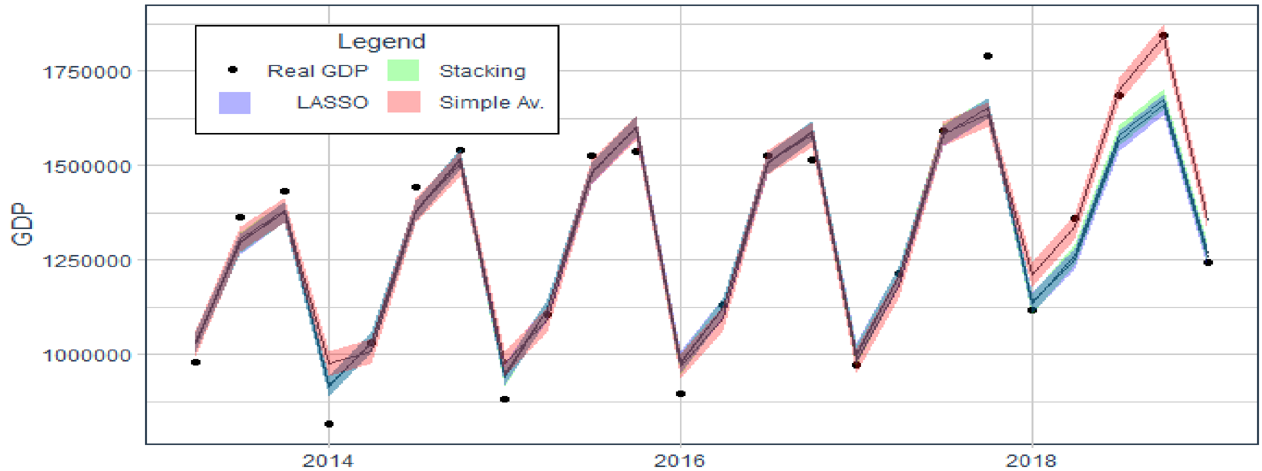

Fig. 9. Stacking, LASSO and Simple Av. test predictions including post-revolutionary data.

and simple average models, it is very close to 0; yet for LSTM, it is –571.5 million EUR and for ECM, –191.4 million EUR. However, considering that both LSTM and ECM models underperformed in the test dataset and other models, like CNN, have more predictive accuracy, this result is more biased compared to other models.

5 Conclusions

The main conclusion of this article is that the Velvet Revolution in Armenia did not have any negative impact on the economy during the first year after political turnover. When the difference in the sum of GDP after the revolution and the same sum for the counterfactual state were measured, the best models (based on their accuracy) out of seven indicated that the difference between the GDP prognosis using only pre-revolutionary data and post-revolutionary GDP was either insignificantly small or positive, which means that the benefits of the revolution outweighed the costs. Moreover, according to the most accurate model, CNN, the Armenian GDP gained a surplus of around 850 million EUR within a year, following the revolution.

Section 1 highlights all the threats and opportunities of the Armenian economy. After the collapse of the Soviet Union, the Republic of Armenia overcame many challenges, including economic occupation, lack of some vital resources (gas and electricity) and electoral fraud, and as a result, the country was left with a government of oligarchs. However, the Armenian revolution in 2018 proved that the people did not give up and they changed the political situation in the country, establishing direct democracy. After coming to power, one of the main goals set by the government was to fight corruption and the shadow economy, and within a year, it had added 130 million USD to the budget, for this purpose. However, abrupt changes are often accompanied by certain negative effects, such as labour inactivity or the damage of public goods during the revolution. This section also conducted a review of the literature highlighting the impact of democracy and political change on economic growth.

In the second section of this article, an empirical analysis is carried out, using NN methods to ascertain whether there were any costs\benefits to the economy following the revolution, compared to the situation in the country had there been no revolution. This section included all the theoretical background of each model, a literature review of NN models in macroeconomics and their implementation.

The results in this section support the idea that for developing countries, some NN models may work better than traditional models; however, it is still recommended to perform structural econometric models to have a point of comparison, as in the case of LSTM which might underperform heavily. In addition, results show that the ensembling models provide a less volatile forecast using information from all models. However, in terms of MAE accuracy, CNN overperforms all three ensembling models. The performance of those models could have increased by excluding the biggest underperformers, ECM and LSTM.

According to model accuracies, CNN is the superior model for this study. Based on this model, the Armenian economy was shown to have gained an additional 850 million EUR from the revolution. The budget surplus that the government gained to fight the shadow economy (130 million USD) only partially explains this surplus. Another explanation may be linked to other factors mentioned in Section 2, such as eliminating monopolies, removing barriers to establishing new businesses, increasing tourism, ensuring the competitiveness of markets and most importantly a more optimistic attitude among the population concerning the future and increased trust in the government. Finally, we can conclude that democracy and political turnover only bring benefits, given that during the revolution, there was no violence and most importantly, no geopolitical game was played between the other superpowers.

As a result, the most accurate models either capture a positive outcome post-revolution or no changes at all; hence, there are no grounds for rejecting the main hypothesis of this article, that is, the benefits of the revolution could be seen even in the first year after the political change.

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