“Company’s financial state forecasting: methods and approaches”

AUTHORS	Shynara Jumadilova https://orcid.org/0000-0001-8509-3688 http://www.researcherid.com/rid/O-2177-2017 Nurlan Sailaubekov https://orcid.org/0000-0002-5004-746X Dana Kunanbayeva

ARTICLE INFO	Shynara Jumadilova, Nurlan Sailaubekov and Dana Kunanbayeva (2017). Company’s financial state forecasting: methods and approaches. *Investment Management and Financial Innovations*, *14*(3), 93-101. doi:10.21511/imfi.14(3).2017.09
DOI	http://dx.doi.org/10.21511/imfi.14(3).2017.09
RELEASED ON	Friday, 06 October 2017
RECEIVED ON	Friday, 16 June 2017
ACCEPTED ON	Friday, 28 July 2017

JOURNAL	"Investment Management and Financial Innovations"
ISSN PRINT	1810-4967
ISSN ONLINE	1812-9358
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10, Sumy,
40022, Ukraine

www.businessperspectives.org

Shynara Jumadilova (Kazakhstan), **Nurlan Sailaubekov** (Kazakhstan),
Dana Kunanbayeva (Kazakhstan)

COMPANY'S FINANCIAL STATE FORECASTING: METHODS AND APPROACHES

Abstract

Planning company's activity is a complex process, in which foresight is of great importance. The paper presents a method to predict financial state of a company using available financial data. For the prediction of quantitative indicators of the company currently there are different ways to build predictive models, such as simple and multiple regressions, autoregressive model and others. In this paper, to predict financial indicators of the company we use econometric modeling techniques. Tools to check the time series for the seasonality and stationarity are used in constructing the models. To check the reliability of the analysis techniques applied backtesting. To apply the developed method we used the values of financial indicators of the Kazakh national oil producing company. However, the method can be used for any company despite its size, industry, and so on. Albeit the method proposed is universal one and enables to predict financial state at any company, it has certain shortcomings and should be used along with fundamental analysis tools. The method proposed in the paper illustrated adequate results with sufficient accuracy according to the backtesting results. Therefore, based on the results of forecasting the financial state indicators, one can conduct a financial analysis of the expected state in upcoming period and use the derived values for future planning.

Received on: 16th of June, 2017
Accepted on: 28th of July, 2017

Keywords econometric models, VECM, predicting, planning, financial state

JEL Classification C58, G30

Shynara Jumadilova, Ph.D., Assistant Professor, International Information Technology University, Kazakhstan.

Nurlan Sailaubekov, Doctor of Economic Sciences, Kazakh Ablai Khan University of International Relations and World Languages, Kazakhstan.

Dana Kunanbayeva, Ph.D. in Economic Sciences, Kazakh Ablai Khan University of International Relations and World Languages, Kazakhstan.

INTRODUCTION

Planning company's activity is a complex process, in which foresight is of great importance. Predicting the future state of the company includes the use of both fundamental analysis using qualitative methods and technical analysis using quantitative methods. Moreover, planning is important element of management, which ensures achievement of company's strategic priorities. Effective financial forecasting is essential tool of company's main goals achieving – maximization of profit and company's value.

Azarenkova et al. (2017) investigated issues concerning financial planning at the enterprise. Also, methods and models of financial forecasting were analyzed and their unification was proposed.

Gottardo and Moisello (2015) studied and predicted the effect on performance of family endowment on the business from the perspective of socioemotional wealth.

Frolov et al. (2017) analyzed financial provision of small businesses and substantiation of its improvement scenarios with the use of foresight instruments. The authors evaluated the criteria of financial provision of small businesses and offered the organizational mechanism of financial provision of small business. They also considered the stages and methods of systemic foresight.

Makarenko and Serpeninova (2017) investigated the issues concerning the relationships between the level of transparency of public companies, their financial efficiency and investment attractiveness. They proved that the transparency level sufficiently influences company's financial state forecasting.

Currently there are different ways to build predictive models, such as simple and multiple regressions, autoregressive model, vector model, error correction model and others.

One type of econometric models recently developed is a vector autoregression (VAR), which is a model of the dynamics of several time series in which the current values of these series depend on past values of the time series. The model was proposed by Ch. Sims (1980) as an alternative to system of simultaneous equations that involve substantial theoretical constraints (Sims, 1980). VAR models are free from the constraints of structural models. However, the problem of the VAR models is in sharp increase in the number of parameters as the number of the analyzed time series and the number of lags increase.

Vector autoregression model is used to express the linear dependencies between the different time series. VAR models generalize the models of one-dimensional autoregression (AR), enabling the use of more than one variable. All the variables in the VAR are treated symmetrically in the structural sense (although the estimated quantitative ratios are not the same); each variable is described by an equation explaining its evolution based on its own lagged values and the lagged values of other variables in the model. VAR modeling does not require much knowledge of the forces affecting variable as structural model of simultaneous equations: the only important thing is to know required list of variables which hypothetically could affect intertemporally each other.

Error correction model (ECM) covers both short-term and long-term relationship between non-stationary variables with the unity order of integration. To this end, these variables should be cointegrated, that is, there must be their linear combination, which is a stationary variable. To test the variables for cointegration and build error correction model S. Johansen (1995) approach is used.

Error correction model is a dynamic system with a feature that the deviation of the current state from long-term relationship is reduced to a short-term dynamic. Error correction model is not a model that corrects the errors in the other model. Error correction models are a category of models of different time series that accurately estimate the rate at which Y variable returns to equilibrium due to changes in the independent variable X. Error correction model is a theoretical approach to assess the short and long term effects on some time series from other ones. Therefore, they are often intertwined with our theories of political and social processes. ECM is useful when working with the integrated data, and it can be used with stationary data as well (Engle & Granger, 1987).

Estimated long-term relationship can be defined by the cointegrating vector, and then this relationship can be used to develop a specified dynamic model that can have an emphasis on long-term or temporary aspect such as two VECM of conventional VAR in the Johansen (1995) test.

Vector error correction model (VECM) adds error correction values in a multi-factor model as a model of vector autoregression. Vector error correction model is a restricted VAR-model developed to apply to non-stationary series, for which it is known that they are cointegrated. VEC-model has cointegrating relations, embedded in the specification so that in the long-run dynamic behavior the endogenous variables converge to their cointegrating relations given short-run dynamic correction. Cointegration term is called regression residuals correction term as the deviation from the long-run dynamic equilibrium is adjusted gradually through a series of particular short-run dynamic adjustments.

Research objective of the paper is to develop a method to predict financial state of a company using available econometric instruments. Subject of the research is a financial data of a company.

1. METHODOLOGY AND DATA

In this paper, in forecasting company's financial indicators, methods of econometric modeling are used. In constructing the models are used tools to check the time series for the seasonality and stationarity.

Economic time series with few exceptions are nonstationary. Nonstationarity is most often seen in the presence of a non-random component $f(t)$, depending on time. If random residual obtained by subtracting from the original series its non-random component $f(t)$, is a stationary time series, the original series is called non-stationary homogeneous one.

In practice, to determine the stationarity/non-stationarity of process is used test for the presence of a unit root. The process is non-stationary and integrated when there are unit roots of the autoregressive polynomial. Integrated time series is non-stationary time series, the some order difference of which is a stationary time series. Such series are also called difference stationary (DS-series). Less than one root is not considered in practice, as these processes are of explosive nature. If the tests confirm the presence of a unit root, then the difference of the original time series is analyzed, and for stationary process of some order differences (first order is usually enough, and sometimes the second one) ARMA-model is constructed.

To apply any of the above listed models, it is necessary to test the seasonality of the time series and, if necessary, to carry out a seasonal adjustment. Seasonality is checked using CensusX12, provided by T. Jackson and M. Leonard (2000).

The decision to include in the equation each additional lagged value of the dependent variable or the random term is taken on the basis of the significance of the relevant factors and analysis of the Akaike, Schwarz and Hannan-Quinn information criterion values.

To check the reliability of the analysis techniques applied, the backtesting is used, that is, forecasting historical data and comparing the estimated values with the actual ones. For each regression equation is held separate backtesting.

During the forecast, the confidence interval is built, within which allowed determination of the estimated values. When this value goes through the confidence interval, it is necessary to bring the calculated values to an acceptable range using correcting factors. Here, acceptable value is 95%.

Predictive models are built using "KazMunaiGas EP" data of consolidated financial states, the Kazakh national oil company for the period 2004–2013. Backtesting of models is carried out using the financial indicators of the company for 2014.

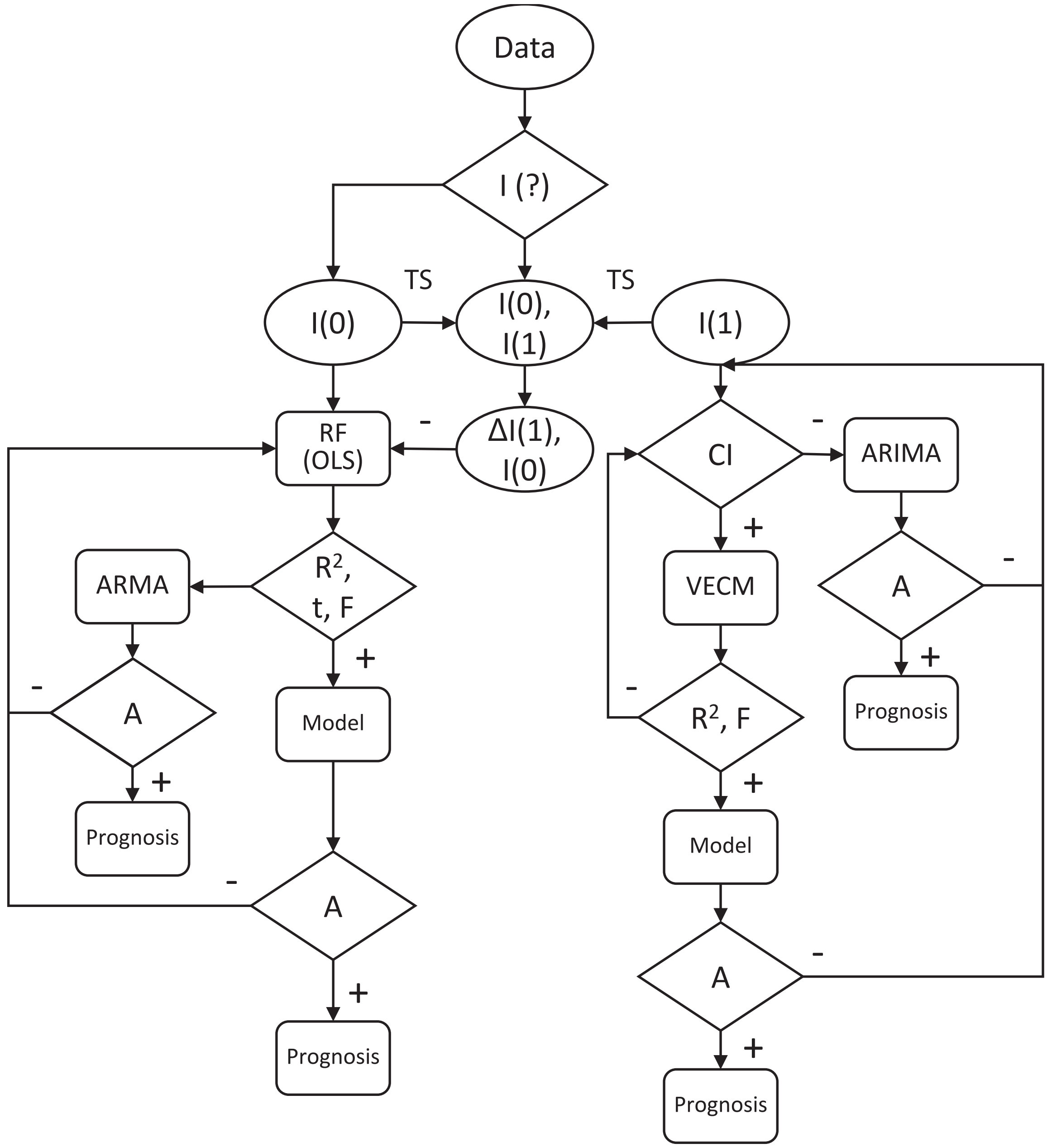
2. METHOD OF THE ECONOMETRIC PREDICTIVE MODELING OF THE COMPANY'S FINANCIAL STATE INDICATORS

There are many modern tools for simulation, and we consider it expedient to choose an adequate method for the simulation of the financial state indicators, as shown in the scheme (Figure 1).

In the proposed method of modeling and forecasting of financial and economic indicators, both autoregressive and cointegration relationship between indicators of the company are identified and, respectively, models are built based on these relationships.

The process of modeling and forecasting of the financial state indicators presented in Figure 1 is carried using EViews software. This process consists of four blocks of procedures performed with the original data set. These data are the indicators of the financial state of the company.

We cover indicators of the financial state of the company generally used in the process of financial analysis and divide them into two groups, according to the methods of forecasting.



Note: Data – data set, I(?) – determining order of integration, ARMA – autoregressive moving average model, ARIMA – autoregressive integrated moving average model, RF (OLS) – regression function, A – testing model adequacy CI – determining presence/absence of cointegration between time series, VECM – vector error correction model, TS – theoretical substantiation, <+> and <–> – positive and negative test results, respectively, Prognosis – computing estimated values of indicators.

Figure 1. Financial state indicators forecasting process chart

The first group comprises indicators projected by balance method: Gross Profit, Net Income. The second group includes other parameters, predicted by econometric methods: Total Assets, Stockholder's Equity, Fixed Assets, Plant and Equipment, Short-Term Liabilities, Cash and Money Securities, Revenues, Earnings Before Taxes, Costs Of Production, Accounts Receivable, Inventories.

To determine the values of the first group of indicators in the forecast period, we need to find the predicted values of the second group of indicators.

The process of econometric modeling and forecasting of the financial state includes the following steps:

I. Data collection and processing.

II. Modeling the financial state indicators.

III. Verification of the model adequacy.

IV. Computing predicted values of the financial state indicators.

I. Data collection and processing

The first block of procedures is a collection and primary data processing. The data are checked for the presence of seasonality using CensusX12. In addition, we adjust from the stationary stochastic seasonality and deterministic seasonality using CensusX12.

II. Modeling the financial state indicators

The second set of procedures, the largest by number of actions, is to construct a model (Figure 1). For convenience, we describe the action of the block by steps.

Step 1. Check the time series on stationarity. To do this, we use the Augmented Dickey-Fuller unit root test (ADF). According to the test results we separate the stationary and integrated series. In the integrated series determine the order of integration. In accordance with the order of integration we group the time series.

Depending on the results of step 1, select one of the alternative steps.

Step 2.1. If the time series are stationary, we select the base indicator, which affects the other indicators. We build an autoregressive model of the base indicator time series and on the basis of the derived model we calculate the predicted value. For other dependent parameters, with the appropriate theoretical foundation, we construct the regression function using the method of ordinary least squares (OLS).

The significance of the model we check using statistics (the coefficient of determination, Student's statistic and Fisher's test). If the statistics values are satisfactory, then we accept the resulting model. If the values are not satisfactory, then we find another factor indicator and construct a model with it, or construct an autoregressive moving average model.

Step 2.2. If the time series are integrated of the same order, then we perform the test for cointegration. Cointegration of time series implies the existence of a stationary linear combination of two or more non-stationary time series. To check the availability of such a combination, there are several methods, such as Johansen test or Engel-Granger test. The corresponding lag is selected by enumerative technique. Cointegrating indicator is selected based on theoretical basis.

Johansen (1995) test provides five cases of deterministic trend:

1) the level data have no deterministic trends and the cointegrating equations do not have intercepts;

2) the level data have no deterministic trends and the cointegrating equations have intercepts;

3) the level data have linear trends but the cointegrating equations have only intercepts;

4) the level data and the cointegrating equations have linear trends;

5) the level data have quadratic trends and the cointegrating equations have linear trends.

If cointegration exists, we build a vector error correction model (VECM). The significance of the model is checked by means of statistics (the coefficient of determination, Student's statistic and Fisher's test). If the statistics values are satisfactory, then we accept the resulting model.

If there is no cointegration, we search another cointegrating indicator. In the absence of such an indicator, we build an autoregressive integrated moving average (ARIMA) model.

Step 2.3. With the theoretical justification of the dependence of time series with different order of integration, we take the difference of the DS-series. Having stationary series, we construct a regression function. The significance of the model is checked by means of statistics (the coefficient of determination, Student's statistic and Fisher's test). If the statistics values are satisfactory, then we accept the resulting model.

III. Verification of the model adequacy

The third block of procedures consists of verifying the adequacy of the models via backtesting. Actual values differ from the baseline, calculated by the model, i.e., y and $\hat{y}_x$. The smaller this difference, the closer baseline values fit to the empirical data, the better the quality of the model. The deviation of actual and estimated values of the indicator for each observation represents the error of approximation. In some cases, the approximation error may be zero. Deviations $\left(y-\hat{y}_x\right)$ are not comparable with each other, except zero. For comparison, it is used a deviation, expressed as a percentage of the actual value.

As $\left(y-\hat{y}_x\right)$ can be either positive value or negative, the approximation error for each observation is taken in absolute value of percentage difference.

Deviations $\left(y-\hat{y}_x\right)$ can be considered as the absolute error of approximation, and $\left|\frac{\left(y-\hat{y}_x\right)}{y}\right|\cdot 100\%$ – as the relative error of approximation (I. I. Eliseeva, 2004).

Thus, using the obtained models we define values for one or more recent values of the time series. Compare them with the actual data; determine the value of the relative error of approximation. If the result of this test is satisfactory, we accept the model and determine the predictive value.

IV. Computing predicted values of the financial state indicators

Using the derived models in point II, we obtain predicted values of financial indicators. To further assess the economic condition of the company in the forecast period, annual values of financial indicators are required. To do this, after the calculation of the estimated quarterly values, we take the values in the fourth quarter as the annual values for the balance sheet indicators and total values of four quarters for the indicators of the profit-and-loss report.

3. IMPLEMENTATION OF THE METHOD FOR FORECASTING THE COMPANY'S FINANCIAL STATE INDICATORS

For modeling financial state indicators of KMG EP we use a sample since 2004Q1 to 2013Q4 (40 observations), provided in the consolidated financial states of JSC "KazMunaiGas EP" for 2004–2013 (KASE, 2015b).

For the modeling procedure via the EViews software, we initially introduce their designation: A – total assets, E – stockholder's equity, FA – fixed assets, PE – plant and equipment, SL – short-term liabilities, CMS – cash and money securities, R – revenues, EBT – earnings before taxes, C – costs of production, AR – accounts receivable, I – inventories.

The first block of procedures includes checking the data for seasonality. To do this, we test the data (values of financial state indicators) for the presence of seasonality using CensusX12.

The test results showed the absence of seasonality in the time series of the sample. We do seasonal adjustment from the stationary stochastic seasonality and deterministic seasonality using CensusX12.

The next step consists of testing the time series on stationarity using the ADF test. The results showed non-stationarity of time series.

To construct appropriate models for forecasting, the group of cointegrating parameters should be identified. As mentioned above, considered oil and gas production is capital intensive. It defines some clear relationship between indicators of financial states. For example, the costs and revenue depend on the production volume. Plant and equipment comprise the bulk of the fixed assets. In addition, when searching cointegrating parameters among the financial state indicators of the company one should take into account that the accounts receivable related to earnings before taxes.

We test on cointegration using the Johansen method. The necessary lag we choose by enumerative technique, from smallest to largest. The results show that the cointegration relations in the given group of indicators exist. Therefore, we test for cointegration this group of indicators for the respective case.

In this way, we obtain the following groups of cointegrated indicators:

1. $\{PE\}$, $\{FA\}$.

In such a capital-intensive business as oil production, the size of the total assets of the company is largely determined by the size of available net assets or equity of the company. This explains the close relationship between the indicators of fixed assets and equity.

2. $\{EBT\}$, $\{AR\}$.

The growth of the company receivables, as a rule, is experienced with growth in sales and earnings before tax, respectively, and vice versa, reducing profit results in the decline in receivables. In this case, the empirical findings are consistent with the relevant theoretical basis.

3. $\{I\}$, $\{A\}$.

The values of assets and inventories have cointegration.

4. $\{E\}$, $\{SL\}$.

In the samples stockholders equity and short-term liabilities have cointegration.

5. $\{C\}$, $\{R\}$.

The cointegration test revealed cointegration between production costs and revenues. Both indicators depend on output.

6. $\{CMS\}$, $\{EBT\}$.

Indicator of cash and money securities showed a cointegration relationship with earnings before tax. Given that we have already identified a functional relationship between earnings before tax and accounts receivable, we take earnings before tax as an explanatory variable to predict CMS.

Build a vector error correction model for these indicators.

4. COMPUTING AND BACKTESTING THE ESTIMATED VALUES OF FINANCIAL STATE INDICATORS OF KMG EP

After building the model, we define values of the respective indicators in the forecast period. Finally, we test the adequacy of the models through backtesting. To do this, we calculate the values of the financial state indicators for 2014 on the basis of forecast values obtained by the model. The values of the Balance Sheet indicators we take equal to the estimated value for the 2014Q4. The values of indicators of the Profit and Loss State for 2014 we take equal to the sum of the estimated values for 4 quarters of 2014. Thus, we obtain the values shown in Table 1. Compare them with the actual values of the financial state indicators and calculate the relative error of approximation. To do this, use the formula, given in I. I. Eliseeva (2004):

$$A = \frac{1}{n} \cdot \sum \left| \frac{(y - \hat{y}_x)}{y} \right| \cdot 100\% \tag{1}$$

Using the balance method calculate the values of the rest of the financial state indicators for the forecast period in 2014 and 2015.

Indicator Gross Profit is calculated as the difference between R and C, so $GP_{2014} = 274527$ mln tenge and $GP_{2015} = 277949$ mln tenge.

Indicator Net Income is calculated as the difference between EBT and CIT (Corporate income tax), that is 20% in 2014. Therefore, $NI_{2014} = 43423$ mln tenge and $NI_{2015} = 127860$ mln tenge.

Table 1. Backtesting of the model adequacy

Indicator	Baseline 2014, in mln tenge	Actual 2014, in mln tenge	A	Baseline 2015, in mln tenge
A	1596903	1483848	7,6	1583572
FA	564449	578474	2,4	543293
E	1449139	1339116	8,2	1495571
PE	298666	156436	90,9	289013
SL	199856	105016	90,3	201759
CMS	686744	715758	4,1	754010
R	987339	845770	16,7	1045597
C	712812	974147	26,8	767648
EBT	54279	61573	11,8	159825
AR	139797	56570	147,1	169209
I	24653	26357	6,5	24628

5. RESULTS INTERPRETATION

As seen in Table 1, this method allows to predict most of indicators with acceptable accuracy. Some indicators are formed by the company's management, based on the values of the basic indicators and management purposes. The largest deviations are observed in accounts receivable, fixed assets and short-term liabilities, which significantly vary and quickly change by the company's management.

In 2014, earnings before tax declined sharply. Despite this, deviation of the predicted value from the actual one was 11.8%.

According to Annual Report of JSC "KazMunaiGas EP" for 2014 (KASE, 2015a), the sharp decline in the value of $\{PE\}$ is due to the fact that the current value of plant and equipment has been reviewed for depreciation due to the fact that fixed assets, including production wells which stop producing commercial quantities of hydrocarbons and are scheduled for liquidation, no longer counted as an asset or when it is expected no future economic benefits from the asset. Any gain or loss arising on derecognition of the asset (calculated as the difference between the net return from sale and the present value of the item) is included in the state of total revenue in the period in which there was such an event.

The bulk of trade receivables are ones from the sale of crude oil to KazMunayGasTrading AG ("KMG Trading"), which is a subsidiary of JSC "National Company KazMunayGas". A significant decrease in overdue receivables is due to the fact that in April and November 2014 the contract with KMG Trading was amended. According to the amended terms, receivables payment from KMG Trading for the subsequent sale of crude oil in RompetrolRefinare S.A. to the related party has been increased from two to three months.

According to the calculation results presented in Table 4 we can conclude the following. It is expected that during 2015 indicators such as total assets and stockholders' equity would increase insignificantly, but revenue and profit of the company would increase. However, according to the current situation with oil prices, we should expect a negative scenario and a possible reduction in revenue towards the lower limit of the confidence interval of the forecast.

Based on the above results of forecasting the financial state indicators, one can conduct a financial analysis of the expected performance of the company in the forecast period, using known methods of financial analysis, as well as the methodology presented in Jumadilova Sh. et al. (2013) and Sh. Jumadilova and N.T. Sailaubekov (2013).

CONCLUSION

In this study, an algorithm of the modeling process of the financial state indicators is developed. Using a sample of KMG EP financial indicators, models of these indicators are built; and the quality and adequacy of the models are verified by relevant calculations.

Forecasting the values of financial state indicators of the company KMG EP is implemented. These estimated values could be used to provide a financial analysis and make recommendations to ensure the stable development of the company.

REFERENCES

1. Azarenkova, G., Pasko, T., Golovko, O., Kovalchuk, Y. (2017). Financial planning and improving of its methods. *Accounting and Financial Control, 1,* 39-47. Retrieved from https://kozmenkopublishing.com/journals/j-accounting-and-financial-control/issue-12/financial-planning-and-improving-of-its-methods
2. Gottardo, P., Moisello, A. M. (2015). The impact of socioemotional wealth on family firms' financial performance. *Problems and Perspectives in Management, 13(1),* 67-77. Retrieved from https://businessperspectives.org/journals/problems-and-perspectives-in-management/issue-47/the-impact-of-socioemotional-wealth-on-family-firms-financial-performance
3. KASE (2015a). Annual Report of JSC "KazMunaiGas EP" for 2014. Retrieved from http://www.kase.kz/ru/emitters/show/RDGZ
4. KASE (2015b). The consolidated financial states of JSC "KazMunaiGas EP" for 2003–2014. Retrieved from http://www.kase.kz/ru/emitters/show/RDGZ
5. Eliseeva, I. (2004). Econometrics. Moscow: Finance and Statistics.
6. Engle, & Granger. (1987). Cointegration and error correction: Representation, estimate, and testing. *Econometrica, 55,* 251-276. https://doi.org/10.2307/1913236
7. Frolov, S., Strilec, V., Balatskyi, I. (2017). Foresight technologies in financial provision of small business in Ukraine. *Problems and Perspectives in Management, 15*(1-1), 200-209. Retrieved from https://businessperspectives.org/journals/problems-and-perspectives-in-management/issue-1-cont-13/foresight-technologies-in-financial-provision-of-small-business-in-ukraine
8. Jackson, T., Leonard, M. (2000). Seasonal Adjustment Using the X12 Procedure. SAS Institute.
9. Johansen, S. (1995). Likelihood-Based Inference in Cointegrated Vector Autoregressive Models. Oxford university press.
10. Jumadilova, S., Sailaubekov, N., & Dildebaeva, Z. (2013). Management of financial and economic sustainability of oil & gas enterprises. *Actual Problems of Economics, 139*(1), 265-273. Retrieved from www.scopus.com
11. Makarenko, I., Serpeninova, Y. (2017). Public companies' transparency in Ukraine: key regulatory requirements. *Public and Municipal Finance, 6*(1), 8-14. Retrieved from https://businessperspectives.org/journals/public-and-municipal-finance/issue-1-contents-6/public-companies-transparency-in-ukraine-key-regulatory-requirements
12. Sailaubekov, N. T., & Jumadilova, S. G. (2013). Estimation of competitiveness of oil and gas companies based on the normative model. Paper presented at the Proceedings of the 3rd IASTED Asian Conference on Modelling, Identification, and Control, AsiaMIC 2013, 260-265. https://doi.org/10.2316/P.2013.799-048
13. Sims, Ch. (1980). Macroeconomics and Reality. *Econometrica, 48*(1), 1-48. Retrieved from http://www.jstor.org/stable/1912017