Scientific article
UDC 330.47
DOI: https://doi.org/10.57809/2025.4.2.13.7

INVESTIGATION OF PLATINUM PRICE SEASONALITY USING HIGH-ORDER AUTOREGRESSION

Andrei Klimentov ✉

Peter the Great St. Petersburg Polytechnic University, St. Petersburg, Russia

✉ andreiklimentov361@gmail.com

Abstract. This research investigates platinum price seasonality using high-order autoregressive modeling. The research object is daily platinum price dynamics (LME data, 2015—2024), focusing on long-term dependencies and cyclical patterns. The method employs stepwise decomposition of a 270-day lag autoregression AR(270) into computationally efficient 15-day lag sub-models, enabling significance testing of all coefficients while minimizing resource demands. Results identify the one-day lag as the dominant predictor, with marginal effects at 6—15-day lags and MAPE (1.15%) confirm model robustness. Conclusions indicate no statistically significant weekly cycles due to the overwhelming influence of short-term lags, though the method's applicability in low-resource environments (e.g., Microsoft Excel) facilitates accessible high-order autoregression.

Keywords: platinum price forecasting, high-order autoregression, seasonal cycles, stepwise decomposition, computational efficiency, lagged coefficients, time series analysis

Citation: Klimentov A. Investigation of platinum price seasonality using high-order autoregression. Technoeconomics. 2025. 4. 2 (13). 70—79. DOI: https://doi.org/10.57809/2025.4.2.13.7

Научная статья
УДК 330.47
DOI: https://doi.org/10.57809/2025.4.2.13.7

ИССЛЕДОВАНИЕ СЕЗОННОСТИ ЦЕНЫ ПЛАТИНЫ С ПОМОЩЬЮ АВТОРЕГРЕССИИ БОЛЬШОГО ПОРЯДКА

Андрей Климентов ✉

Санкт-Петербургский политехнический университет Петра Великого,
Санкт-Петербург, Россия

✉ andreiklimentov361@gmail.com

Аннотация. В данном исследовании изучается сезонность цен на платину с использованием авторегрессионного моделирования высокого порядка. Объектом исследования является ежедневная динамика цен на платину (данные LME за 2015-2024 гг.) с акцентом на долгосрочные зависимости и циклические закономерности. Метод использует пошаговую декомпозицию авторегрессии AR(270) с запаздыванием в 270 дней на эффективные в вычислительном отношении подмодели с запаздыванием в 15 дней, что позволяет проверять значимость всех коэффициентов при минимизации затрат ресурсов. Результаты показывают, что задержка на один день является доминирующим предиктором, с незначительными эффектами при задержке на 6-15 дней, а MAPE (1,15%) подтверждает надежность модели. Выводы указывают на отсутствие статистически значимых недельных циклов из-за подавляющего влияния краткосрочных задержек, хотя применимость метода в средах с низким уровнем ресурсов (например, Microsoft Excel) облегчает доступ к авторегрессии высокого порядка.

Ключевые слова: прогнозирование цен на платину, авторегрессия высокого порядка, сезонные циклы, пошаговая декомпозиция, вычислительная эффективность, коэффициенты с запаздыванием, анализ временных рядов

Для цитирования: Климентов А.Р. Исследование сезонности цены платины с помощью авторегрессии большого порядка // Техноэкономика. 2025. Т. 4, № 2 (13). С. 70–79. DOI: https://doi.org/10.57809/2025.4.2.13.7

Introduction

Forecasting the price dynamics of semi-precious and precious metals is a critical task, as these prices significantly impact various economic sectors and industries. Platinum, for instance, is widely used in automotive manufacturing, medicine, and electronics. Platinum prices are influenced by macroeconomic factors, industry-specific trends, and seasonal fluctuations. At the same time, modern research highlights the complex interaction of macroeconomic news and structural demand changes in the formation of seasonal patterns of precious metals, including platinum (Elder, 2012; Mirkin, 2014).

Investigating price seasonality and identifying long-term cycles is of particular interest. Understanding periodic components in precious metal price dynamics can improve long-term forecasting accuracy (Mirkin, 2012).

Classical works like (Box, 1976) laid the foundation for autoregressive (AR) models, now widely applied to precious metal price forecasting (Troutman, 1979; Morimune, 1995). However, identifying long-term trends and cyclical patterns requires more complex models.

High-order vector autoregression models AR(p), where p is the lag order, can capture linear dependencies across extended time intervals. These models face challenges including high computational complexity and numerous coefficients (Svetunkov, 2022; Bogomolov, 1996). Alternative approaches, such as Bayesian estimation methods (Chib, 1994), are also aimed at solving problems of high dimensionality and multicollinearity in models with large lags, although they require other computing resources. Diverse methods that could improve autoregression models are observed today, for example, complex-valued modelling (Stein, 2002; Phillips, 1987). This study employs a stepwise decomposition method for high-dimensional AR models proposed in (Svetunkov, 2012).

Materials and Methods

Platinum price data was sourced from the London Metal Exchange (LME) open database. The data is represented as timeseries with one day steps of platinum mean price values in stock market. The daily time series covers 23 November 2015 to 29 November 2024, with September–November 2024 reserved for validation.

The AR(270) model allows to present the general view:

$$y_{270} = a_0 + a_1 y_{269} + a_2 y_{268} + \ldots + a_{270} y_1 \tag{1}$$

where $a_0, a_1, \ldots, a_{270}$ are coefficients of autoregressive model and $y_1, \ldots, y_{270}$ the price with the appropriate time shift.

In order to get model (1) it is necessary to construct 18 models with 15-days lag which reduces the computational complexity. These models could be given in the following form:

$$\begin{gathered} \widehat{y_{15}} = b1_0 + b1_1 y_{14} + \ldots + b1_{15} y_1 \\ \widehat{y_{30}} = b2_0 + b2_1 y_{29} + \ldots + b2_{15} y_{15} \\ \widehat{y_{45}} = b3_0 + b3_1 y_{44} + \ldots + b3_{15} y_{31} \\ \ldots \\ \widehat{y_{270}} = b18_0 + b18_1 y_{269} + \ldots + b18_{15} y_{255} \end{gathered} \tag{2}$$

where bk coefficients correspond to the k model equations.

For computational convenience and to investigate the regression with a 135-day lag, the model derivation was divided in two stages. In the first stage, coefficients for the AR(135) and AR(135–270) models were obtained, where the former accounts for the influence of elements with lags ranging from 1 to 135 days, while the latter covers lags from 135 to 270 days.

Each of the models above (AR(135) and AR(135-270)) consist of 9 models from (2). Therefore, they could be written in the form:

$$\begin{gathered} y''_{135} = \alpha_0 + \alpha_1 \widehat{y_{15}} + \alpha_2 \widehat{y_{30}} + \ldots + \alpha_9 \widehat{y_{135}} \\ y''_{270} = \alpha_{10} + \alpha_{11} \widehat{y_{150}} + \alpha_{12} \widehat{y_{165}} + \ldots + \alpha_{18} \widehat{y_{270}} \end{gathered} \tag{3}$$

where $\alpha_0, \ldots, \alpha_{18}$ coefficients of models (2) linear combination.

In the second stage, the equation (4) as a linear combination of models (3) could be constructed:

$$\begin{gathered} y_{270} = \beta_0 + \beta_1 y''_{135} + \beta_2 y''_{270} \\ y_{270} = \beta_0 + \beta_1 (\alpha_0 + \alpha_1 \widehat{y_{15}} + \alpha_2 \widehat{y_{30}} + \ldots + \alpha_9 \widehat{y_{135}}) + \\ + \beta_2 (\alpha_{10} + \alpha_{11} \widehat{y_{150}} + \alpha_{12} \widehat{y_{165}} + \ldots + \alpha_{18} \widehat{y_{270}}) \end{gathered} \tag{4}$$

where $\beta_0, \beta_1, \beta_2$, coefficients which allow to compose AR(270) model from AR(135) and AR(135-270) models.

Subsequently, it is only necessary to substitute the equations of models (2) into (3) and (4). By grouping coefficients, we can then derive the target coefficients of model (1). These coefficients may be expressed in the form:

$$a_0 = \beta_0 + \beta_1\alpha_0 + \beta_1\alpha_1 b1_0 + \ldots + \beta_2\alpha_{18} b18_0$$
$$a_1 = \beta_2\alpha_{18} b18_1 \quad (5)$$
$$\ldots$$
$$a_{270} = \beta_1\alpha_1 b1_{15}$$

Thus, we can construct an AR(270) regression model that accounts for platinum price dynamics with a 270-day depth, enabling identification of long-term dependencies and cycles.

Subsequently, statistically significant coefficients should be identified to build a refined model exclusively incorporating these coefficients, which yields optimal predictive accuracy.

The steps above can be implemented in Microsoft Excel using the Data Analysis tool package. After constructing the first set of models, the AR(135) model according to equation (3) can be developed, producing the comparative plot of actual data versus model predictions shown in Figure 1.

Fig. 1. The plot of AR(135) regression.

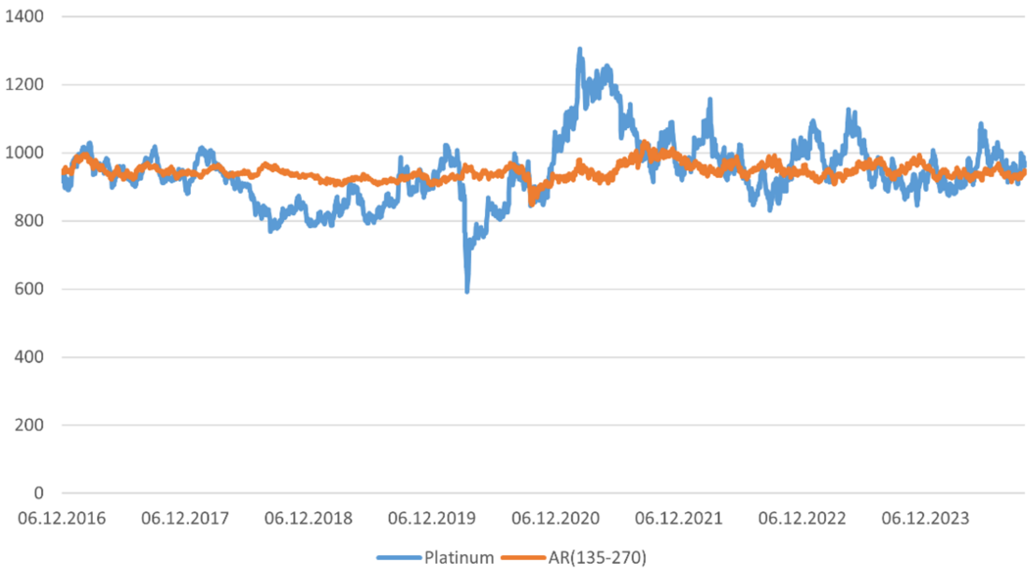

Fig. 2. The plot of AR(135-270) regression.

The graph demonstrates substantial agreement between actual data and model predictions. Subsequently, analogous procedures should be performed for the remaining nine models (2), then combined as specified in equation (3). This yields the AR(135–270) regression covering lags from 135 to 270 days (Figure 2).

Subsequently, using equations (4) and (5), we can construct the comprehensive AR(270) autoregression model, which combines the two preceding models. The comparative plot of the full model against actual data is shown in Figure 3.

Fig. 3. The plot of AR(270) regression.

Moreover, the contribution of different coefficients to the overall model must be evaluated. The coefficients exhibiting the greatest impact are $a_1, a_6, a_7, a_8, a_{10}, a_{11}, a_{13}, a_{15}$. Their values are presented in Table 1.

Table 1. The most valuable coefficients

a_1	0.9936
a_6	-0.0651
a_7	0.0593
a_8	-0.0261
a_{10}	0.0502
a_{11}	-0.0346
a_{13}	0.0456
a_{15}	-0.0351

The values demonstrate that coefficient a_1 contributes significantly more than other coefficients, though the listed coefficients still exhibit marginal influence on the model.

In addition, an autoregression model incorporating only these significant coefficients was constructed and based on the corresponding elements above (Figure 4).

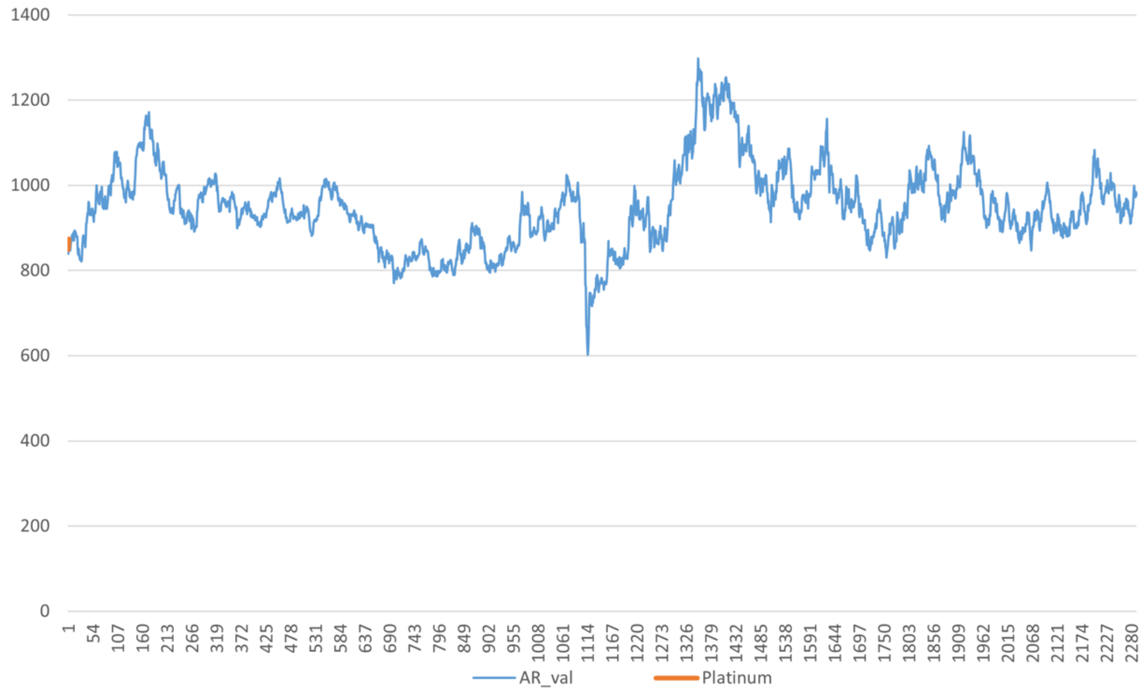

Fig. 4. The plot of AR with inly valuable elements.

The given plot demonstrates that the autoregression model with valuable elements also allows to get high quality description of platinum prices.

Results and Discussion

After several models were constructed their quality with AIC criterium and sum of squared deviations were rated. The results of this rating are provided in Table 2.

Table 2. Values of AIC and sum of squared deviations for constructed models

Model	Sum of squared deviations	AIC
AR(15)	501046.43	5.40
AR(30)	6463860.00	7.97
AR(45)	10553145.40	8.46
AR(60)	13663363.90	8.73
AR(75)	15389746.90	8.85
AR(90)	16672730.03	8.94
AR(105)	17929456.29	9.02
AR(120)	18498608.69	9.06
AR(135)	19189262.52	9.10
AR(150)	19630640.97	9.13
AR(165)	19896583.86	9.15

Model	Sum of squared deviations	AIC
AR(180)	19931981.53	9.16
AR(195)	19251665.32	9.13
AR(210)	19013775.30	9.13
AR(225)	18924874.53	9.13
AR(240)	18914368.36	9.14
AR(255)	18927227.47	9.15
AR(270)	18917953.72	9.15
AR(1-135)	473310.95	5.41
AR(150-270)	17927793.70	9.14
AR(1-270)	451061.00	5.40
AR_val	501420.61	5.40

The visualization of Table 2 is represented in Figures 5 and 6.

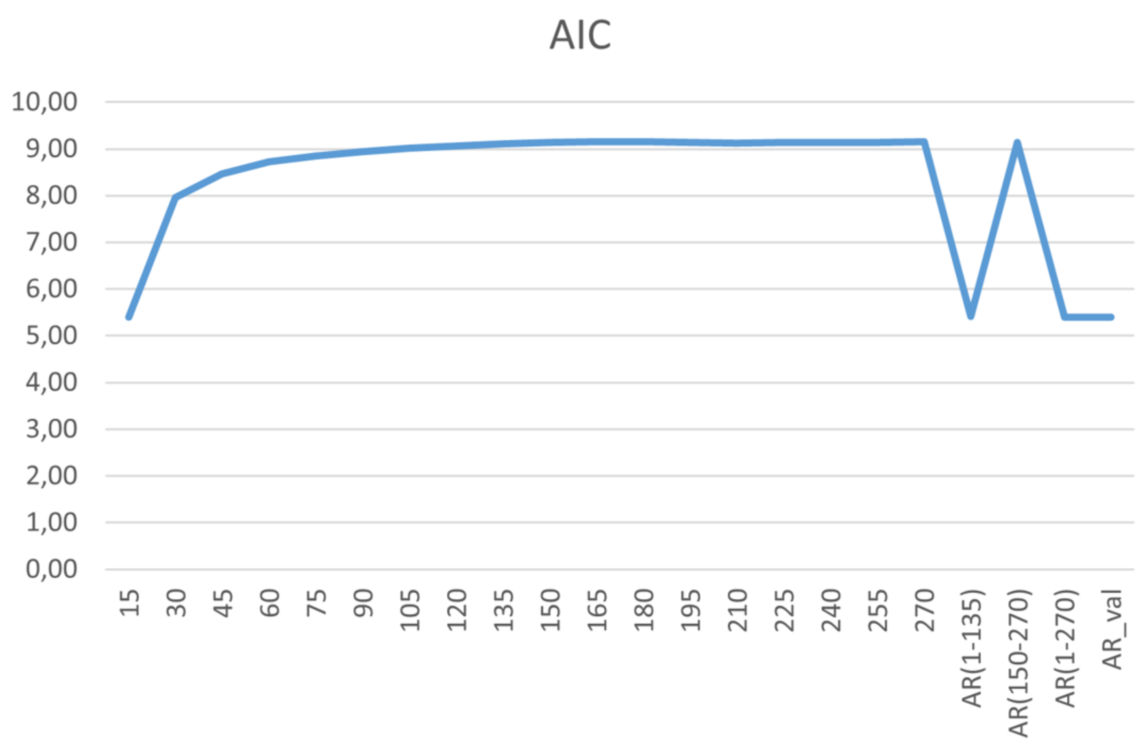

Fig. 5. The plot of AIC values for models.

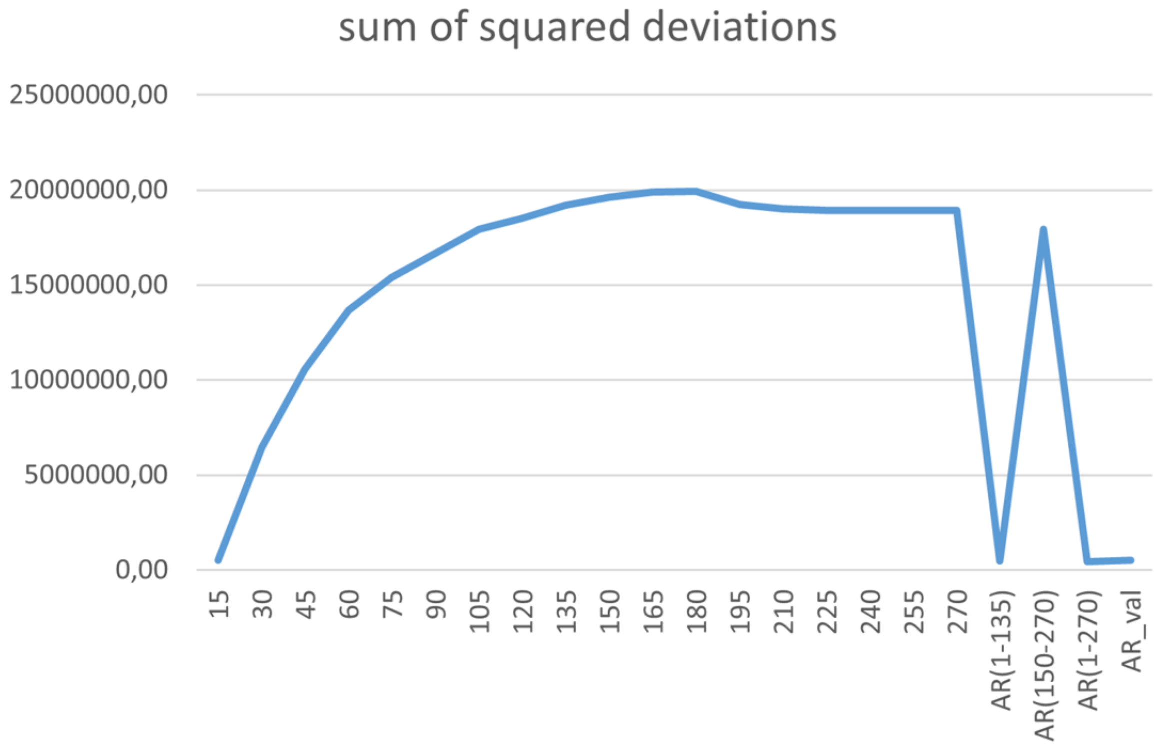

Fig. 6. The plot of sum of squared deviations for models.

Based on the data provided, it can be seen that all models with valuable coefficients from Table 1 have the best values. You can also calculate the average percentage error of MAPE using a model with significant coefficients, which will be 1.15%. This value indicates the high quality of the resulting model.

The overwhelming significance of the one-day lag aligns with findings in ML-based studies, where short-term technical indicators often dominate predictions for precious metals (Cohen, 2022). This suggests that platinum prices are primarily driven by immediate market reactions rather than latent seasonal cycles.

Conclusion

The method employed in this study enables the construction of a high-order autoregression with a 270-day lag. This allows for the assessment of the impact of the platinum price from over six months prior on its current price. Furthermore, this method facilitates the evaluation of the significance of all coefficients.

Additionally, the method is not computationally intensive. This is because it involves computing a low-order regression at each stage, making it feasible for implementation even using tools like Microsoft Excel.

Following the evaluation of the constructed models, it was concluded that the platinum price is most significantly influenced by its value on the preceding trading day. This result is consistent with the well-known high sensitivity of precious metals markets to the latest available information and short-term changes in supply and demand (Batten, 2008), which may overshadow weaker seasonal signals. A minor influence was also observed from data with lags ranging from 6 to 15 days, corresponding to a cycle of 1-3 trading weeks. However, since the influence of these elements is an order of magnitude lower than that of the coefficient, it is not possible to draw a definitive conclusion regarding the presence of weekly cycles in platinum price dynamics. It is important to note that the conclusion that there are no statistically significant weekly cycles should be interpreted with caution within the framework of the chosen linear AR specification. As emphasized in the literature (Hansen, 2005), complex nonlinear dependencies or structural shifts can be masked in linear models, and alternative specification methods (for example, models with time-varying parameters or threshold models) could potentially reveal other patterns.

REFERENCES

Batten J.A., Ciner C., Lucey B.M. 2008. The Macroeconomic Determinants of Volatility in Precious Metals Markets. SSRN Electronic Journal, 65-71. doi:10.1016/j.resourpol.2009.12.002

Bogomolov R.A., Krasheninnikov V.R. 1996. Autoregression vector random fields. Pattern Recognition and Image Analysis. Advances in Mathematical Theory and Applications 6(1), 224.

Box G.E.P., Jenkins D.M. 1976. Time series analysis forecasting and control.

Chib S., Greenberg E. 1994. Bayes inference in regression models with ARMA(p, q) errors. Journal of Econometrics 64, 183–206. doi:10.1016/0304-4076(94)90063-9

Cohen G. 2022. Algorithmic Strategies for Precious Metals Price Forecasting. Mathematics 7(10), 1134. doi:10.3390/math10071134

Elder J., Miao H., Ramchander S. 2012. Impact of macroeconomic news on metal futures. Journal of Banking & Finance 1(36), 51–65. doi:10.1016/j.jbankfin.2011.06.007

Hansen B.E. 2005. Challenges for econometric model selection. Econometric Theory 01(21).

Kharin Yu. 1999. Robustness of statistical forecasting by autoregression model under distortions. Theory of Stochastic Processes 5, 84-90.

Mirkin Ya.M. 2014. International practice of forecasting world prices in financial markets (raw materials, stocks, exchange rates).

Morimune K. 1995. Estimating the rank of co-integration when the order of a vector autoregression is unknown. Mathematics and Computers in Simulation 39(3), 265-271.

Murtala Sh., Hur S., Park Y. 2023. Simplified Framework for Fault Prediction in Radar Transmitter based on Vector Autoregression Model. PHM Society Asia-Pacific Conference 4(1). doi:10.36001/phmap.2023.v4i1.3627.

Phillips P.C.B. 1987. Towards a unified asymptotic theory for autoregression. Biometrika 74(3), 535.

Savchenko V.V., Shkulev A.A. 2002. Adaptive estimator of random time series prediction on the basis of autoregression observations model. Avtometriya 2, 35-42.

Stein Sh.H. 2002. Vector autoregression and the dynamic multiplier: A historical review. Journal of Policy Modeling 24(3), 283.

Svetunkov S. 2012. Complex-Valued Modeling in Economics and Finance. Springer New York. doi:10.1007/978-1-4614-5876-0

Svetunkov S.G. 2024. A method for constructing vector autoregressions of any complexity. Economic Science of Modern Russia 3, 37-50. doi:10.33293/1609-1442-2024-3(106)-37-50

Svetunkov S.G., Samarina E.S. 2023. Nonlinear vector autoregressions in short-term price forecasting. П-Economy 16(6), 155-166. doi:10.18721/JE.16610

Svetunkov S.G., Bazhenova M.P., Lukash E.V. 2022. Prospects of using vector autoregressions in economic forecasting. Modern Economics problems and solutions 6, 44-57.

Troutman B.M. 1979. Some results in periodic autoregression. Biometrika 66(2), 219.

Exchange T.L.M. Monthly volumes. London Metal Exchange. URL: https://www.lme.com/Market-data/Reports-and-data/Volumes/Monthly-volumes (accessed: 14.05.2025).

СПИСОК ИСТОЧНИКОВ

Batten J.A., Ciner C., Lucey B.M. 2008. The Macroeconomic Determinants of Volatility in Precious Metals Markets. SSRN Electronic Journal, 65-71. doi:10.1016/j.resourpol.2009.12.002

Bogomolov R.A., Krasheninnikov V.R. 1996. Autoregression vector random fields. Pattern Recognition and Image Analysis. Advances in Mathematical Theory and Applications 6(1), 224.

Box G.E.P., Jenkins D.M. 1976. Time series analysis forecasting and control.

Chib S., Greenberg E. 1994. Bayes inference in regression models with ARMA(p, q) errors. Journal of Econometrics 64, 183–206. doi:10.1016/0304-4076(94)90063-9

Cohen G. 2022. Algorithmic Strategies for Precious Metals Price Forecasting. Mathematics 7(10), 1134. doi:10.3390/math10071134

Elder J., Miao H., Ramchander S. 2012. Impact of macroeconomic news on metal futures. Journal of Banking & Finance 1(36), 51–65. doi:10.1016/j.jbankfin.2011.06.007

Hansen B.E. 2005. Challenges for econometric model selection. Econometric Theory 01(21).

Kharin Yu. 1999. Robustness of statistical forecasting by autoregression model under distortions. Theory of Stochastic Processes 5, 84-90.

Миркин Я.М. 2014. Международная практика прогнозирования мировых цен на финансовых рынках (сырье, акции, курсы валют).

Morimune K. 1995. Estimating the rank of co-integration when the order of a vector autoregression is unknown. Mathematics and Computers in Simulation 39(3), 265-271.

Murtala Sh., Hur S., Park Y. 2023. Simplified Framework for Fault Prediction in Radar Transmitter based on Vector Autoregression Model. PHM Society Asia-Pacific Conference 4(1). doi:10.36001/phmap.2023.v4i1.3627.

Phillips P.C.B. 1987. Towards a unified asymptotic theory for autoregression. Biometrika 74(3), 535.

Savchenko V.V., Shkulev A.A. 2002. Adaptive estimator of random time series prediction on the basis of autoregression observations model. Avtometriya 2, 35-42.

Stein Sh.H. 2002. Vector autoregression and the dynamic multiplier: A historical review. Journal of Policy Modeling 24(3), 283.

Svetunkov S. 2012. Complex-Valued Modeling in Economics and Finance. Springer New York. doi:10.1007/978-1-4614-5876-0

Светуньков С.Г. 2024. Метод построения векторных авторегрессий любой сложности. Экономическая наука современной России 3, 37-50. doi:10.33293/1609-1442-2024-3(106)-37-50

Светуньков С.Г., Самарина Е.С. 2023. Нелинейные векторные авторегрессии в краткосрочном прогнозировании цен. П-Economy 16(6), 155-166. doi:10.18721/JE.16610

Светуньков С.Г., Баженова М.П., Лукаш Е.В. 2022. Перспективы использования векторных авторегрессий в экономическом прогнозировании. Современная экономика проблемы и решения 6, 44–57.

Troutman B.M. 1979. Some results in periodic autoregression. Biometrika 66(2), 219.

Exchange T.L.M. Monthly volumes. London Metal Exchange. URL: https://www.lme.com/Market-data/Reports-and-data/Volumes/Monthly-volumes (дата обращения: 14.05.2025).

INFORMATION ABOUT AUTHOR / ИНФОРМАЦИЯ ОБ АВТОРЕ

KLIMENTOV Andrei R. – student.
E-mail: andreiklimentov361@gmail.com
КЛИМЕНТОВ Андрей Романович – студент.
E-mail: andreiklimentov361@gmail.com

Статья поступила в редакцию 28.05.2025; одобрена после рецензирования 04.06.2025; принята к публикации 09.06.2025.

The article was submitted 28.05.2025; approved after reviewing 04.06.2025; accepted for publication 09.06.2025.