“Applied aspects of time series models for predicting residential property prices in Bulgaria”

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APPLIED ASPECTS OF TIME SERIES MODELS FOR PREDICTING RESIDENTIAL PROPERTY PRICES IN BULGARIA

Abstract

Accurate housing price forecasts play a critical role in balancing supply and demand in the residential real estate market, as well as in achieving the goals of various stakeholders – buyers, investors, construction contractors, public administration, real estate agencies, special investment purpose companies, etc.

The present study aims to investigate the relationship between specific predictors and build a suitable model for forecasting housing prices in Bulgaria. In this regard, a study was conducted on transactions with residential real estate in the city of Sofia for the period from the first quarter of 2016 to the fourth quarter of 2021. The ARIMA model is used in the development to predict the values of the variables. Eight models are tested for the researched factors (24 in total). On this basis, the price per square meter of residential property was predicted, including estimated values from the ARIMA model for the parameters involved in the regression equation.

The result showed that there is a strong relationship between the analyzed predictors and the studied variable – price per square meter of housing. The tested models are adequate and the statistical requirements for forecasting the prices of residential properties in Bulgaria are complied.

Keywords residential properties, real estate market, housing, prices, income, credit, multivariate linear regression, ARIMA modeling, short horizon predictability, Bulgaria

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INTRODUCTION

The COVID-19 pandemic, the war in Ukraine, like any crisis, can cause uncertainty in the economic environment. The consequences one is currently observing are high inflation rates, rising gas and electricity prices, disrupted supply chains. All this creates the feeling of significant uncertainty, and it is normal for potential investors (economic agents in general) to materialize their resources, for example, in real estate (residential properties).

Dynamics is one of the main characteristics of the residential real estate market. It is largely due to the uncertain environment in which various economic factors are at play, as well as the expectations of key market players (e.g., buyers, investors, developers, Real Estate Investment Trusts, real estate agencies, etc.). The market dynamics has to be oriented towards and sought in the causal relationship between residential property and residential property prices. Property prices are influenced by numerous factors. This makes it even more difficult to accurately assess the impact that each factor has. Theoretically, according to some authors, most factors can be taxonomized depending on the impact they have. At the same time, there is no consensus among theoreticians on the factor ranking concerning the extent of their impact on residential property prices.

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And here arises precisely the need to provide a relatively accurate and objective forecast for the price of residential properties. In this context, the forecast of the price of residential properties is an important stage of decision making by potential investors-buyers regarding the set of strategies, approaches, policies for financing these properties. Accurate forecasting of residential property prices is ultimately important to all stakeholders.

1. LITERATURE REVIEW

The residential real estate market is characterized by significant dynamics (Bydłosz et al., 2010) due to customer expectations, environmental uncertainty, the development of bank lending, etc. The market is influenced by numerous factors that should be taken into account when determining real estate prices, which are definitely a key prerequisite for a successful business (e.g., investors in residential real estate). Determining the market price as the most probable selling price an asset would fetch in the marketplace is influenced by the stochastic nature of the market. If the market is considered as an economic system, then it functions and is influenced by many factors. These factors, in turn, can be considered as variables that form the result indicator – the estimated market value (Gribovskii, 2009, p. 84). All the above-mentioned predetermines the probabilistic nature of the analysis and evaluation process, which gives us the opportunity to apply the ARIMA model in calculating the estimated price of the analyzed asset.

Residential real estate prices are a major factor, influencing the development of the world economy (Mussapirov et al., 2019; Seitzhanov et al., 2020; Pukala, 2021; Labunska et al., 2017; Koval et al., 2019; Nikolova-Alexieva et al., 2022). More data become available as examples of the residential real estate market rise or decline. The movement of house prices over the years is highly persistent, and house prices are prone to significant increases and decreases (Al-Marwani, 2014, pp. 1, 3, 37). Getting an accurate picture of them (e.g., prices and rents) is essential for various stakeholders. For example, for the potential homebuyers housing is a necessity (Temür et al., 2019). It is of great importance to institutional investors, REITs (Real Estate Investment Trusts), public administration, banking sector, etc.

The dynamics of the residential real estate market should be sought in its causal relationship with housing prices. According to Miller et al. (2011), housing prices play an important role in GDP growth. Furthermore, civil construction is one of the leading sectors of the economy (Moro et al., 2020), and real estate is a medium and long-term investment industry, which has a long return period (Huang et al., 2011). Last but not least, the real estate market is mainly determined by the financial market (Anghel & Hristea, 2015).

Knowing the essence and peculiarities of the real estate market, demand, supply and prices is a condition for their effective functioning. Real estate management activity is one of the problems of modern theory and practice. It is essential for reaching the set results of the respective company. As a type of entrepreneurial activity, real estate management is the execution of all operations related to corporate real estate: investment, construction, ownership, use, betting, leasing, trust management. Depending on the situation, it can mean (Goremaykin, 2006):

- adoption of a decision and formation of property rights;
- management of the specific object in the process of its exploitation;
- organizing events to achieve the set goals;
- implementation of real estate management functions.

Within the general cycle of corporate property management, taking into account the specifics of different real assets, which allows increasing their effective use and adapting an algorithm for real estate management. The following exemplary stages can be distinguished (Iliychovski et al., 2014): Inventory and audit of real estate; Valuation of real assets; Planning and conducting activities to increase efficiency; Monitoring and regulation of the real estate management process.

All the above mentioned is the reason for developing various techniques and methods for model building for real estate price forecasting. Knowing the market and the factors influencing its values is crucial for the analysis of business cycles of the economy (Baghestani, 2017), public property development, decision-making by a company's management (especially real estate entrepreneurs) (Gupta et al., 2019).

A problem related to the prices of residential properties that economists try to solve is about the factors influencing them, the degree of their influence. Berry and Dalton (2004) emphasize the role of the interest rate and the demand of housing with investment intention. According to Luo et al. (2007), buyers' expectations are leading in the formation of residential property prices. A number of authors give priority to the level of inflation (Aizenman & Jinjarak, 2014; Wei & Cao, 2017), others to the level of unemployment (Bork & Møller, 2015; Risse & Kern, 2016), to foreign direct investment (Chow & Xie, 2016).

The beginning of the theoretical illumination of the problem with the formation of prices for residential properties is set by Lancaster (1966). Later, Harrison and Rubinfeld (1978) and Li and Brown (1980) used hedonic methods to study prices. On this base, the hedonic price forecasting models proposed by various authors (Stadelmann, 2010; Liu, 2013; Nicholls, 2019).

In the past decades, much of the social science research focused on refining increasingly complex mathematical models to predict social and economic trends (Temür et al., 2019). They have been applied both separately and in combination in the time series analysis, taking into account the advantages and disadvantages of each one. This study refers to the use of modern time series price forecasting methods in the form of automatic forecasting algorithm and the ARIMA model, in particular. It has been applied to forecasting the production and consumption of electricity (Ediger & Akar, 2007; Albayrak, 2010), forecasting bank stock market prices (Koutroumanidis, 2011), forecasting water quality, predicting global temperature values, etc. It has also been used to forecast real estate prices (Dejniak & Dąbrowski, 2017; Jadevicius & Huston, 2015). Real estate price forecasts can be performed by applying autoregressive models, and specifically, the Box-Jenkis methodology – ARIMA (Box et al., 2016, pp. 98-106). It is generally predicated on the assumption that time series are stationary or can be made stationary (Hyndman & Athanasopoulos, 2018).

Combining and applying ARIMA and regression models to forecast residential property prices can be used as a measure in both the second and fourth stages of real estate management. Having a housing price forecasting model can assist real estate management and improve real estate market efficiency (Calhoun, 2003).

As a result of the review of literary sources related the prices of residential properties, the purpose of the present development is determined – to investigate the relationship between specific predictors and build a suitable model for forecasting the prices of residential properties in Bulgaria.

2. METHODOLOGY

The methodology is based on the application of statistical methods for the analysis of time series – regression analysis (multiple regression – application of the method of least squares) and ARIMA-models in order to find the best option.

In regard with the set goal, firstly the following algorithm is presented for applying the regression-correlation analysis when finding the indicative value "per square meter of real estate":

- identification of factors;
- implementation of regression analysis;
- determining the indicative value per square meter of real estate.

Identification, as an element of the algorithm for real estate forecasting, proves necessary in terms of establishing the ratios and the optimality of the factors that have been used. This stage reflects the relationships between processes and phenomena, as well as the factors that determine the state of the asset parameters under study. Identification is the most important stage for the overall effect of

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the valuation, as it forms the basis of operational, strategic and other analytical decisions. This is due to the fact that it is the starting phase, i.e., the point, where the evaluation methodology begins.

When forecasting the residential real estate price, the following formula is adopted for the application of regression analysis:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots, \tag{1}$$

where Y is the dependent variable in the regression equation – estimated value per square meter area; X – the independent variable in the regression equation; (X_1 – income per person, X_2 – credit per person); α outlines the constant value of the market value; β reflects the relationship between dependent and independent variables in the regression equation (β_1-market value/income per person, β_2 market value/credit per person).

In practice, in order to determine an indicative value of residential real estate, i.e., in order to apply the regression analysis, it is necessary to accumulate a substantial amount of information.

Determination of the indicative value per square meter of living area. To illustrate the possibility of applying the regression-correlation analysis when forecasting the price per square meter of residential area, a significant volume of information should be accumulated. Based on the calculations, a type of regression equation is also selected. To check the model, the coefficient of determination is used first. It varies from 0% to 100%. It shows how much of the variation in the outcome variable Y is explained by the factors in the regression model. Second, the significance level of the F-test is applied to test the model, in theory the lower it is, the more strongly the listed factors affect the dependent variable (i.e. the predicted value). This is supported by the P-value of the model, whose low values are an argument for a low probability of error. For model testing, a confidence interval is also used. For this purpose, a confidence level is calculated, and in case the estimated price is within the interval, it would confirm the quality of the model.

ARIMA model represents a time series forecasting approach (Hyndman & Athanasopoulos, 2018). One of the two most widely used approaches to time series forecasting provide complementary approaches to the problem. ARIMA models adequately and sufficiently satisfactorily describe exactly the dynamics of phenomena subject to the impact of various variables. A significant advantage of these models is that they are applicable to non-stationary dynamic statistical series, and most economic series are characterized by the presence of a trend. The ARIMA model aims to describe the autocorrelations in the data. Their general form is a combination of a p-th order autoregressive model and a q-th order moving average model (Hyndman & Athanasopoulos, 2018):

$$\begin{aligned} Yt = b0 + b1Y_{t-1} + \ldots + bpY_{t-p} - q_1 E_{t-1} - \\ -q_2 E_{t-2} - \ldots - q_q E_{t-q}, \end{aligned} \tag{2}$$

when applying the models, their parameters are evaluated.

Each component in ARIMA functions as a parameter with standard notation. For them, these are p, d, and q, where integer values replace the parameters to indicate the type of ARIMA model being used. The parameters can be defined as: p – the number of lag observations in the model; d – the number of times the raw observations differ; q – row of the moving average.

A second place is the presentation of the ARIMA model algorithm. Its original type uses an iterative three-step approach to modeling (Box, 2016):

- model identification and model selection;
- parameter estimation;
- statistical model checking.

In connection with one of the research objectives, a residential property prices forecast should be added.

Being an element of the algorithm for real estate forecasting, identification proves necessary in terms of identifying the characteristics of the analyzed time series.

The first step is to identify the order and determine the number of lags, i.e. the study includes data calculation, and generating autocorrelation function plot and partial autocorrelation function plot.

Parameter estimation is the second step. It involves structuring the ARIMA model. The Gretl and NumXL software products are used to process the data, test different variants to arrive at the one that best fits a given variable.

The third step is statistical model checking. It is performed by using a correlogram of the residuals. It is assumed that the residuals are random and normally distributed. If not, there are probably data that have not been reported.

Based on the accumulated data and the methodology of the ARIMA model described above, prices are forecasted for the selected periods.

The analysis and practical application of the model involve using Gretl and NumXL packages, based on data on quarterly prices per square meter of residential properties (one – bedroom apartments are taken as an example) (Imoti.net, 2022), income per person (National Statistical Institute, 2022) and credit per person (Bulgarian National Bank, 2022).

3. RESULTS AND DISCUSSION

The first task to be completed in this study is to identify the main factors influencing the real estate prices. A great number of factors affect property prices. This also makes it difficult to accurately assess the impact that each factor has. Authors have used a number of criteria to group the factors. According to Asaul (2013, pp. 86-287), factors that affect the value of real estate are divided into the following groups – objective factors, psychological factors, physical factors, value and legal factors. Sternik (2022) identifies twenty-three factors affecting the value of residential real estate. Theoreticians believe that most factors can be targeted depending on the level of influence (at a macro level, at a regional level and at local level). In this case, the factors need to be ranked by an expert (expert team). At the same time, there is no consensus among authors on the ranking of factors depending on the degree of their influence on residential real estate prices. Ranking of factors has not been largely discussed in the asset valuation literature; there has not been such ranking described yet; it is believed this should be done by an expert assessor. The following factors are the most important:

- value of residential construction;
- household income;
- regional infrastructure;
- residential area;
- bank loan requirements;
- builder's reputation;
- level of influence of macroeconomic factors;
- transaction costs.

Apart from the above-mentioned factors, there are other factors affecting property value that should be taken into account – location, number of storeys, building construction, etc.

The income per person and credit per person are tied to the price per square meter of residential real estate, i.e. predictors such as personal income and personal credit are used in the study by applying regression analysis. Regression analysis is a statistical method used for the estimation of possible functional dependencies between two or more random variables (Petkov, 2010).

The second task is to link the three variables and establish the relationships among them. The regression-correlation analysis is applied in order to illustrate the relationships among the three factors by using the following data (see Table 1).

Table 1. Data on price per square meter income per person and credit per person for the period January 1, 2016 – January 1, 2021

Date	Price per square meter / BGN	Income per person – BGN	Credit per person – BGN
1.1.2016	1,681	1,199.45	386
1.4.2016	1,629	1,202.89	397
1.7.2016	1,854	1,245.70	407
1.10.2016	1,950	1,274.66	400
1.1.2017	1,952	1,248.01	409
1.4.2017	1,828	1,310.34	417
1.7.2017	1,987	1,343.95	418
1.10.2017	1,903	1,366.03	384
1.1.2018	1,986	1,338.64	384
1.4.2018	1,906	1,407.45	385
1.7.2018	1,826	1,447.47	391
1.10.2018	1,957	1,480.16	455
1.1.2019	2,170	1,460.56	467

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Table 1 (cont.). Data on price per square meter income per person and credit per person for the period January 1, 2016 – January 1, 2021

Date	Price per square meter / BGN	Income per person – BGN	Credit per person – BGN
1.4.2019	2,131	1,482.96	455
1.7.2019	2,288	1,628.83	485
1.10.2019	2,296	1,694.27	512
1.1.2020	2,264	1,651.96	527
1.4.2020	2,219	1,632.91	537
1.7.2020	2,257	1,679.93	548
1.10.2020	2,339	1,721.38	574
1.1.2021	2,421	1,768.01	606
1.4.2021	2,589	1,818.20	591
1.7.2021	2,878	1,851.72	585
1.10.2021	2,775	1,954.55	598

Table 2. Regression analysis results from quantitative assessment of the price per square meter

Source: Authors' own calculation.

Indicators	Income per person	Credit per person	ALFA (α)
Beta	1.041	0.843	162.257
T-stat	3.203	0.948	0.9
R2	0.872	–	–
Ff	68.213	1.17E-09	–
P-value of the model	< 0.0001	–	–

Based on the calculations, the regression equation is as follows:

$$Y = 162.2568 + 1.0413x_1 + 0.8429x_2. \quad (3)$$

To validate the regression model, the coefficient of determination is used, which is 0.8720; therefore, the model obtained explains 87.20% of the price changes under the influence of the analyzed factors. This shows that the predictors included in the model explain over 87.20% of the changes in the dependent variable, i.e. the changes in the dependent variable are only 12.80%, which is due to factors other than those included in the model. The P-value of the model being < 0.0001 serves as an argument for accepting the dependence under study as statistically significant. In the case at hand, a strong dependence between the analyzed factors has been found. On the basis of the regression equation and the application of the ARIMA model, appraisers can forecast real estate prices over a longer period and compare the estimates obtained from application of the models.

The ARIMA model focuses on autocorrelation that shows to what extent current observation at a point in time is related to the observation at a previous point in time. Specifically, changes in the real estate prices per square meter are analyzed (according to data for property prices in the Buxton district, Sofia – one-bedroom apartment[1]).

Changes in real estate prices, income per capita and credit per person are analyzed. Figure 1 shows a trend of gradual increase in prices, especially from the 2nd quarter of 2020, while the other two parameters show smooth trend during the analyzed period.

To trace the trends of residential real estate prices, it is necessary to forecast the historical data from Figure 1 (as well as the other two analyzed variables).

The first step is to determine the order and the number of lags, i.e. data study with calculations and graphical representation of autocorrelation function and partial autocorrelation function is included. This is visually presented in Figure 2.

Figure 2 shows autocorrelation that is one lag behind in time, which is the reason for using a first-order autoregression model.

The second step is parameter estimation that involves structuring the ARIMA model. Data are processed, different variants are tested to arrive at the best one at a price per square meter (1,1,1), i.e. there is one lag behind in time of autoregression, one lag in moving average and one order of integration for both. The main parameters of the model are shown in Table 3.

The third step is statistical model checking. It is performed by using a correlogram of the residuals.

1 For the sake of this study, a residential real estate market in Sofia (Buxton district in the southwestern part of the capital city) is chosen. The neighborhood is located between Bratya Buxton Blvd., Ring Road and Tsar Boris III Blvd.), as it is the largest and most representative neighborhood for a city in Bulgaria. Most transactions in terms of number and value take place in this real estate market. Based on accumulated data much research has been carried out and various studies have been conducted. They can be defined as representative studies, and possibly used by experts for other regions of the country, taking into account the specifics of each region.

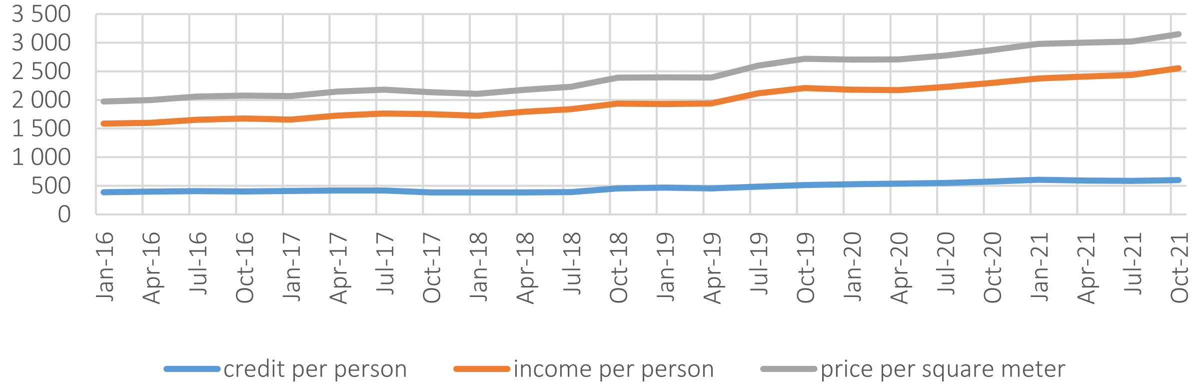

Figure 1. Changes in the parameters under study from the first quarter of 2016 to the fourth quarter of 2021

Source: Authors' own research.

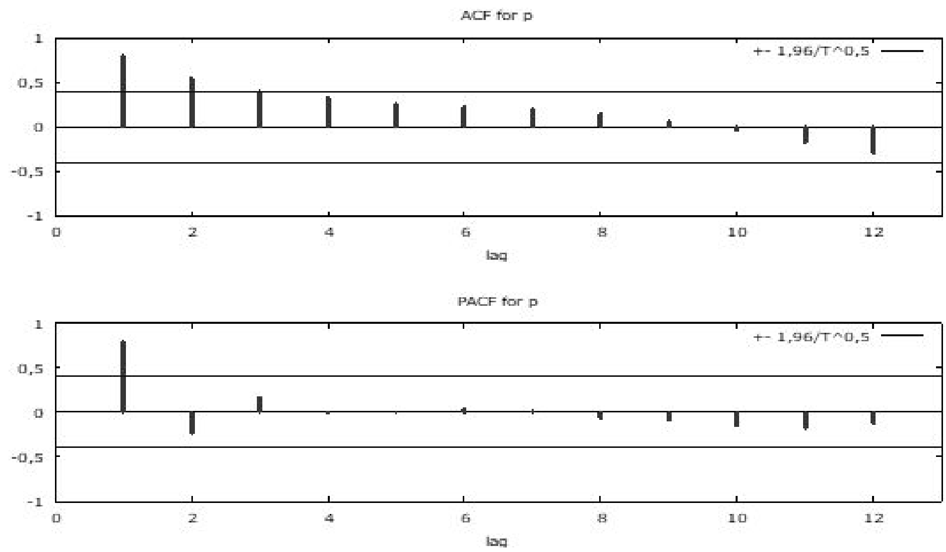

Figure 2. Autocorrelation plot of the autocorrelation function "price per square meter" and autocorrelation plot of partial autocorrelation function "price per square meter"

Table 3. ARIMA (1,1,1) model parameters – price per square meter

Source: Authors' own calculation.

indicators	Coefficient	Std. error	z	p-value
const	43.9473	7.07828	6.2088	< 0.00001***
phi_1	0.638268	0.187094	3.4115	0.00065***
theta_1	–1	0.1335	–7.4907	< 0.00001***
Schwarz criterion	293.3454	Akaike criterion	288.8034	–

Note: *** – p-value < 0.01.

In theory, the assumption is that the residuals are random and normally distributed. If this is not the case, there are probably data that have not been reported. It can be concluded from Figure 3 that all the data in the model chosen are reported and the residuals are random.

Based on the data and using ARIMA, the prices per square meter of residential real estate can be forecasted. It is graphically presented in Figure 4.

Figure 4 and Table 4 show a gradual upward trend in the price per square meter – from 2,774

Source: Authors' own research.

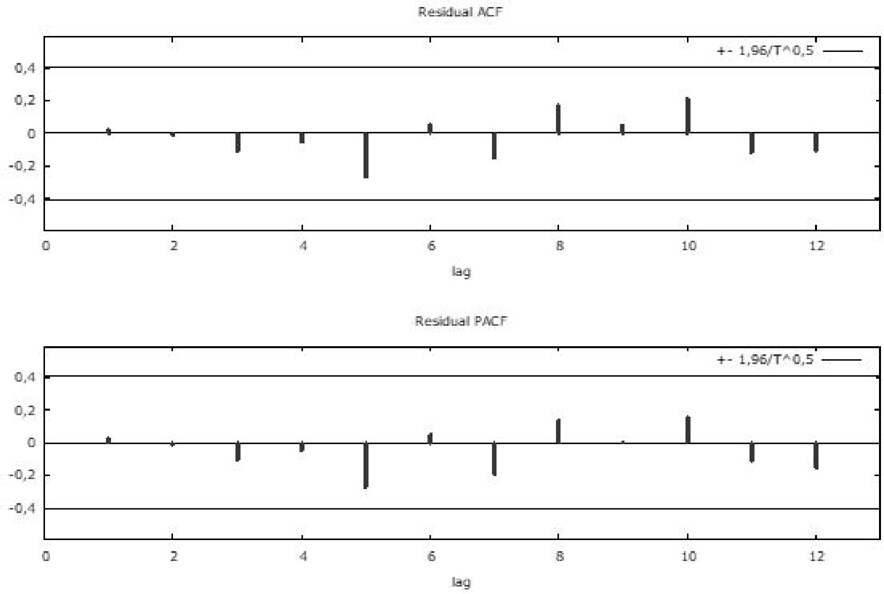

Figure 3. Plot of the autocorrelation function of the ARIMA (1,1,1) model residuals "price per square meter" and Plot of the partial autocorrelation function of the ARIMA (1,1,1) model residuals "price per square meter"

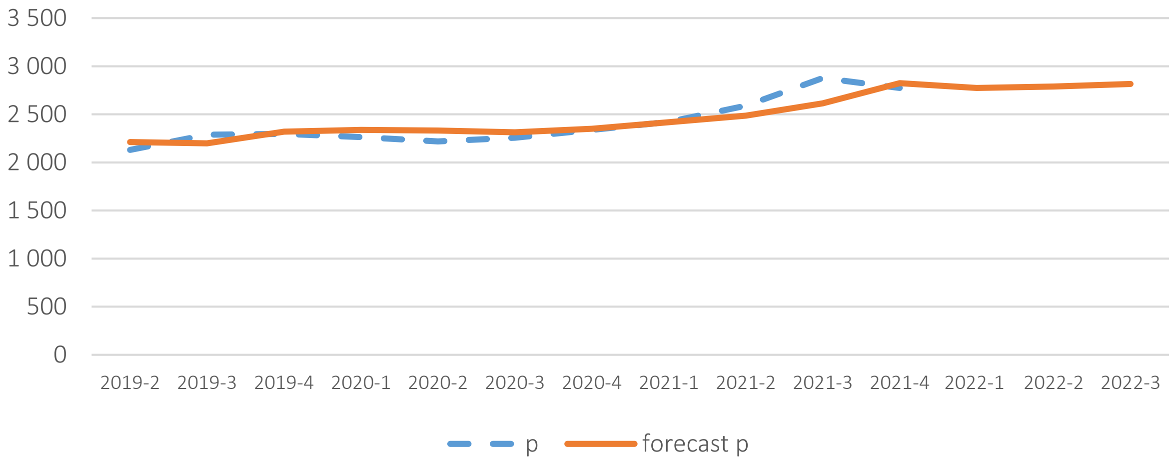

Figure 4. Estimated price per square meter of real estate for three periods

Table 4. Estimated values of "price per square meter"

Source: Authors' own calculation.

Obs.	p	Prediction	Std. error	95% interval
2022:1	Undefined	2,774.33	104.194	(2,570.12, 2,978.55)
2022:2	Undefined	2,789.80	123.608	(2,547.53, 3,032.07)
2022:3	Undefined	2,815.57	130.693	(2,559.42, 3,071.73)

BGN in first quarter of 2022 to 2,816 BGN in third quarter of 2022. When the standard error for the respective period is calculated, the interval over which the price per square meter moves is found.

Performing the algorithm according to the presented scheme (steps) for one of the tested variables makes it possible to apply the ARIMA models in the analysis and forecasting of prices in the real estate market.

Source: Authors' own calculation.

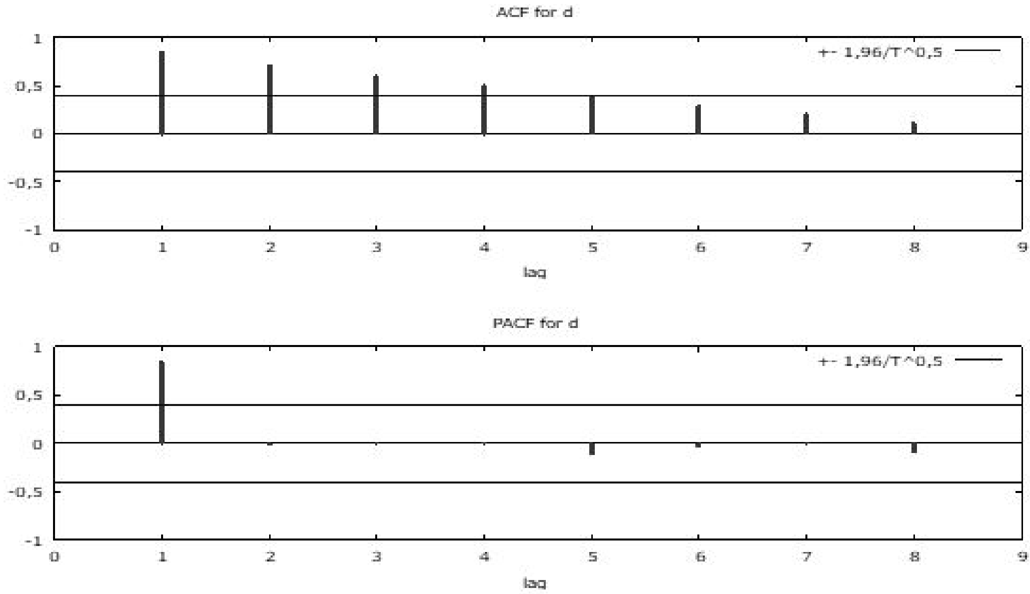

Figure 5. Plot of the autocorrelation function – "income per person" and Plot of partial autocorrelation function – "income per person"

Table 5. ARIMA (2,1,0) model parameters – "income per person"

Source: Authors' own calculation.

indicators	Coefficient	Std. Error	z	p-value
const	32.0642	5.36555	5.9759	< 0.00001***
phi_2	–0.480082	0.183286	–2.6193	0.00881***
Schwarz criterion	241.2638	Akaike criterion	237.8573	–

Note: *** – p-value < 0.01.

The same steps are followed for the other two factors – "income per person" and "credit per person".

The first step that is taken for the "income per person" factor is to determine the order and the number of lags, i.e., it involves data study with calculations and graphical representation of autocorrelation function and partial autocorrelation function. This is visually presented in Figure 5.

Autocorrelation with one lag behind in time is observed, which allows constructing first-order autoregressive model. Structuring the ARIMA model includes testing of different variants in order to choose the one that best fits "income per person" (2,1,0), i.e. presence of two lags (a specific lag 2 is identified in the testing of multiple models and indicated due to autocorrelation in the residuals) behind in time for autoregression and one order of integration for both. The model is shown in Table 5.

The next step is model diagnostics. It includes analyzing the properties of residuals from the fitted model. If the residuals have the properties of white noise, the model is correctly specified and can be used for making forecasts. The statistical model checking is performed by using a correlogram of residuals.

Figure 6 indicates that all data are reported in the selected model, and the residuals appear to be random. On this basis, forecasting of personal income for three periods ahead can now be performed.

Figure 7 and Table 6 show smooth upward trend in income per person over the period 2022:1–2022:3 from BGN 1,986 to BGN 2,016. Having calculated the standard error for the respective period, the interval over which the income per person moves can be found.

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Source: Authors' own calculation.

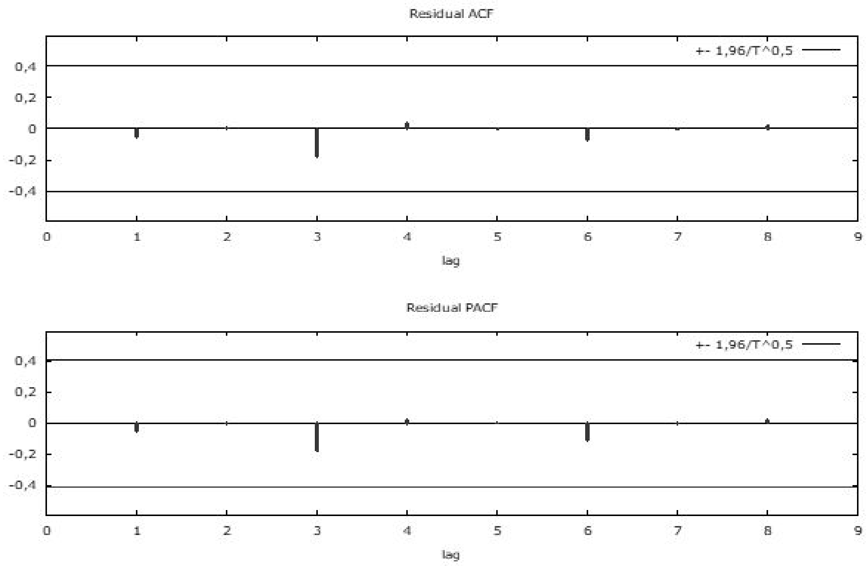

Figure 6. Autocorrelation plot of residuals from the ARIMA (2,1,0) model "income per person" and Partial autocorrelation plot of residuals from the ARIMA (2,1,0) model "income per person"

Source: Authors' own research.

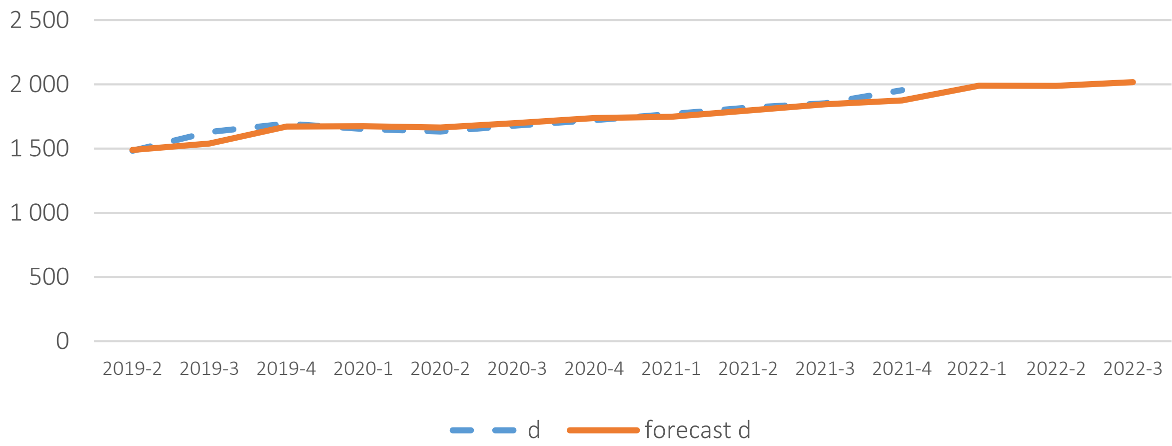

Figure 7. Estimated "income per person" for three periods

Table 6. Estimated values of "income per person"

Source: Authors' own calculation.

Obs.	p	Prediction	Std. error	95% interval
2022:1	Undefined	1,985.92	36.968	(1,913.46, 2,058.37)
2022:2	Undefined	1,984.01	52.280	(1,881.54, 2,086.47)
2022:3	Undefined	2,016.41	55.701	(1,907.23, 2,125.58)

The algorithm and calculations for the "credit per person" are as follows: again, first determine the order and the number of lags, i.e. data study with calculations and graphical representation of autocorrelation function and partial autocorrelation function are included. This is visually presented in Figure 8.

Figure 8 shows that autocorrelation with one lag behind in time is observed, which allows constructing a first-order autoregressive model.

Structuring the ARIMA model includes processing of data, testing of different variants in order to choose the one that best fits "credit per person" (1,1,1),

Source: Authors' own calculation.

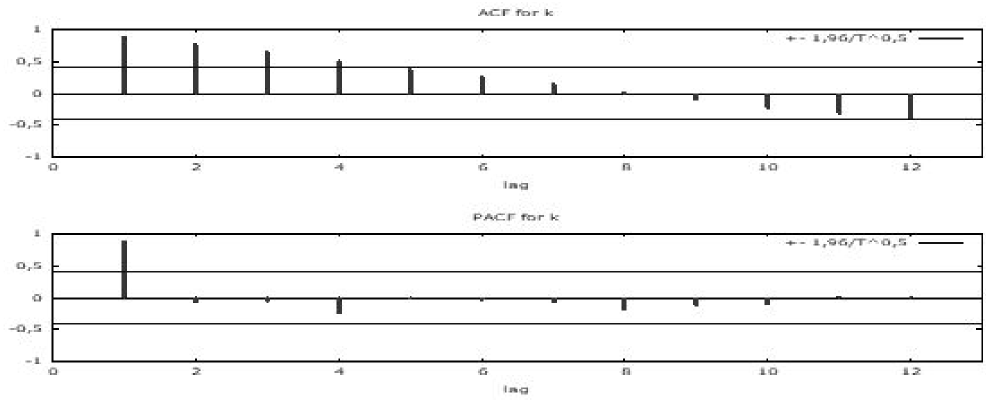

Figure 8. Plot of the autocorrelation function – "credit per person" and Plot of partial autocorrelation function – "credit per person"

Source: Author's own research.

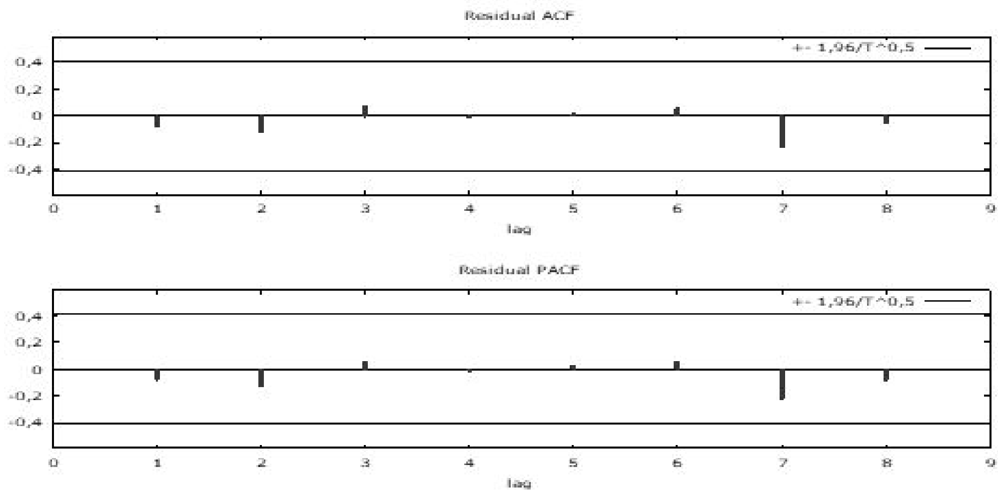

Figure 9. Autocorrelation plot of residuals from the ARIMA (1,1,1) model "credit person" and Partial autocorrelation plot of residuals from the ARIMA (1,1,1) model "credit per person"

Table 7. ARIMA (1,1,1) model parameters – credit per person

Source: Authors' own calculation.

Indicators	Coefficient	Std. error	z	p-value
const	8.84676	4.48337	1.973	< 0.0485**
phi_1	–0.524840	0.236251	–2.222	0.0263**
Theta_1	0.919895	0.183770	5.006	5.57e-07***
Schwarz criterion	209.3446	Akaike criterion		204.8027

Note: **– p-value < 0.05; *** – p-value < 0.01.

i.e. presence of one lag behind in time for autoregression, one lag in moving average and one order of integration for both. The model is shown in Table 7.

The statistical model checking is performed by using a correlogram of residuals.

Data in Figure 9 show that all data are reported in the selected model and the residuals appear to be random. On this basis, forecasting personal credit for three periods ahead can now be performed.

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Source: Author's own research.

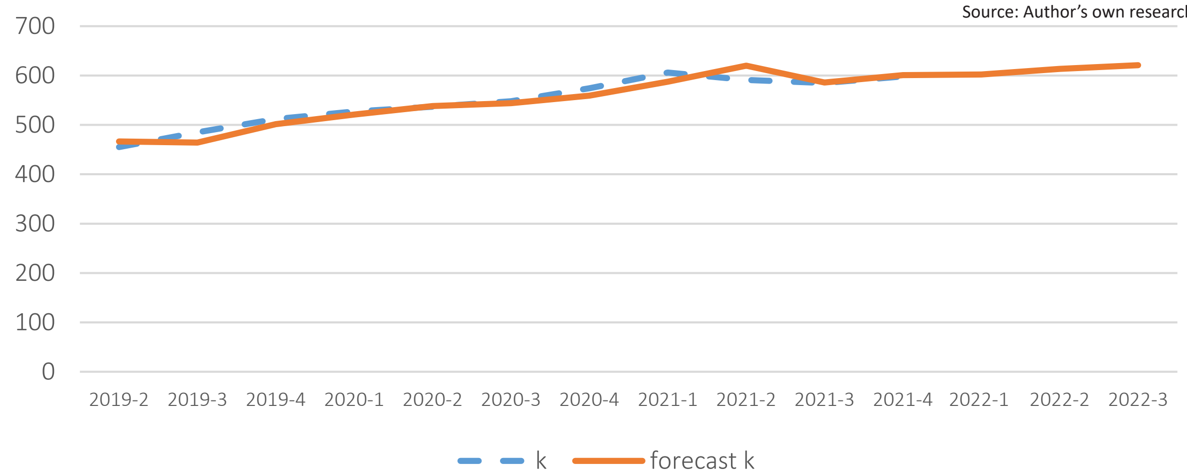

Figure 10. Estimated "credit per person" for three periods

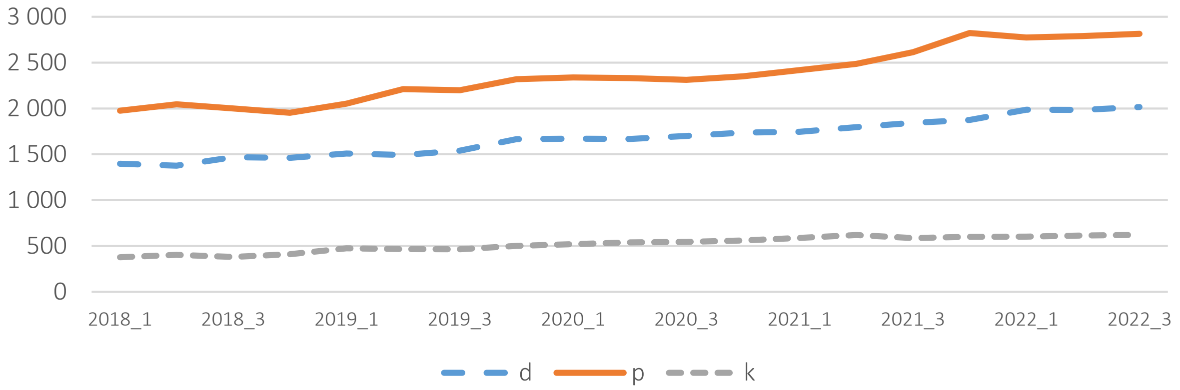

Figure 11. Data on studied parameters and forecasts for three periods

Figure 10 and Table 8 show a gradual upward trend in the credit per person – from BGN 602 in first quarter of 2022:to BGN 621 in third quarter of 2022.

The third task in this study is to use the regression equation (1) and the ARIMA model for forecasting the analyzed parameters by separate periods.

Calculations are displayed in tabular form (see Table 9).

Table 9 shows that the predicted values for price per square meter, obtained by using the regression equation, fall within the specified interval, with a permissible error.

Forecasts are visually presented in Figure 11.

Figure 11 shows a gradual increase in all studied parameters over the next three periods. In this way, the purpose of the study is fulfilled, namely, to propose how to forecast residential property prices in Bulgaria. In the course of the study and the performed calculations, the hypotheses are confirmed.

The regression model, which tested the relationship between the analyzed predictors, confirmed the hypothesis, i.e. is shown by the calculations performed (Equation (1) and the data from Table 2). To validate the regression model, the coefficient of determination is used, which is 0.8720. This indicates that the predictors included in the model explain over 87.20% of the variation in the dependent variable. The p-value of the model < 0.0001 serves as an argument for accepting the studied dependence as statistically significant. In the case under consideration, a strong dependence was established between the analyzed factors.

The forecasts made with the ARIMA model are adequate and serve to forecast the price of residential properties and determine the price interval per square meter of residential property. The graph

Table 8. Estimated values of "credit per person"

Source: Authors' own calculation.

Obs	p	Prediction	Std. error	95% interval
2022:1	Undefined	602.09	17.126	(568.53, 635.66)
2022:2	Undefined	613.43	29.396	(555.82, 671.05)
2022:3	Undefined	620.97	35.748	(550.91, 691.04)

Table 9. Estimated values of "price per square meter" calculated on the basis of regression equation and data from the ARIMA model

Source: Authors' own calculation.

Period of time	Estimated value	Interval
first forecast period	2,738	2,570-2,979
second forecast period	2,745	2,548-3,032
third forecast period	2,785	2,559-3,072

in Figure 4 shows a gradual upward trend in the price per square meter – from 2,774 to 2,816 BGN. When the standard error for the respective period is calculated, the interval over which the price per square meter moves is found. In practice, the use of both models for forecasting the analyzed parameters for separate periods shows approximately the same results. The calculations are presented in tabular form (Table 4 and Table 9). It is found that the estimated values for the price per square meter obtained by regression equation are about BGN 30 per square meter lower, which is about 1% deviation from the estimated value of the ARIMA model. In this way, the second hypothesis that the predictions made by the two models are comparable is also confirmed. This is a successful and effective way to predict the values of the studied parameters.

In the past few years, one has witnessed the interest of a number of authors in the use of mathematical models to predict certain economic phenomena. They have been applied both separately and in combination in the time series analysis, taking into account the advantages and disadvantages of each one.

For example, Jadevicius and Huston (2015) apply the ARIMA model to house prices forecasting in Lithuania. Twenty ARIMA models – from (1,0,0) to (4,0,4) – were generated in the study. According to the authors, model (3,0,3) has produced the most accurate forecasts. They also propose to use the analyzed model in infrastructure and social housing planning (Dua et al., 1999). The Bayesian model of reference included sales of residences, house prices, mortgage rate, real personal disposable income and unemployment rate. According to Moro et al. (2020, p. 48), it is proposed the use of a regression equation to analyze factors influencing Beijing's home sales. They used predictors such as per capita disposable income, population size, median home price and home sales. Stevenson (2022) applies the ARIMA model to forecast rental pricing. The model under consideration should be given higher priority in short-term forecasts. Moro et al. (2020) generate twenty models for home price prediction in São Paulo, Brazil. According to the authors, the combination of models (in their study of SARIMA and MPL) has led to a forecasting error reduction of up to 20%.

Temür et al. (2022) also applied a hybrid model to predict housing sales in Turkey (ARIMA and LSIM). According to them, this combined model can be applied in various sectors of the economy.

The three tasks set in this study have been completed. The factors that affect the prices of residential properties have been highlighted. Key variables such as "income per person" and "credit per person" have been studied. The variables are correlated and a relationship between the price per square meter of residential real estate, personal income and personal credit has been established. Secondly, the ARIMA model has been used to predict the values of the three variables. Eight ARIMA models – from (1, 0, 0) to (2, 2, 2) were used for the drivers under study (24 in total). They were selected according to the ARIMA models and data used for prices per square meter of residential real estate (1,1,1), income per per-

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son (2,1,0) and credit per person (1,1,1). Thirdly, the price per square meter of residential property has been projected, including the estimated value of the ARIMA models for the predictors in the regression equation.

In general, the obtained results suggests that the application of the ARIMA model in combination with regression analysis and correct ranking of drivers is a sufficiently reliable and successful way to predict various parameters.

CONCLUSION

This study aimed to investigate the existence of a relationship between specific predictors and subsequently build appropriate models for forecasting the prices of residential properties in Bulgaria. The methodology that has been approved is based on the application of statistical methods for the analysis of time series – regression analysis (multiple regression – application of the method of least squares) and ARIMA models in order to find the best option.

In the current development, income per person, credit per person in real estate transactions were tied to the price per square meter of residential real estate, i.e. the predictors are used such as income per person and credit per person. This was accomplished using regression analysis. The model that tested the relationships between the analyzed predictors established a strong relationship between the analyzed factors.

The forecasts made using the ARIMA model are adequate and serve to forecast the price of residential properties and determine the price interval per square meter of residential property. With a calculated standard error for the relevant period, the interval in which the price per square meter should move is also obtained.

At the present moment in Bulgaria, the problem with the possibilities of forecasting the prices of residential properties is insufficiently illuminated. The development of their market, in order to track the fluctuation of their prices, requires the application of different forecasting models. In addition, in the world theory, they use the hedonic method of pricing, regression analysis, artificial neural networks, etc.

AUTHOR CONTRIBUTIONS

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Investigation: Svetoslav Iliychovski.
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Software: Mariana Petrova.
Supervision: Teodora Filipova.
Validation: Mariana Petrova.
Visualization: Svetoslav Iliychovski.
Writing – original draft: Svetoslav Iliychovski, Mariana Petrova.
Writing – review & editing: Teodora Filipova.

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