On the specificity of modeling market dynamics

Natalya V Kontsevaya
Department of data analysis, decision making and financial technology
Financial University under the Government of the Russian Federation, Moscow, Russian Federation, 49 Leningradsky Ave., Moscow, 125993

E-mail: kontsevaya07@list.ru

Abstract: The paper presents a systematic approach to the selection of methods and algorithms suitable for modeling the dynamics of market indicators. The directions and stages of modeling and forecasting market dynamics in the study of short time series based on the use of fictitious and lag variables, as well as adaptive methods, are formulated. It is shown how the specificity of the data and the size of the series of observations affect the choice of suitable mathematical methods. A range of models suitable for approximating short time series has been determined. Studying the example of labor market research, the choice of the Holt-Winters multiplicative model as the best is substantiated. The model makes it possible to adequately approximate the damping of the oscillation amplitude synchronously with the initial process. When studying the dynamics of real estate market prices, the possibilities of using lag variables as a leading indicator for the purpose of short-term forecasting are shown.

1. Introduction
The more time analysts spend in monitoring the dynamics of market indicators, the stronger the desire becomes if not to predict, then at least explain the current market behavior. Over the past decade, this desire has increased by many times due to the accumulation of a huge amount of information sufficient for quantitative analysis and machine learning. As a result, big data created big problems in some areas of applied analysis due to the comprehensive theoretical interpretation of machine algorithms. In the case of short series of observations, with a naturally limited history of observations, the problem of qualitative models remains unresolved.

To date, the majority of scientific research is presented in the field of mineral wealth markets and electricity markets, which is associated with the possibility of identifying and quantifying economic indicators that determine the volume of consumption and affect the demand and pricing of market assets. However, the bulk of the financial markets remains without adequate approximations, although recently innovative ideas of dynamics modeling are continuously being tested. This is due to the fact that large histories of price changes have been collected, creating room for modeling maneuvers. For markets with a small history, such as the labor market or the real estate market in Russia, the problem of assessing future market conditions is even more acute, because most researchers pay attention exclusively to the analysis of current conditions and the description of the causes of changes. The aim of this study is to systematize approaches to modeling market dynamics, to select and justify the most appropriate models and methods depending on a particular market being studied.
2. Review of approaches to the analysis of market observations

The study of financial markets and development of the pricing theory over the past decades have undergone rapid development, starting with the studies of Nobel Prize winners: Tobin (1981), Markowitz (1990), Sharp (1990), Engle (2003) and ending with Mortensen (2010), Fama (2013) and Shiller (2013), etc. Among domestic researchers of financial markets, the approaches of Vorontsovsky, Davnis, Lukashin, Nedosekin were recognized. The use of nonlinear dynamics methods for modeling the financial market, begun by Mandelbrot, Brock, Hsieh, has been developed by Peters, Vege, Sornette, Malinetsky, Dubovikov, Potapov, Yanovsky and others in the last decades.

Financial markets are the most difficult to analyze, having unique characteristics. Irregular catastrophic events in financial markets (collapses) traditionally focus the interest of researchers. The classical approach to analysis is based on the selection of leading factors influencing market processes, their assessment and interpretation of influence. On the other hand, there are quantitative approaches, for example, based on the ARCH and GARCH models, which assume a statistical dependence on the selected factors. The parameters of these models are extremely sensitive to changes in economic indicators, which creates difficulties for modeling and forecasting in the long term. The sensitivity problem is the linearity of the models. At the same time, nonlinear models are many times more complicated than linear ones both in construction and in interpretation, and therefore they are not popular in practical research.

The classical economic theory describes the equilibrium of financial markets as a result of the interaction of economic agents that act rationally, relying on the same information [1]. This approach encounters the following difficulties: first, there are characteristic heavy tails for the distribution of logarithmic profitability [2]. Second, financial time series are characterized by a long memory. There are various approaches to assessing the depth of memory, see, for example, [3]. Third, financial time series have fractal properties [4], a confirmation of this is the similar observable patterns presented on different time scales. In addition, at certain points, most investors cease to be rational, contributing to the emergence of bubbles in the financial markets, followed by a market crash. The contradictions between the theory of market equilibrium and the observed patterns led to the emergence of alternative approaches to modeling financial markets.

A long history of observations provides an advantage in the form of accumulated gigantic data arrays that can be successfully used for machine learning to search for patterns. Machine learning (ML) is attracting increasing attention today among the specialists who process large volumes of data, including in a market economy. ML-based applications that combine elements of statistics, mathematical optimization, pattern recognition, intellectual analysis, and artificial intelligence can be useful for studying the effects of changes in market prices, the effectiveness of advertising, the scoring issues in banking, etc.

The problem of applying methods, algorithms, and tools of machine learning is presented in the studies of many researchers. ML algorithms are successfully used not only in the field of market research, but also in many other areas of the economy. In [5], the methodological foundations of machine learning are formulated. ML algorithms used in recommended systems are considered in [6]. In [7, 8], reviews of the application of ML forecasting methods for tax and bank interest rates are presented; in [9], the effect of limited money supply on market indicators is considered.

Machine learning is a broad enough term. In traditional programming, the general formulation of the ML problem can be represented as follows. There is a limited set of parameters or situations and a number of possible reactions. There is a relationship between reactions and situations, but it is unknown. A finite set of pairs of correspondence is known, determined by the forming sample. Having a training model, it is possible to algorithmically restore the relationship between input and output data. At the same time, the trained system gains the ability to adequately respond to data outside the training sample. An additional problem in practice is the likelihood that the input may be incomplete and unstructured. This situation requires the development of additional special data processing methods. There are many ML methods, for example, “random forest”, “regression trees”, “support vectors” [10], etc. One of the common characteristics of most methods is that ML algorithms repeatedly evaluate a model for a limited
piece of data, and then test it for another piece. In this case, a “penalty for complexity” is applied, which best fits the data in terms of the mean square error of forecasting. There is a certain specificity of using ML in the trading space. Instead of the term “model”, the term “signal” is usually used because the purpose of trading is to generate transactions based on certain signals. Actual prediction in such cases can be a relatively simple controlled learning using linear or logistic regression. The approaches to pattern recognition methods were especially useful for the pioneers of algorithmic trading, such as, for example, the hedge fund “Renaissance Technologies”. Hedge funds, brokers and traders use artificial intelligence to find signals to optimize trading for higher returns.

Of course, there are areas where big data created the possibility of a qualitative leap and breakthrough to a new level of modeling, these are areas related to marketing, advertising, and the social sphere. By and large, turning to the classification scheme of methods of economic-mathematical modeling, this is the sphere of decision-making in conditions of partial uncertainty. Targeted advertising, scoring systems, risk assessment issues – these are the happy areas of research that have gained a lot from the use and study of big data.

Despite the largest volumes of accumulated historical data, the field of research of market indicators has not received any breakthrough modeling technologies, nor a systematic approach to analysis, nor predictive capabilities.

In this regard, several questions arise:

- is there a data set sufficient for high-quality modeling;
- is it possible to identify current market states;
- is it possible to forecast future market states.

At the moment, these questions are rather rhetorical, perhaps they will remain such, but the problems of the approach to big data analysis based on machine learning are already visible today.

The main question to the results obtained on the basis of learning is a question of trust. A high percentage of accurate approximations within the collected sample does not provide the same accuracy during extrapolation, and the question of confidence intervals of estimates remains open.

Machine learning excludes the possibility of building an economic theory, and if there is no theory, then there is no way to identify contradictions, assess current and future crisis moments. There are attempts to set up indicators according to the “black swans” principle, but they run rampant, and some of them, of course, at some point will be informatively useful, but rather because of their number. As if one, without models for predicting the weather, would turn to dice with faces: sun, cloudy, rain, etc., then one of several throws would give an accurate forecast.

Thus, machine learning demonstrates excellent results in classification problems with a fixed number of groups or clusters obtained in a natural way, for example, groups of borrowers or consumers. However, when turning to the issues of modeling market indicators, the complexity of the initial data increases by many times. Ready-made groups or market conditions do not exist, i.e. the task of identifying the current state becomes practically unsolvable. Moreover, it is impossible to solve the problem of assessing the future state of the market.

Successful solutions to such problems and the development of algorithmically effective strategies are possible on a micro-temporal scale, subject to different physical speeds of information processing by financial markets players.

At present, as it is known, algorithmic trading accounts for the vast majority of counterparty interactions in financial markets. The times of technical analysis in the hands of traders, their personal trading systems and “black boxes” have sunk into oblivion, unless used for personal reasons or in connection with the need to work with medium-term and long-term investment horizons, but in these cases always there is the possibility of resorting to index funds, which are impossible to beat in the long run.

Thus, today the time has come for machines and professionals; it remains only to choose who one can currently trust more – the machine intelligence or the intelligence of a trained and experienced analyst?
The answer will depend on the area of tasks. In many economic areas, the human approach is preferable to the machine approach. By it, one can understand the construction of an algorithm of an explainable, logical, consistent process under study. With such a conceptual approach, it is possible to create a methodological base, and the issues of forecasting and evaluating the results are solved.

In matters of market research, both approaches are possible to use when researching financial markets with a huge amount of accumulated quantitative information for analysis. In practice, well-known pricing models are used; their minus is discreteness in measuring predictor variables; therefore, their effectiveness is limited. These models are not applicable on short time-frames and are more interesting theoretically.

Multifactor models have been very popular in the recent past and high hopes were put on them. With the accumulation of data, many analysts’ illusions turned out to be untenable, and the long-term forecasting horizon ceases to be interesting for investors.

At the same time, in some markets large data sets were not collected, for example, this is the labor market, with quarterly measurement and publication of data, or the real estate price market, the official information on which is processed, weighted, averaged and published monthly.

Using machine learning with historically short time series is not possible. Econometric approaches remain in the hands of analysts, the diversity of which requires a systematic approach and analysis in the study of various markets. The authors will consider some varieties of market dynamics with naturally limited historical periods of observation and a rare frequency of measurement of indicators, will formulate the problems that arise when modeling the relevant market indicators and will outline ways to solve them.

3. Methods of modeling the dynamics of the labor market

The first example is the labor market, which for historical reasons has a limited set of empirical data, which is why it is difficult for econometric modeling. Economic and mathematical modeling of the labor market is based, first of all, on the traditional econometric approach. Classical works on statistical modeling and forecasting are the studies by Anderson, Box, Jenkins, Kendal, Magnus, Mkhitaryan, Ayvazyan and others. Among scientists who are concerned with the problems of modeling the labor market, Gimpelson, Layard, Olivetti, Richter, Freeman, Earl and others should be noted. Of the domestic authors involved in modeling labor market indicators, the most famous are Andryunin, Korovkin, Lapina, Sabiryanova, Chizhov and others. Their research highlights a wide range of theoretical and practical issues of modeling labor market indicators. For the most part, these are methods of economic and mathematical modeling based on classical correlation-regression or cluster analysis.

At the same time, it should be noted that the specifics and features of modeling regional labor markets are not well understood. First of all, this concerns the study of indicators of the youth employment exchange. The youth labor market is one of the most important foci of government attention. Tensions in youth employment have been increasing in recent years. On the one hand, raising the retirement age may aggravate youth employment problems by reducing the number of vacancies. On the other hand, in the future, there may be massive staff reductions in many areas of employment due to new smart technologies that will allow massively thinning out such areas of employment as financial and accounting activities, education and medicine. Opportunities arising from the use of artificial intelligence can free up thousands of jobs related to decision-making based on pattern recognition, as well as in tasks of classification and the search for patterns.

Another feature of youth unemployment is “the lack of experience and the presence of ambition”, which is not always welcomed by employers. Thus, every year it becomes increasingly difficult for young people to be in demand, especially at the regional level.

Therefore, in order to make an impression of current trends in the labor market and to understand the immediate prospects, this study examines the processes occurring in the labor market in one of the million-plus cities closest to Moscow – Voronezh.

The informational basis of the study was the statistical data of the Voronezh Region Employment Office and the Voronezh Statistical Office. The dynamics of employment market indicators includes a
pronounced seasonal component, unlike many socio-economic indicators that could be selected as potential predictors. As a result, cross-correlations are not enough to build ordinary regression models.

The number of vacancies and, accordingly, the number of employed unemployed, directly depend on the climate season, i.e. the dynamics of labor market indicators will include a seasonal component. Given the strict periodicity of changes in the market created by climatic fluctuations, suitable classes of models that provide high-quality approximation can be, first, harmonic analysis methods, second, adaptive methods in the case of a multiplicative model and, third, regression models using dummy variables. In recent years, many methods have been developed for decomposing market series of observations into sums of cyclic components. These methods do not cause practical interest, due to the impossibility of interpreting the resulting models and the impossibility of constructing correct predictive estimates based on them.

The first option is to construct a model of dynamics with periodic oscillations based on the Fourier expansion. The procedure of harmonic expansion in a Fourier series can be represented as follows:

\[ Y_t = a_0^Y + \sum_{K=1}^{q} \left( a_K^Y \cos 2\pi f_K (t - 1) + b_K^Y \sin 2\pi f_K (t - 1) \right) \]  

(1)

where \( t = 1, 2, ..., N \), \( a_0^Y = \bar{Y} \), \( \bar{Y} = \sum_{t=1}^{N} Y_t / N \)

\[ a_K^Y = \frac{2}{N} \left[ \sum_{t=1}^{N} Y_t \cos 2\pi f_K (t - 1) \right] ; \quad b_K^Y = \frac{2}{N} \left[ \sum_{t=1}^{N} Y_t \sin 2\pi f_K (t - 1) \right] \]  

(2)

where \( f_K = K/N \); \( q = \begin{cases} N/2, & \text{if } N \text{ is even} \\ (N-1)/2, & \text{if } N \text{ is odd} \end{cases} \)

Fourier decomposition does not allow building a qualitative model due to the presence of long-term market trends, which, in addition to the main movement vector, are accompanied by a change in the amplitude of market fluctuations. Thus, it is not possible to build a meaningful model for initial observations, therefore, the parameters are not shown, but the simulation results will be presented in graphical format in figure 1 along with other dynamics models. As follows from figure 1, in the initial data there is a general negative trend of a decrease in the number of people employed against the background of a decrease in the amplitude of the seasonal wave. Such a character of the process under study suggests as optimal the model with a combination of a linear trend and a seasonal component superimposed multiplicatively.

This problem can be solved using the Holt-Winters method, which is a modification of the exponential smoothing method for seasonal series. The Holt-Winters multiplicative model with a linear growth of the trend-seasonal time series looks as follows [11]:

\[ Y_p(t + k) = [a(t) + k \cdot b(t)] \cdot F(t + k - L), \]  

(3)

where \( k \) – prediction period;
\( Y_p(t) \) – the calculated value of the indicator for \( t \) period;
\( a(t), b(t) \) and \( F(t) \) – coefficients of the model, which are adapted (specified) while moving from the members of the series with the number \((t-L)\) to \(t\);
\( F(t + k - L) \) – the value of the seasonality coefficient of the period for which the corresponding indicator is calculated. \( L \) is the seasonality period (for quarterly data \( L = 4 \)).

Recalculation (adaptation) of the parameters \( a(t), b(t) \) and \( F(t) \) for the value of \( t \) is as follows:

\[ a(t) = a_1 \frac{Y(t)}{F(t-L)} + (1 - a_1)[a(t) + b(t - 1)] \]  

(4)

\[ b(t) = a_3[a(t) - a(t - 1)] + (1 - a_3)b(t - 1) \]  

(5)

\[ F(t) = a_2 \frac{Y(t)}{a(t)} + (1 - a_2)F(t - L) \]  

(6)
4. Results and Discussion
The smoothing parameters $\alpha_1$, $\alpha_2$ and $\alpha_3$ “are optimized in this study based on the criterion of minimizing the residual sum of squares” [12] (shown in table 1).

Table 1. Holt-Winters model adaptation parameters.

| $\alpha_1$ | $\alpha_2$ | $\alpha_3$ |
|------------|------------|------------|
| 0.17       | 0.81       | 0.01       |

The modeling results for all three models are presented in figure 1. The Holt-Winters model is essential, statistically significant and adequate to the data under study. The determination coefficient is 0.77; the OLS prerequisites are fulfilled (see table 2 in [12]).

Table 2. Test results for the implementation of the OLS method prerequisites.

| t-statistics | R/S criterion | dw-statistics | r(1) |
|--------------|---------------|---------------|------|
| -0.69        | 4.85          | 2.05          | -0.12|

Let us compare the results of modeling the trend-seasonal process obtained using the multiplicative model with the results of the additive model, in which the systematic and periodic components are included in the form of a linear combination.

It is possible to linearly take into account seasonal deviations in the dynamics model by introducing dummy variables that determine seasonal factors. In general, the model will look as follows:

$$Y_t = \beta_0 + \beta_1 \cdot t + \delta_1 d_1 + \delta_2 d_2 + \delta_3 d_3 + \epsilon_t$$  \hspace{1cm} (7)

$$d_i = \begin{cases} 1 & \text{for quarter } i \\ 0 & \text{for other cases} \end{cases}, \hspace{1cm} i = 1, 2, 3$$

In figure 1, the results of modeling the number of people employed on the basis of the three abovementioned models are presented for the purpose of visual analysis and comparison of model accuracy. Details on the study of the dynamics of the regional youth employment market are available in [12].

Table 3. Regression statistics.

| R-square | 0.76 |
|----------|------|

Table 4. Results of modeling based on dummy variables.

| Coefficients | Standard error | t-statistics | P-value |
|--------------|---------------|--------------|---------|
| Y-crossing   | 3 212.44      | 252.63       | 12.72   | 0.00    |
| Quarter I    | -710.29       | 261.57       | -2.72   | 0.01    |
| Quarter II   | 1 716.19      | 261.20       | 6.57    | 0.00    |
| Quarter III  | 1 068.13      | 260.99       | 4.09    | 0.00    |
| t variable   | -42.79        | 6.16         | -6.94   | 0.00    |

The advantage of a model with dummy variables is a simple economic interpretation of the model parameters. So, the average rate of decrease in the number of employed people was 42 people per
quarter. At the same time, quarters II and III are characterized by a large number of vacancies and employed people, this is a direct consequence of climatic reasons, because for the summer months, agricultural work is also characteristic, and the functioning of temporary feeding and resting points occurs during a vacation period when young people have the opportunity for temporary work. The results of modeling displayed in table 4 testify to the significance of the model as a whole and of individual parameters in particular.

Table 5. Test results for the implementation of the OLS method prerequisites.

| t-statistics | R/S criterion | dw-statistics | r(1) |
|--------------|---------------|---------------|------|
| -0.03        | 4.78          | 2.42          | -0.18|

Figure 1. Modeling seasonal wave dynamics.

A comparison of all models makes it possible to opt for an adaptive model, in connection with the possibility of taking into account the damping of the oscillation amplitude synchronously with the initial process, while the use of dummy variables would be justified in the case of a constant amplitude of seasonal changes.

Thus, despite the severity of the problem of analyzing the dynamics of the labor market caused by a short history of observations, ways to solve it do exist. Adaptive methods are the best choice in this case; in particular, this is the Holt-Winters multiplicative model.

5. Methods for modeling real estate pricing

Now let us consider the approaches to modeling the dynamics of the real estate market. The most common modeling format in the real estate price market is regression pricing models. Numerous applied studies indicate that, despite the many factors involved in the pricing process of real estate, most of them are ineffective for solving the tasks of evaluating objects due to the difficult access to information. Moreover, official statistics are published monthly, which limits the length of time series. At the same time, dynamics modeling per se is fraught with difficulties such as non-stationary processes, sudden changes in trends caused by crisis periods, denomination of banknotes, fluctuations in exchange rates, etc.

The models obtained from the study of trends are a tool for analyzing and forecasting prices in the real estate market during the period of “quiet” development of processes in the market, while keeping the prevailing trends, which is unusual for the Russian market. High-order polynomials are often used
in practice as an approximation of trends. These are models that do not reflect the internal mechanisms of price movements. For such models, the forecast becomes unstable. Nonlinear models with a high probability give a greater error in forecasting than models with a simpler structure. In practical studies, scholars also often turn to autoregressive models that reveal the relationship between current and previous market states.

In recent years, researchers’ interest in assessing the prospects of the real estate market has been growing both in connection with the investment interest and with the crisis in the national economy. However, most of the works are devoted to the study of the mechanism of market functioning and issues of its regulation, see, for example, [13].

Studies on the dynamics of market indicators are presented by researchers much less often, and most of the works contain an assessment of the quality and significance of the proposed models without evaluating the prognostic capabilities, see, for example, [14, 15]. A quantitative forecast of future market conditions was made in [16, Sternik, & Sternik, 2018]: “Taking into account the actual result of 2017, the price forecast for the housing market of most Russian cities for 2018 is a likely change in prices within +/- 1.5–2.0%, which means continued stagnation with an undefined horizon”. Thus, the forecasts by modern researchers and analysts come down to expectations of holding current price levels in the near future and the absence of significant trends.

When constructing pricing models, it is necessary to take into account the fact that the market reacts to changes in macro-indicators with different delays and amplitudes, which must be taken into account when examining the model specifications. See as an example the dynamics of the Moscow real estate market over the past few years (after the 2008 crisis).

The modeling procedure is proposed to be divided into two stages [17]. “At the first stage, it is planned to make a preliminary selection of economic factors that may be associated with pricing processes in the residential real estate market. A preliminary model was built:

\[ Y = 61.26 + 1.96X_1 + 0.74X_2 + 26.76X_3 \]

\[ (R^2 = 0.87) \quad (S_{a1} = 0.51) \quad (S_{a2} = 0.22) \quad (S_{a3} = 4.91) \]

where \( X_1 \) – the monetary volume of transactions in the real estate market (in USD billion); \( X_2 \) – the RTS Index; \( X_3 \) – the price of a barrel of Brent crude oil.

The model is high-quality with statistically significant parameters; the relative approximation error for the indicated historical period was 13.5%, due to large errors at some points in time that can be leveled by shifting the series of observations of the explanatory variables”.

At the second stage, the task was set on selecting a lag period for the reaction of the market to a change in a factor sign in the form of adding a lag variable.
Many economic macro-indicators in Russia are tied to the cost of oil, and oil is often the subject of global speculation and is able to change in price despite fundamental indicators. In this regard, in times of crisis (mid-2008 and the end of 2014), the price of oil collapses more rapidly than the economic indicators that depend on it. It is at these moments that oil ceases to “explain” real estate prices; on the contrary, it becomes a driver of future changes with a delay. If one adjusts the model for accounting for the cost of oil (by 2 lags), then a proactive indicator is obtained, which, given the share of its influence on the cost of a square meter, allows building forecast estimates for the next 1-2 quarters.

Having a “proactive indicator that has a decisive role in changing the price of Moscow real estate, one can use this opportunity to assess its future value. However, the assumptions made can be true only if the situation on the stock and commodity markets remains unchanged, which is unlikely and no less difficult to predict than the trends of any financial markets” [17].

6. Results and Discussion
The authors illustrate the idea of forecasting based on a leading indicator on a simpler model. Let us reduce the sample, leaving the history starting in the summer of 2008. In this post-crisis period, demand and activity of the real estate market is not a significant factor, and the model has a simpler form:

$$Y = -246.23 + 1.20X_1 + 33.80X_2$$

$$\left( R^2 = 0.87 \right) \quad \left( S_{a1} = 0.13 \right) \quad \left( S_{a2} = 2.25 \right)$$

where $X_1$ – the RTS index; $X_2$ – the price of a barrel of Brent crude oil with a two-quarter delay.

| Parameter               | The RTS index | Oil price |
|-------------------------|---------------|-----------|
| Coefficient of elasticity | 0.39          | 0.68      |
| Delta coefficient        | 0.35          | 0.65      |

The main conclusions drawn above for the three-factor model remain unchanged – “the price of oil is still the dominant factor both in terms of its share of influence and the level of reaction of the price per square meter to a change in the price of a barrel. Cheaper oil by 1% causes a decrease in the price per square meter of Moscow residential space by an average by 0.68% in the study area, while a change of 1% in the stock market index will serve as a driver of change by 0.4% in the price of a square meter in the corresponding direction”.

The relative error of the adjusted model is 10%, the model is statistically significant, it explains the cost of a square meter for 87%, with a satisfactory accuracy of approximation. The second regression coefficient allows concluding that the price of a square meter decreases with the price of a barrel falling by USD 1 by about USD 34.

Having a “proactive indicator that has a decisive role in changing the price of Moscow real estate, one may use this opportunity to assess the future value of Moscow real estate. Because for the last two studied quarters, oil fell by almost USD 19, one could expect by the end of the second quarter of 2016 a cheaper square meter a little more than USD 600 compared to the beginning of 2016. Thus, our estimate was approximately USD 2,000 per square meter, which, with an average exchange rate of 70 rubles per dollar, gives the average cost of a square meter of Moscow real estate about 140 thousand rubles, which almost coincided with the real price” of a square meter in the specified period.

7. Conclusions
This paper shows the ways and steps of calculating short-term forecasts of market dynamics in the study of short time series based on the use of dummy and lag variables, as well as adaptive models.

Using the example of the study of price dynamics in the Moscow real estate market, the possibility of obtaining forecast estimates in the market sphere using lag variables has been demonstrated.
Formulations of this kind of problem and the proposed phased approach to its solution can be of interest both to contractors in the housing market and can be used in the learning process as illustrations of the applied capabilities of econometrics. Modeling the dynamics of short time series, using the example of the youth labor market research, makes it possible to make an informed choice of the Holt-Winters multiplicative model as the best. This adaptive method allows adequately approximating the attenuation of the oscillation amplitude synchronously with the initial process, while the use of dummy variables in modeling seasonality in the market would probably be justified in the case of a constant amplitude of oscillations.

The specifics of different markets, in the case of short series of observations, limit the range of models useful for research, as was shown in this paper. The proposed approaches to modeling market dynamics can be useful in the study of other market indicators with a short history, represented by monthly or quarterly observations for a short historical period.

References
[1] Campbell Y, Lo A W, MacKinlay A C 1997 The Econometrics of Financial Markets Princeton University Press (Princeton, NJ)
[2] Plerou V, Gopikrishnan P, Amaral L N, Meyer M and Stanley H E 1999 Scaling of the distributions of fluctuations of financial market indices, Phys. Rev. 60 pp 6519-6529
[3] Kontsevaya N V 2009 On Modeling the Indicators of the Foreign Exchange Market and the Possibilities of Optimizing Models Audit and Financial Analysis 1 pp 74-79
[4] Mandelbrot B 1997 Fractals and Scaling in Finance (New York: Springer)
[5] Webb G I, Pazzani M J, Billsus D 2001 Machine learning for user modeling User modeling and user-adapted interaction 11 (1-2) pp 19–29
[6] Seydametova Z S 2018 System of Recommendations in Electronic Commerce Academic Reports of the Crimean Engineering and Pedagogical University 3(61) pp 119-126
[7] Andini M, Ciani E, G de Blasio, D'Ignazio A, Salvestrini V 2018 Targeting with machine learning: An application to a tax rebate program in Italy Journal of Economic Behavior & Organization 156 pp 86–102
[8] Chakraborty C 2017 Machine learning at central banks Bank of England. Working Paper 674 September 1 p 89
[9] Athey S 2018 The impact of machine learning on economics [Electronic resource] The Economics of Artificial Intelligence: An Agenda University of Chicago Press Access mode: https://www.nber.org/chapters/c14009.pdf.
[10] Mullainathan S, Spiess J 2017 Machine learning: an applied econometric approach Journal of Economic Perspectives 31 (2) pp 87–106
[11] Kosovtseva T R, Belyaev VV 2016 Technologies for Processing Economic Information Adaptive Forecasting Methods Tutorial (St. Petersburg: ITMO University) p 31
[12] Kontsevaya N V 2016 On a Systematic Analysis of Youth Unemployment: General Tasks and Particular Models of market Indicators Economics, Statistics and Information Technology. Bulletin of UMO 2 pp 72-77
[13] Novikov B D 2000 Market and Real Estate Valuation in Russia (Moscow: Ekzamen) p 512
[14] Kisel T N, Palastrova Ya I 2016 Analysis of the Main Trends in Price Changes in the Real Estate Market of Moscow during the Period of Economic Instability Economics and Entrepreneurship 2 pp 847-851
[15] Tsatsaronis K, Zhu H 2004 What Drives Housing Price Dynamics: Cross-country Evidence BIS Quarterly Review (March) pp 65-78
[16] 17. Sternik G M, Sternik G M 2018 Factors and Development Trends of the Russian Market of Multi-Unit Housing in 2017 (Moscow: Housing Strategies) 5(3) pp 251-304
[17] Kontsevaya N V 2016 On Modeling the Real Estate Market and the Possibility of Predicting the Price of a Square Meter Economics, Statistics and Informatics. Bulletin of UMO 4 pp 31-34