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Efficiency of Authored Mixed Prediction Model with Application to the Labor Market

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Abstract

The aim of this article is to evaluate the prediction of time series using a model containing wavelets. The research hypothesis is: "Models that take into account wavelets are an effective tool for predicting employment". To verify the hypothesis, an original model was devised. The model is based on wavelet analysis with Daubechies wavelets and an exponential alignment model. The exponential alignment model been appropriately modified by the introduction of wavelet functions. The results obtained show that a model that partially includes wavelets is an effective tool in the prediction and analysis of employment

Keywords: wavelets, employment, labor market, prediction, wavelet transform

1. Introduction

Prediction of time series from a mathematical point of view consists of determining its conditional expectation for the moment ahead of the current time by a fixed number of observations called the prediction horizon. Mathematical formulas are used for this purpose. Among models based on mathematical formulas expressed explicitly, we can identify, among others, nonparametric estimators and neural predictors (see: Biernacki, 2009). Other interesting models are those based on neural networks and wavelet analysis (see: Daubechies 1989, Hadaś-Dyduch, 2014, 2015a, 2015b, 2015c, 2016a, 2016b, 2016c; Meyer, Sellan & Taqqu, 1999, Vidakovic, Mueller, 1994). Also interesting are algorithms that use ARIMA, ARMA. FARMA with artificial neural networks (see: Biernacki, 2016; Hadaś-Dyduch, 2017a) and stochastic models (Biernacki, 2007). Although stochastic models are based on Markov processes and therefore differ in complexity and approximation accuracy.

This article on the prediction of employment uses wavelet analysis and the Brown exponential alignment model. A combination of proprietary and authored adaptive and wavelet methods, provided interesting prediction results, which are presented later in this article. The authored prediction model has been named the wavelet-exponential model.

Previous research results show that the use of artificial neural networks, wavelet analysis wavelet-neural network and other combinations of wavelets for prediction of a time series gives good prediction results (See: Meyer, Sellan & Taqqu, 1999; Hadaś-Dyduch, 2017b; Hadaś-Dyduch & Hadaś, 2017; Hadaś-Dyduch, Dyduch, Hadaś, 2017; Hadaś-Dyduch, Dyduch, & Hadaś, 2017; Vidakovic & Mueller 1994). Employment can be studied using different methods and approaches. The labor market can also be examined through the prism of the models proposed in (Pietrzak, 2010; Zieliński, 2015).

Macroeconomic phenomena are most often modeled using structural multi-equation models, or systems of equations describing dependencies occurring in the economy. Examples are the Keynesian aggregate demand model (Gruszczyński, Kluza, & Witek, 2003), the Tinbergen, Theil, Klein, Welfe models (Welfe, Karp, & Kelm, 2002; Welfe, 2012, 2013) and models proposed by Milo (Milo & Łapińska-Sobczak, 2002). Their authors, working on them, aimed at achieving a specific result - the best possible reflection of macroeconomic reality with the help of many mathematical formulas. The article proposes an alternative solution, less complicated, based on a wavelet analysis.

2. Method

In this work, we tested wavelet analysis. The core of the proposed, proprietary model to predict the short-term is the Brown method, known as one of the methods for exponential smoothing and most often used for a number with no trend. The Brown method is based on the fact that the time series of the forecasted variable is smoothed with the aid of the moving average, while the weights are determined according to the exponential order. Depending on the conclusions resulting from the decomposition of the series, we adjust the appropriate exponential smoothing method. The most commonly known and used include: the simple Brown exponential smoothing model, Holt's linear model and Winters model – the additive and multiplicative version. In the proposed authored approach, forecasted time series variables are smoothed using wavelets.

In this work, does not describe the exponential smoothing method in detail. The method is described in detail in, among others, the following items: (Gardner, 1995; Chen, Ryan, & Simchi - Levi, 2000; Trigg & Leach, 1967; Hyndman, Koehler, Ord, & Snyder, 2008; Brown & Meyer, 1961; Kalekar, 2004).

2.1 Wavelet Analysis

Wavelet analysis consists of decomposing a time series into components that are shifted and scaled versions of a function called a basic wavelet. This decomposition may have a different character depending on the type of wavelet transform used. In the case of discrete analysis, which most often appears in prognostic applications, the effect of the transformation are wavelet coefficients defined for octaves of frequency, which result in an economical representation of the data. In addition, considering only octaves of frequency may be justified in the case of analysis of economic processes, for which - it seems - the use of frequency intervals rather than single frequencies should not be associated with excessive loss of information, which will happen in particular in processes whose dynamics depends on the dyadic time scale.

In other words, wavelet analysis is a signal analysis technique that uses a variable window size. It allows the use of long sampling intervals for a better description of low frequencies, and denser sampling in order to obtain high frequency information. The wavelet transform divides the signal into the sum of orthogonal component signals for different time resolutions. Thanks to this, it is possible to separately analyze the signal components in various spatial resolutions. The wavelet transform divides the analyzed signal into component signals resulting from the mapping of the basic wavelet, after the shift and scaling operation on the analyzed signal.

The simplest wave was created in 1910. It was originally called the Haar development, from the name of the creator of the wavelet - Alfred Haar. Haar wavelets are a family of orthogonal and orthonormal functions. It should be mentioned that the Haar wave is the simplest wave and has no practical application. The most frequently used wavelet is the Daubechies wavelet, with db1 being the Haar wavelet. In the research presented in this article, a Daubechies wavelet was used, which, as mentioned before, is associated with the Haar wavelet.

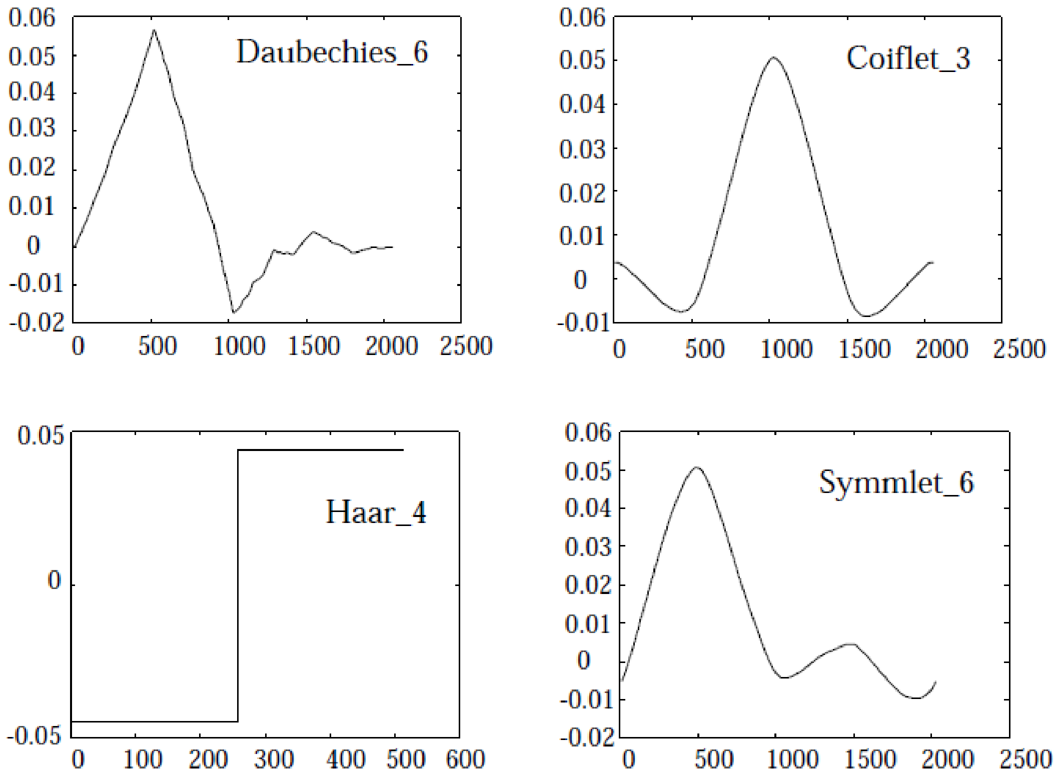


Figure 1. Several different families of wavelets. The number next to the wavelet name represents the number of vanishing moments (A stringent mathematical defnition related to the number of wavelet coefficients) for the subclass of wavelet

Source: Graps, 1995.

It should be noted that each wavelet has its advantages and disadvantages. For example, a Coiflet wavelet, characterized by a relatively small asymmetry and an increase in the width of the carrier. The choice of wavelet type is decided by the individual or by the use of objective methods. The selection of the mother wavelet with the use of a statistical test consists of checking whether, after the decomposition, there is still useful information in the details. The method uses the assumption that if the details contain less information, then the mother-wavelet better reflects the nature of the data.

3. Algorithm

The proposed algorithm for the prediction can be described as follows (see also: Hadaś-Dyduch, 2015c, 2016c; Hadaś-Dyduch, Dyduch, Hadaś 2017):

1) Extension of time series forecasted variable y_1, y_2, ... y_n

Classically, "the DWT (Discrete wavelet transforms (DWT), including the maximal overlap discrete wavelet transform (MODWT), analyze signals and images into progressively finer octave bands) is defined for sequences with length of some power of 2, and different ways of extending samples of other sizes are needed. Methods for extending the signal include zero-padding, smooth padding, periodic extension, and boundary value replication (symmetrization). The basic algorithm for the DWT is not limited to dyadic length and is based on a simple scheme: convolution and downsampling. As usual, when a convolution is performed on finite-length signals, border distortions arise" (Math Works).

In the literature the following series extension methods are suggested : Zero-padding , Symmetrization, Smooth padding of order 1, Smooth padding of order 0, Periodic-padding. This article proposes the symmetrization method. The symmetrization method is a method which assumes that signals or images can be recovered outside their original support by symmetric boundary value replication. Symmetrization has the disadvantage of artificially creating discontinuities of the first derivative at the border, but this method works well in general for images.

2) Determination of appropriate coefficients, on the basis of the following formula:

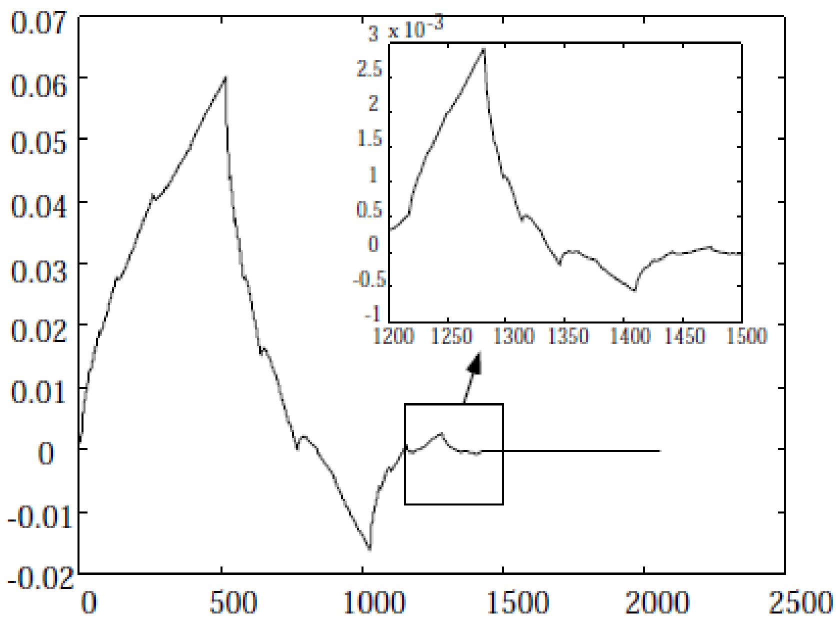
$$a_k = \sum_{r=k+0}^{k+3} \varphi(r-k) p_r\,, \quad k \in \{0,1,2,\ldots,2^n-1\},$$

φ - Daubechies wavelets scaling function, which can be written as follows:

$$\varphi(r) = \frac{1+\sqrt{3}}{4}\varphi(2r) + \frac{3+\sqrt{3}}{4}\varphi(2r-1) + \frac{3-\sqrt{3}}{4}\varphi(2r-2) + \frac{1-\sqrt{3}}{4}\varphi(2r-3)$$

$$\sum_{k\in Z} \varphi(k) = 1\,, \quad \varphi(r) = 0 \;\; for \;\; r \le 0 \vee r \ge 3\,.$$

Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments for a given support. “The Daubechies wavelet transforms are defined in the same way as the Haar wavelet transform by computing running averages and differences via scalar products with scaling signals and wavelets. The only difference between them consists of how these scaling signals and wavelets are defined. For the Daubechies wavelet transforms, the scaling signals and wavelets have slightly longer supports, i.e., they produce averages and differences using just a few more values from the signal. This slight change, however, provides a tremendous improvement in the capabilities of these new transforms. They provide us with a set of powerful tools for performing basic signal processing tasks. These tasks include compression and noise removal for audio signals and for images, and include image enhancement and signal recognition. (Meyer, Sellan, & Taqqu, 1999).



Figiure 2. The fractal self-similiarity of the Daubechies mother wavelet

Source: Graps, 1995.

3) Application of the approximation function that has the form (assuming that the initial series takes the form:

$p_0, p_1, \ldots, p_{2^n-2}, p_{2^n-1}$ it is: $y_1, y_2, \ldots, y_n = p_0, p_1, \ldots, p_{2^n-2}, p_{2^n-1}$:

$$\tilde{f}(r) = a_{-2}\varphi(r+2) + a_{-1}\varphi(r+1) + a_0\varphi(r) + \cdots + a_{2^n-1}\varphi(r - [2^n-1]).$$

4） The construction of a series of smoothed form. We assume that the series smooth has the form: is: $\hat{y}_1, \hat{y}_2, \dots, \hat{y}_n$

5) Defining and solving the problem:

$$Min\left\{\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\left(\alpha\hat{y}_t+(1-\alpha)y_{t-1}\right)-y_t\right)^2}\right\},$$

assuming that $\alpha \in \langle 0,1 \rangle$.

1. For the adopted parameter α, with the task of minimizing solved, we determine the forecast for one period ahead using the formula: $\hat{\hat{y}}_{t+1}^{P} = \alpha \cdot \hat{y}_t + (1-\alpha) \cdot y_t$, wherein $\hat{y}_t$ is the value of smoothed wavelets, and $\alpha \in [0, 1]$- is called a smoothing constant, finessed so as to minimize errors ex-post forecast.

4. Result

In this part of the paper we present the results of the implementation of the proprietary wavelet model described in Chapter 1. For the implementation of the model the time series was chosen showing the number of unemployed people in countries in the Eurozone (the series included in the study covers the period 1997-2016 ((EA11-2000, EA12-2006, EA13 -2007, EA15-2008, EA16-2010, EA17-2013, EA18-2014, EA19), the annual average, 1000 people).). Data on the number of unemployed people in the Eurozone used to implement the model was taken from the Eurostat database (Figure 3).

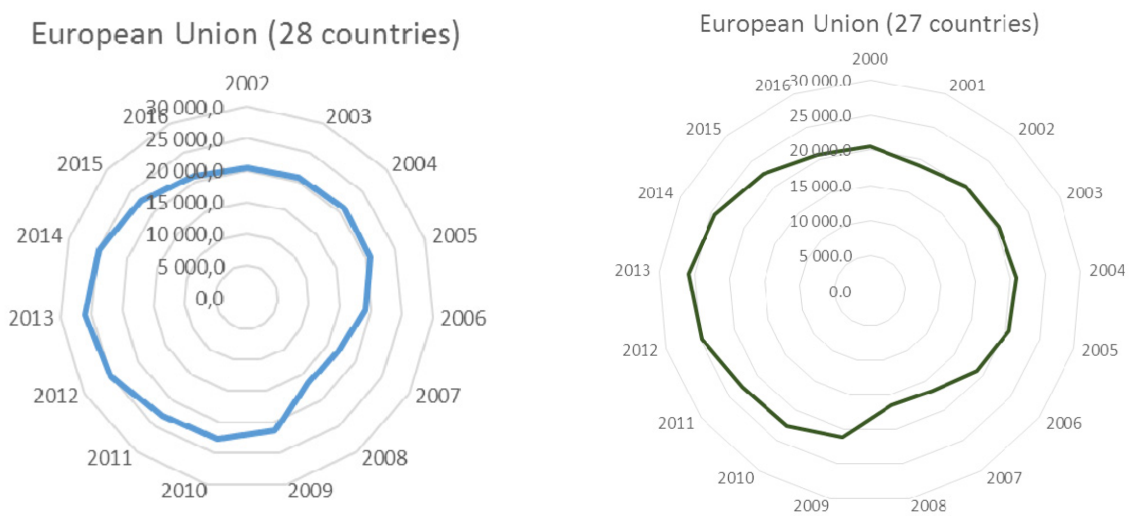


Figure 3. Unemployment by duration of unemployment (1 000), age from 15 to 74

Source: Own study based on data from Eurostat.

On the basis of the algorithm described in the previous section and the estimated alpha parameter value, we arrived at a forecasted number of unemployed people in Eurozone countries for the subsequent period, ie. for the nineteenth period. First, extension is made to a series of data, and then the resulting number is smoothed using wavelets.

The predicted number of unemployed in the Eurozone in 2016 as calculated by our authored model, ie. the exponential-wavelet alignment model, is 20918.65 [1000 people]. The value obtained does not match 100% with the actual value as it is subject to error. The remainder of the model is shown in Figure 4.

Figure 4. The remainder of the model

Source: Own elaborations

5. Discussion

The prediction results are acceptable. The prediction error using the proposed authored model is low in comparison with other predictive methods of the same category. The lowest error using proposed alternative methods of prediction (from the same group, ie. from the group of adaptive methods) is burdened by a naive prediction method (APE is approx. 3%). However, this is just a coincidence, as mistakes in extinct forecasts in the years 1997-2014 as determined by the naive method are very large. Applying the exponential alignment method to the prediction gives a rate of error oscillating around 8%.

6. Conclusion

The article presents the alignment method combined with exponential wavelet analysis. Daubechies wavelets were applied to the study. However, there are many families and varieties of analyzing wavelets, such as Meyer, Morlet, Daubechies, Haar or "Mexican hat". Wavelets must have finite energy and an average value of zero. Depending on the analyzing wavelets used, various properties of the tested signal can be specified. For example, the wavelet "Mexican Hat" is useful for assessing the distribution and values of local minima and maxima of the signal, while the Morlet wavelet is used to assess the amplitude and frequency included in the signal. The results obtained by the authored prediction methods are relatively low compared with those obtained by other adaptation methods. For example, an APE error for alpha minimizing extinct forecast errors in the classical method of exponential alignment amounts to about 8.5%, while in the classical creeping trend method with the harmonic scales prediction method it stands at around 8%. These results indicate that the proposed algorithm can also be used for long term prediction as resulting prediction errors are relatively small. It can be argued that the presented model can be an effective tool for forecasting macroeconomic indicators, the prediction of which is very difficult due to the complexity of the mechanism of the market, especially factors affecting this market. Analysis of the labor market is a very important issue, because the standard of living, consumption, and consequently production, fertility and so on all depend on employment. In further studies, wavelet models should be applied for the prediction of employment in European countries. Research shows that the macroeconomic indicators of various countries are correlated with one another.

References

Biernacki, A. (2009). Numerical Evaluation of the Random Walk Search Algorithm. In Man-Machine Interactions. Springer Berlin Heidelberg. 533-540. https://doi.org/10.1007/978-3-642-00563-3_56

Biernacki, A. (2012). Tracking scaling effects in mutual funds return time series. *Acta Physica Polonica B, 43*(11). https://doi.org/10.5506/aphyspolb.43.2103

Biernacki, A. (2016). Analysis and modelling of traffic produced by adaptive HTTP-based video. *Multimedia Tools and Applications*, 1-22. https://doi.org/10.1007/s11042-016-3623-8

Biernacki, A. (2007). Stochastic models for VoIP Traffic and their applications. Parallel and Distributed Computing and Networks. 144-149.

Brown, R. G., & Meyer, R. F. (1961). The fundamental theorem of exponential smoothing. *Operations Research*, *9*(5), 673-685. https://doi.org/10.1287/opre.9.5.673

Chen, F., Ryan, J. K., & Simchi‐Levi, D. (2000). The impact of exponential smoothing forecasts on the bullwhip effect. *Naval Research Logistics (NRL)*, *47*(4), 269-286. https://doi.org/10.1002/(sici)1520-6750(200006)47:4<269::aid-nav1>3.0.co;2-q

Daubechies, I. (1989, September). Wavelets: A tool for time-frequency analysis. In *Multidimensional Signal Processing Workshop, 1989, Sixth* (p. 98). IEEE. https://doi.org/10.1109/mdsp.1989.97051

Gardner, E. S. (1985). Exponential smoothing: The state of the art. *Journal of forecasting*, *4*(1), 1-28. https://doi.org/10.1002/for.3980040103

Graps, A. (1995). An introduction to wavelets. *IEEE computational science and engineering*, *2*(2), 50-61. https://doi.org/10.1109/99.388960

Gruszczyński, M., Kluza, S., & Winek, D. (2003). Ekonometria, red. *M. Gruszczyński, Wyd. WSHiFM, Warszawa*.

Hadas-Dyduch, M. (2014). Non-classical algorithm for time series prediction of the range of economic phenomena with regard to the interaction of financial market indicators. *Chinese Business Review*, *13*(4). https://doi.org/10.17265/1537-1506/2014.04.002

Hadaś-Dyduch, M. (2015a). Effectiveness of Direct and Non-direct Investment in the Stock Market Indices. *China-USA Business Review*, *14*, 10-20. https://doi.org/10.17265/1537-1514/2015.01.002

Hadaś-Dyduch, M. (2015b). *Wavelets in Prediction: Theory, Method, Simulation*. Scholar's Press. https://doi.org/10.15611/me.2015.11.04

Hadaś-Dyduch, M. (2015c). Polish macroeconomic indicators correlated-prediction with indicators of selected countries. *Proceedings of the 9th Professor Aleksander Zelias International Conference on Modelling and Forecasting of Socio-Economic Phenomena* (pp. 68-76). Foundation of the Cracow University of Economics, Cracow.

Hadaś-Dyduch, M. (2015d). Prediction of wavelets analysis. *Financial management of Firms and Financial Institutions, Proceedings (Part I.) 10th International Scientific Conference* (pp. 341-348).

Hadas-Dyduch, M. (2016a). Wavelets as Basis Functions in the Adaptation's Methods: Author's Model for Forecasting Short-Term. *Chinese Business Review*, *15*(1), 8-17. https://doi.org/10.17265/1537-1506/2016.01.002

Hadaś-Dyduch, M. (2016b). Econometric-wavelet prediction in spatial aspect. *The 10th Professor Aleksander Zelias International Conference on Modelling and Forecasting of Socio-Economic Phenomena. Conference Proceedings. Cracow: Foundation of the Cracow University of Economics* (pp. 45-52).

Hadaś-Dyduch M. (2016c). Model - Spatial Aproach to Prediction of Minimum Wage. *Proceedings of the International Scientific Conference Quantitative Methods in Economics Multiple Criteria Decision Making XVIII. Vratna: Letra Interactive* (pp. 134-138).

Hadaś-Dyduch M. (2017a). Artificial neural networks as one of the methods to alleviate edge effects in wavelet analysis of macroeconomic indicators. *8th International Scientific Conference "Analysis of International Relations 2017. Methods and Models of Regional Development". Conference Proceedings, Publishing House of the University of Economics in Katowice* (pp. 21-27).

Hadaś-Dyduch M. (2017b). Analysis of globalization by wavelets through the prism of the selected Euro Area. *17th International Scientific Conference Globalization and Its Socio-Economic Consequences, University of Zilina, 4th–5th October 2017* Rajecke Teplice, Slovak Republic (pp. 605-612).

Hadaś-Dyduch M., Dyduch R. (2017). Economy and finance through the prism of globalization. *IOSR Journal of Economics and Finance (IOSR-JEF)*, 8(5), 25-31.

Hadaś-Dyduch M., Hadaś A. (2017). Wavelet Daubechies as a tool supporting stock index prediction in the author's multi-component and multi-stage model. *IOSR Journal of Business and Management (IOSR-JBM), 19*(10), 59-66.

Hadaś-Dyduch M., Dyduch R., & Hadaś A. (2017). The Forecast of Macroeconomic Indicators on The Basis of Similarity. Copyright Model Approach. *Journal of Research in Business and Management. Quest Journals*, *05*(06), 35-40.

Hyndman, R., Koehler, A. B., Ord, J. K., & Snyder, R. D. (2008). *Forecasting with exponential smoothing: the state space approach*. Springer Science & Business Media. https://doi.org/10.1007/978-3-540-71918-2

Kalekar, P. S. (2004). Time series forecasting using holt-winters exponential smoothing. *Kanwal Rekhi School of Information Technology*, *4329008*, 1-13. https://doi.org/10.1109/icitacee.2015.7437762

Meyer, Y., Sellan, F., & Taqqu, M. S. (1999). Wavelets, generalized white noise and fractional integration: the synthesis of fractional Brownian motion. *Journal of Fourier Analysis and Applications*, *5*(5), 465-494. https://doi.org/10.1007/bf01261639

Milo, W., & Łapińska-Sobczak, N. (2002). *Stabilność rynków finansowych a wzrost gospodarczy*. Wydaw. Uniwersytetu Łódzkiego.

Pietrzak, M. B. (2010). Application of economic distance for the purposes of a spatial analysis of the unemployment rate for Poland. *Oeconomia Copernicana*, *1*(1), 79-98. https://doi.org/10.12775/oec.2010.005

Trigg, D. W., & Leach, A. G. (1967). Exponential smoothing with an adaptive response rate. *Journal of the Operational Research Society*, *18*(1), 53-59. https://doi.org/10.1057/jors.1967.5

Welfe, A., Karp, P., & Kelm, R. (2002). *Makroekonometryczny kwartalny model gospodarki Polski*. Wydaw. Uniwersytetu Łódzkiego.

Welfe, W. (2012). Multicountry and Regional Macroeconometric Models. *Comparative Economic Research, 15*(4). https://doi.org/10.1007/978-3-642-34468-8

Welfe, W. (2013). Macroeconometric Models. Advanced Studies in Theoretical and Applied Econometrics. https://doi:10.1007/978-3-642-34468-8

Zieliński, M. (2015). Unemployment and labor market policy in Visegrad Group countries. *Equilibrium*, *10*(3), 185-201. https://doi.org/10.12775/equil.2015.032

Vidakovic, B., & Mueller, P. (1994). Wavelets for kids. *Instituto de Estadística, Universidad de Duke*. https://doi.org/10.1007/bf03003960