

Use of ANN model in economies

Jasmina Četković^{1*}, *Miloš Knežević*², and *Miloš Žarković*¹

¹University of Montenegro, Faculty of Economics, 81000 Podgorica, Montenegro

²University of Montenegro, Faculty of Civil Engineering, 81000 Podgorica, Montenegro

Abstract. In this paper, the authors made their contribution by constructing a model for the forecast of average annual net earnings in the EU countries. The model is based on the artificial neural network (ANN) use and for the needs of its creation the authors have presented their proposal for a model entry – economic variables that determine earnings. Generally, implementing an economic policy aimed at preventing stagnation of earnings levels can be achieved by running a sustainable earnings policy and our model can be used as an acceptable tool in the function of keeping that policy.

1 Introduction

From the macroeconomic point of view, sustainable economic growth is key to maximizing aggregate demand. Furthermore, earnings are an important source of household income, thus significantly affecting the living standard of the population. Therefore, there has lately been a growing need for monitoring and analyzing earnings trends. Recent literature offers a large number of studies analyzing different determinant earnings and examining the level of their impact. Starting from the fact that the design and determinants of earnings in the internal labor markets are some of the most complex issues in labor and personnel economics [1], for the purpose of examining the correlation between earnings and human capital, high educational level (high school and university degree) and unskilled and semi-skilled work have been used as earning determinants. In the study of the differences in the aggregate real wages adjustment among the 18 OECD countries in the manufacturing sector during the business cycle [2], earnings determinants included nominal wages/earnings in manufacturing) deflator, consumer price index (CPI) deflator, gross domestic product (GDP) deflator, producer price index (PPI) deflator, manufacturing employment and industrial production.

Investigating the flexibility of earnings in developing countries and comparing the results of research with similar studies, one of the studies analyzed the determinants of earnings rigidity such as GDP, rate of employment, skilled and unskilled employees [3]. Furthermore, starting from a number of circumstances on the labor market caused by the economic crisis, the study of the correlation between real wage earnings and different regional characteristics was based on the use of independent variables in regression models. They represent the annual real GDP per capita, annual real labor productivity, higher education graduates, share of workers in the total number of employers' and share of

* Corresponding author: cetkovicjasmina2@gmail.com

employees in private companies [4]. The study of possible structural changes caused by the introduction of euro in the relations among wages, prices and unemployment in the leading European economies was based on the use of certain variables, such as GDP in current prices and total GDP, implicit price deflator, employees, harmonized unemployment rate, consumer prices index, etc. [5]. Determining real wages in balance by combining labor supply and demand can be based on the following variables: education, FDI, real GDP growth, real exchange rate and population [6]. Furthermore, the UK-based survey identified certain long-term payroll determinants for the period 1860-2004, such as constant-price GDP, prices, nominal broad money, interest rates, employment, unemployment and working population, nominal average weekly wage earnings, nominal hourly wage rates, normal hours, world prices, a trade union membership measure, the replacement ratio from unemployment benefits and the nominal effective exchange rate [7]. By investigating the phenomenon of screening discrimination, key variables have been selected to explain this phenomenon, such as current performance, initial performance, age, education differences, etc. [8].

However, in recent macroeconomic modeling, the application of the method of neural networks in the forecast of key macroeconomic variables is present, which represents a valuable analytical basis for the development of strategies in the economies of these countries. With a higher degree of sensitivity and efficiency compared to conventional models, models based on the use of ANN can achieve greater precision in the forecast of economic growth and business cycles [9, 10], inflation forecast [11], changes in the growth rate of per capita consumption [12], credit risk in banking [13], economic variables movement forecast in different markets etc. [14].

2 Materials and methods

For the purposes of our earnings forecasting model, a multilayer perceptron with Backpropagation algorithm was used as one of the most commonly used types of ANNs [15]. One of the reasons for selecting this type of ANN is its ability to solve complex problems, which would otherwise require the use of a complicated mathematical apparatus.

The Backpropagation algorithm, used in this paper, has been clarified in several ways and one of them will be shown here [16].

The neuron activation signal in the layer j , for the linear input function is:

$$x_{jk}^{(l)} = \sum_{i=0}^{N_{l-1}} w_{ij}^{(l)} u_{ijk}^{(l)} = \sum_{i=0}^{N_{l-1}} w_{ij}^{(l)} v_{ik}^{(l-1)}, \quad (1)$$

where $w_{ij}^{(l)}$ is the weight coefficient in layer l , $u_{ijk}^{(l)}$ is the signal at the i -th input of the neuron at the excitation of the network with the i_k , and the v_{ik} is the output of the neuron.

When the vector of the input signal i_k invokes the network, the output signal of the neuron is:

$$v_{jk}^{(l)} = f_j^{(l)}(x_{jk}^{(l)}), \quad (2)$$

where $f_j^{(l)}$ is an activation function, and $x_{jk}^{(l)}$ is a neuron activation signal when the input signal vector is at the input of the network.

The error function describes minimizing the difference between the desired response t_k and the network response o_k due to the i_k invoke in the following way:

$$\varepsilon_k = \frac{1}{2} \sum_{s=1}^n (o_{sk} - t_{sk})^2 = \frac{1}{2} \sum_{s=1}^n (v_{sk}^{(N_L)} - t_{sk})^2. \quad (3)$$

To determine the connections weights, the partial derivatives of the error function are counted as follows:

$$\frac{\partial \varepsilon_k}{\partial w_{ij}^{(l)}} = \frac{\partial \varepsilon_k}{\partial x_{jk}^{(l)}} = \frac{\partial x_{jk}^{(l)}}{\partial w_{ij}^{(l)}}. \quad (4)$$

From

$$x_{jk}^{(l)} = \sum_{i=0}^{N_{l-1}} w_{ij}^{(l)} w_{ik}^{(l-1)}, \quad (5)$$

it follows

$$\frac{\partial x_{jk}^{(l)}}{\partial w_{ij}^{(l)}} = v_{ik}^{(l-1)}. \quad (6)$$

In that case, it is

$$\frac{\partial \varepsilon_k}{\partial w_{ij}^{(l)}} = \delta_{jk}^{(l)} v_{ik}^{(l-1)}, \quad (7)$$

where

$$\delta_{jk}^{(l)} = \frac{\partial \varepsilon_k}{\partial x_{jk}^{(l)}}. \quad (8)$$

For hidden layers it is:

$$\delta_{jk}^{(l)} = \frac{\partial \varepsilon_k}{\partial v_{jk}^{(l)}} \frac{\partial v_{jk}^{(l)}}{\partial x_{jk}^{(l)}} = \frac{\partial \varepsilon_k}{\partial v_{jk}^{(l)}} f_j^{(l)}(x_{jk}^{(l)}) = f_j^{(l)'}(x_{jk}^{(l)}) \sum_{s=1}^{N_{l+1}} \frac{\partial \varepsilon_k}{\partial x_{sk}^{(l+1)}} \frac{\partial x_{sk}^{(l+1)}}{\partial v_{jk}^{(l)}} = f_j^{(l)'}(x_{jk}^{(l)}) \sum_{s=1}^{N_{l+1}} \frac{\partial \varepsilon_k}{\partial x_{sk}^{(l+1)}} w_{jk}^{(l)} \quad (9)$$

The output layer is:

$$\delta_{1k}^{(N_L)} = (o_{jk} - t_{jk}) f_j^{(N_L)'}(x_{jk}^{(N_L)}) \quad (10)$$

where N_l is the number of neurons in layer l .

By including

$$\delta_{jk}^{(l)} = \frac{\partial \varepsilon_k}{\partial x_{jk}^{(l)}} \quad (11)$$

into the term for hidden layers, it gets:

$$\delta_{jk}^{(l)} = f_j^{(l)'}(x_{jk}^{(l)}) \sum_{s=1}^{N_{l+1}} \delta_{sk}^{(l+1)} w_{js}^{(l+1)} \quad (12)$$

Calculation is done through the weight adjustment and the forward phase. The next phase is backforward phase. The weights are adjusted by the gradient downhill rule:

$$w_{ij}^{(l)new} = w_{ij}^{(l)old} - \eta \frac{\partial \varepsilon_k}{\partial w_{ij}^{(l)}} \quad (13)$$

The use of the Backpropagation algorithm requires differentiation of the activation function. The most commonly used activation function is a sigmoidal function. The reason

for this is in its differentiability, i.e. the simplicity of derivatives computing and their characteristic of the universal approximator.

For logistic function:

$$y = f(x) = \frac{1}{1+e^{-x}} \quad (14)$$

derivative is

$$y' = \frac{df(x)}{dx} = y(1 - y) \quad (15)$$

and the neurons are:

$$\delta_{1k}^{(N_L)} = o_{jk}(1 - o_{jk})(o_{jk} - t_{jk}) \quad (16)$$

and

$$\delta_{jk}^{(l)} = v_{jk}^{(l)}(1 - v_{jk}^{(l)}) \sum_{s=1}^{N_{l+1}} \delta_{sk}^{(l+1)} w_{js}^{(l+1)} \quad (17)$$

In t sample presentation, if $\Delta w_{ij}^{(l)}(t)$ is a weight change of $w_{ij}^{(l)}$, then it is

$$\Delta w_{ij}^{(l)}(t) = -\eta \frac{\partial \varepsilon_k}{\partial w_{ij}^{(l)}} \quad (18)$$

where ε_k is an error in response to of the network for the training of the p_k sample.

Taking into account the previously defined mathematical framework, the constructed model of annual net earnings estimation is based on statistical data representing model inputs and outputs, referring to 26 European countries in the period from 2005 to 2016. The basic assumption in developing this model is that the use of artificial intelligence – ANN can accurately predict the amount of average annual net earnings with inputs within the network training limits. The model should indicate the character and degree of influence of the input on the model output – the amount of the average annual net earnings. It also should indicate to the decision makers which of the input parameters should vary in order to increase the annual average net earnings. ANN training was conducted on 11 inputs and 1 output. Outputs are: GDP, GDP per capita, real GDP growth rate, income inequality, unemployment rate, FDI, HICP – inflation, VAT, labor productivity, upper secondary and post-secondary non-tertiary education and tertiary education. Previously, several actions were carried out and they included: collection and analysis of data, data preparation for defining the model, and finally model development.

Network training was done with 253 data series. ANN, which showed a good prognostic model, consisted of 2 hidden layers with 10 neurons. The validation set was selected as 20% of the data from the training set in the random schedule. ANN is trained within the MS Excel program. Minor deviations from the training session are shown. Based on the network initiation with input data from the size range used in training, it is possible to make of the dependency of the output from any input. The control of the forecast was carried out on 26 test data with which the network was not trained, with a reliability of around 87%.

3 Results and discussion

Generally, our research has shown that forecast models, based on the use of ANN, possess a satisfactory degree of precision. Namely, the forecasting model for EU earnings made for the purpose of this research suggests an average deviation of the real from the forecast size to 13%. Figure 1 below shows this difference for the three selected EU countries of different levels of development.

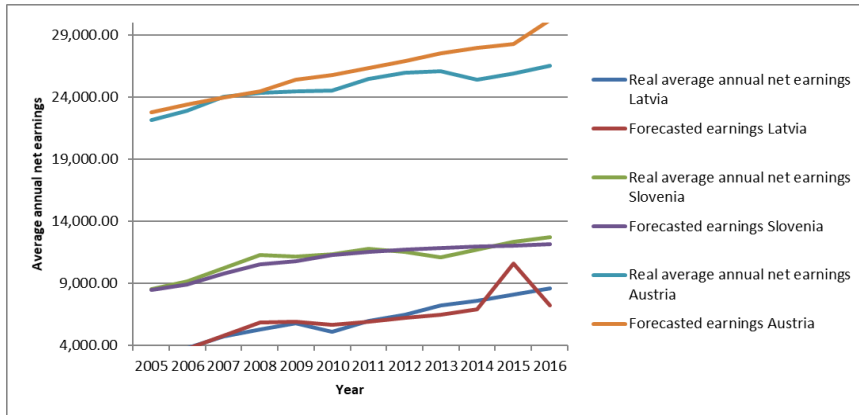


Fig. 1. Deviation of the real average net annual earnings from the forecasted earnings. Source: Eurostat data and authors' own calculation.

The prediction model has enabled us to make forecasting of the dependence of output from the selected variable that we fluctate in the given boundaries by fixing 10 variables and defining the eleventh variable within the boundaries in which the network is trained (Table 1) as presented later in this paper. This dependency was tested on the example of EU countries of varying degrees of development, with GDP per capita serving as a criterion for classifying those countries in the high, middle and low-developed economies.

Based on the developed forecast model, we established the dependence of the output variable – average annual net earnings on the changes in the GDP growth rate in the countries with different levels of development. In the observed countries, regardless of the level of development, the increase of GDP growth rate is not followed by the expected growth of earnings. Actually, the increase of the GDP growth rate leads to a moderate fall in earnings.

Economic factors that have the greatest impact on the changes in real earnings are GDP growth and price inflation. In the period of GDP growth, a real growth of earnings is expected. However, it is possible that, in the conditions of economic growth, average earnings stagnate or fall. Over the past few years, emerging and developing economies have been experiencing a trend of slowing or declining the earnings growth. In deflationary conditions, nominal wages, adjusted downwards, will lead to stagnating or falling of real wages in the medium term (Global Wage Report, 2016/17). This was the case with the United Kingdom for the period 2010-15 (UK Office for National Statistics, 2018). The cause of the earnings fall has increased labor market flexibility and increased competition. Such a manifestation requires a reexamination of the existing economic model, starting from the leading economies. Finally, our forecast model has confirmed the observed trends on the example of EU countries.

Furthermore, in all the observed countries of different development levels, due to the growth of GDP per capita, there is an increase of the output variables in the forecast model. Moreover, at lower levels of GDP per capita, there is a certain increase in earnings, which mainly lags behind the growth of GDP per capita, while at higher levels of GDP per capita, a relative growth in earnings is noticeably slowing down.

Some recent analyses are based on the divergences between the GDP per capita and household income trends. It was observed that GDP per capita overstates the increase in real income of typical households. Thus, one study showed that GDP per capita grew faster than median household income in most of the 27 OECD countries over a certain period of time, while the magnitude of this divergence varied considerably. GDP per capita and income in all the countries grew during the observed period, with GDP per capita growing faster than income in most countries. The degree of divergence was based on the stagnation of median household income, as indicated by numerous studies [17]. In addition, it was noticed that the degree of divergence is higher in a number of countries in transition, where the median household income is significantly lagging behind the GDP per capita.

In all the observed countries, high unemployment rates are largely accompanied by a weak decline in earnings. Lower growth of earnings is dominant at lower and middle levels of unemployment.

Theoretically, improvement of business conditions creates effects on the unemployment rate and negotiating power of employees, i.e. wages. This leads to the correlation between unemployment rates and wages. Given that, market conditions have a different impact on high and low earners; this approach is less clear if labor market flows are in correlation with wide distribution of wages. As workers with median and above median wages have better conditions to find a new job and move from one employer to another, then labor market conditions will have a weaker impact on their negotiating position and wages. Contrary, workers below the median wage are not in such position and have fewer alternatives in the market, so improving the conditions in the labor market more directly reflects their negotiating position and earnings.

According to the cruixed Phillips Curve for 2017 and the first quarter of 2018, there is a negative correlation between wage growth, measured by the Employment Cost Index (BLS, 2018) and non-employment rate, which means that the lower/higher unemployment rate signifies high/low wage growth. Furthermore, the literature emphasizes the issue of correlation between unemployment and wage growth in relation to expected inflation [18].

In the observed highly and middle-developed countries, labor productivity growth is predominantly accompanied by the earnings growth trend, although there is a negative correlation between these two sizes, i.e. productivity growth was accompanied by a weak decline in earnings.

Furthermore, the legitimacy of the movement of output variables under the influence of changes in labor productivity in less developed countries is not as clear as in highly and medium-developed countries. Namely, in the observed countries it was recorded that labor productivity growth leads to a smaller decrease or lower growth of the output size, which means that the earnings in these countries do not show the same sensitivity to the changes in labor productivity, nor is this sensitivity significant.

Numerous studies point to the problem of wage growth and productivity growth "decoupling", while some research suggests that this problem is overstated and cannot be used to explain the imbalance between profits and earnings. However, Feldstein's recent analysis suggests that the relevance of relationship between earnings and labor productivity is the key determinant of the employees' living standards, as well as the distribution of income between labor and capital [19]. Wage inequality significantly increased in the 1970s and this is a real problem in decoupling. Therefore, economic science for the last two decades has focused on identifying the cause of wage inequality. According to the Economic Policy Institute's survey [20] in the United States, in the period from 1973 to 2016, an increase in inequality prevented potential growth from translating into current wage growth for most workers, which resulted in stagnation of wages.

Based on the UK Office for National Statistics survey, higher productivity in certain industries leads to higher wages in those industries (UK Office for National Statistics,

2018). In addition, the question is whether high productivity growth industries have a high wages growth. The answer to this question depends on what is the measure of earnings. In the case of RCW (real consumption wage), the correlation between earnings and productivity is not reliable, and if the RPW (real product wage) is used, the correlation is much better at the industry level and aggregate level. Although the relationship between earnings and productivity is not stable, it turns out to be positive in most observed periods of time [21].

In the highly developed countries, higher levels of FDI were followed by a lower decline in average annual net earnings. At lower FDI levels, there is also a lower percentage growth in earnings with the FDI rise. In addition, at higher levels of FDI, earnings decline, expressed in percentage, is slightly higher than at lower and middle levels of FDI.

In the observed medium-developed countries with the increase in FDI, there is a trend of a smaller fall in the output variable – average annual net earnings, while the trend of falling earnings, expressed in percentage, is weaker at higher levels of FDI. The lower developed countries show a similar legality between the FDI and the output variable.

Otherwise, theoretical and empirical research indicates a different impact of FDI inflows on the observed output size in our model, as indicated by a review of the research that follows. According to the standard economic approach – Wage Spillover Effect of FDI [22-25] the increase in marginal productivity of labor is caused by any increase of real wage. FDI effects are permanently higher productivity of local workforce and higher wages that can be provided by foreign investors. Therefore, this approach suggests a possible positive impact on earnings. In accordance with another theoretical approach – Wage Bargaining Effect of FDI [26, 27], multinational companies have a dominant role in Wage Bargaining and the so-called mobility advantage. The final effect of a link between the flow of FDI and wages is negative or neutral.

Recent empirical studies differ in the interpretation of the impact of FDI on labor income. In order to get specific information about the impact of FDI on labor income, the first research direction uses data at company and sector level. The second direction includes aggregate data and panel and is based on monitoring a large number of countries over a longer period. Part of the research [22, 25, 27-31] indicates that FDI inflows increase the level of average wages. Some studies suggest the negative impact of FDI on real or nominal wages [26, 32]. Finally, certain empirical research [33-35] did not indicate a clear link between FDI and the labor income.

4 Conclusions

Forecasting the value changes of the output variable under the influence of changes of certain input variables, a high degree of coincidence is found with the findings of relevant theoretical and empirical research in the aspect of the observed economic variables interdependency based on the developed forecast model. We note that for a possible rough and rapid estimate of average annual net earnings, it is possible to use a trained neural network with a reliability of about 87%. We consider the level of reliability very high as it has to do with the modeling of the economic system. A high level of accuracy of the developed forecast model was achieved by incorporating a large number of sets of reliable input parameters.

Conflicts of interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

References

1. C. Pfeifer, *Economic Letters* **99**, 570-573 (2008)
2. J. Messina, C. Strozzi, J. Turunen, *Journal of Economic Dynamics & Control* **33**, 1183-1200 (2009)
3. W. Ahmed, M. A. Choudhary, S. Khan, S. Naeem, G. Zoega, *Economic Modelling* **38**, 296-304 (2014)
4. Z. Goschin, *Procedia Economics and Finance* **8**, 362-369 (2013) DOI: 10.1016/S2212-5671(14)00102-6
5. R. Girardi, P. Paruolo, *Economic Modelling* **35**, 643-653 (2013) DOI: 10.1016/j.econmod.2013.08.009
6. R. Cabral, A. V. Varella Mollick, *Economic Modelling* **64**, 141-152 (2017) <http://dx.doi.org/10.1016/j.econmod.2017.03.013>
7. J. L. Castle, D. F. Hendry, *Journal of Macroeconomics* **31**, 5-28 (2009)
8. Pinkston, J. C. (2003). Screening discrimination and the determinants of wages, *Labour Economics*, 10, 643-658.
9. L. Feng, J. Zhang, *Economic Modelling* **40**, 76-80 (2014) DOI: 10.1016/j.econmode.2014.03.024
10. J. Moody, *Economic forecasting: challenges and neural network solutions*, In Proceedings of the International Symposium on Artificial Neural Networks, Hsinchu, Taiwan, December 1995 (1995)
11. E. Nakamura, *Economic Letters* **86**, 373-378 (2005) DOI: 10.1016/j.econlet.2004.09.003
12. D. Farhat, *Artificial Neural Networks and Aggregate Consumption Patterns in New Zealand*, University of Otago Economics Discussion Papers No. 1205 (2012)
13. M. J. B. Hall, D. Muljawan, L. Suprayogi & Moorena, *Using The Artificial Neural Network (ANN) to Assess Bank Credit Risk: A Case Study of Indonesia*, Discussion Paper Series 2008_06, Department of Economics, Loughborough University, revised Jul 2008 (2008)
14. J. Cetkovic, S. Lakic, M. Lazarevska, et al., *Assessment of the Real Estate Market Value in the European Market by Artificial Neural Networks Application*, Complexity (2018) <https://doi.org/10.1155/2018/1472957>
15. I. A. Basheer, M. Hajmeer, *Journal of Microbiological Methods* 43(1), 3-31 (2000) DOI: 10.1016/S0167-7012(00)00201-3
16. S. A. Hamid, *Primer on Using Neural Networks for Forecasting Market Variables*, Working Paper No. 03 (2004)
17. B. Nolan, M. Roser, S. Thewissen, *GDP per capita versus median household income: what gives rise to divergence over time?* Institute for New Economic Thinking at the Oxford Martin School, INET Oxford Working Paper no. 2016-03 (2016)
18. D. Aaronson, D. Sullivan, *Recent Evidence on the Relationship Between Unemployment and Wage Growth*, Federal Reserve Bank of Chicago Working Paper, no. 2000-27 (2000) https://papers.ssrn.com/sol3/papers.cfm?abstract_id=255578
19. M. Feldstein, *Journal of Policy Modeling* **0(4)**, 591-594 (2008) DOI: 10.3386/w13953
20. EPI – Economic Policy Institute, *The Productivity–Pay Gap*, Retrieved May 31, 2018 (2017) <https://www.epi.org/productivity-pay-gap/>

21. A. Tuckett, Does productivity drive wages? Evidence from sectoral data, Retrieved May 19, 2018 (2017) <https://bankunderground.co.uk/2017/03/30/does-productivity-drive-wages-evidence-from-sectoral-data/>
22. B. Aitken, A. Harrison, R. E. Lipsey, *Journal of International Economics* **40**, 345-371 (1996) [http://dx.doi.org/10.1016/0022-1996\(95\)01410-1](http://dx.doi.org/10.1016/0022-1996(95)01410-1)
23. J. Stiglitz, Capital Market Liberalization, Economic Growth, and Instability, *World Development* **28(6)**, 1075-1086. DOI: 10.1016/S0305-750X(00)00006-1
24. B. Decreuse, P. Maarek, FDI and the labor share in developing countries: A theory and some evidence, MPRA Paper No. 11224, Retrieved June 1, 2018 (2008) https://mpra.ub.uni-muenchen.de/11224/1/MPRA_paper_11224.pdf
25. R. E. Lipsey, F. Sjöholm, *Journal of Development Economics* **73 (1)**, 415-422 (2004)
26. R. M. Vijaya, L. Kaltani, *Journal of World-Systems Research* **13(1)**, 83-95 (2007) <https://doi.org/10.5195/jwsr.2007.361>
27. M. Gopinath, W. Chen, *The Journal of International Trade & Economic Development* **13(2)**, 231-231 (2004) <https://doi.org/10.1080/0963819042000246619>
28. R. E. Lipsey, Home and host-country effects of foreign direct investment. Challenges to globalization: analyzing the economics (University of Chicago Press, Chicago, 2004)
29. OECD, Do Multinationals Promote Better Pay and Working Conditions?. Retrieved March 29, 2018 (2008) <http://www.oecd.org/employment/emp/43244752.pdf>
30. O. Onaran, E. Stockhammer, *Structural Change and Economic Dynamics* **19 (1)**, 66-80 (2008)
31. O. Onaran, E. Stockhammer, *European Journal of Industrial Relations* **15(3)**, 317-338 (2009)
32. N. Majid, What is the Effect of Trade Openness on Wages, ILO Employment Strategy Papers, no. 2004/18 (2004)
33. H. Gorg, D. Greenaway, *The World Bank Research Observer* **19 (2)**, 171-197 (2004) <https://doi.org/10.1093/wbro/lkh019>
34. A. Nichols, S. Zimmerman, Measuring trends in income variability (The Urban Institute, Washington, DC, 2008)
- U.S. Congressional Budget Office, Trends in earnings variability over the past 20 years. Retrieved May 26, 2018 (2007)