



Research Article

© 2020 Mantas Markauskas and Asta Baliute.
This is an open access article licensed under the Creative Commons
Attribution-NonCommercial 4.0 International License
(<https://creativecommons.org/licenses/by-nc/4.0/>)

Modelling Technological Progress Evaluation: Case of Lithuanian Manufacturing Industry

Mantas Markauskas

*PhD Student, School of Economics and Business,
Kaunas University of Technology,
Kaunas, Lithuania*

Asta Baliute

*Assoc. Prof. Dr., School of Economics and Business,
Kaunas University of Technology,
Kaunas, Lithuania*

DOI: <https://doi.org/10.36941/mjss-2020-0058>

Abstract

The goal for this research is to build a framework for analysis of technological spillover effect between sectors in Lithuanian manufacturing industry and assess whether predictors of the created model closely follow dynamic fluctuations of technological progress assessed values. Analysis of academic literature suggested using Granger causality test and vector autoregression (VAR) model to analyze intersectoral technological progress spillover effect in any manufacturing industry. Granger causality test can suggest a potential relationship between technological progress values of particular sectors in manufacturing industry while VAR model can define the exact form and extent of spillover effect. VAR models identify presence of intersectoral technological spillover effect in case of 15 out of 18 sectors in Lithuanian manufacturing industry. In case of a few sectors error terms of VAR models are not stationary suggesting that additional exogenous variables need to be included to increase accuracy of estimated coefficients before these models can be used in further analysis. After minor changes presented VAR models can be used for sensitivity analysis analyzing how changes in different sectoral level parameters affect economic development of manufacturing industry as a whole.

Keywords: *Technological progress, Technological Spillover, Manufacturing industry, Vector autoregression, Intersectoral Spillover*

1. Introduction

Theories of economic growth are essential to understand what factors lead to sustainable economic development of different markets. In neoclassical growth theories technological progress is a major factor in explaining consistent economic progress during long term periods. Despite its importance, there are critiques various of technological progress assessment methodology. Neoclassical growth theories, like Solow model, analyze technological progress as and exogenous variable, which can lead to lack of understanding which factors lead to structural changes of technological progress values. Long-run growth of income per capita in such models requires exogenous improvements in

technology in order to generate the expected productivity growth (Crafts 1995). According to Burkett (2006), one of the most important problems with neoclassical approach to technological progress effect on economic growth is the joint analysis of all factor inputs. Jerzmanowski (2006) agrees to the notion and adds that mismeasurement of inputs and omission of important variables can lead to erroneous technological progress effect on economic growth as technological progress affecting variables are not included into models where technology is analyzed as an exogenous parameter. For these reasons neoclassical growth theories do not indicate changes in which particular factors lead to sustainable and most efficient economic growth. Thus, some improvements in evaluation of technological progress need to be made to better understand economic development tendencies.

One of the ways to improve technological progress evaluation is by assessing the measure as endogenous variable. Inclusion of technological progress in economic growth models as dependent variable helps to analyze which exact factors and to what extent affect technological progress fluctuations. It also helps to examine whether technological progress spillover effect between countries and sectors exist, which immensely alters the way economic growth theories should be utilized in analyzing economic growth. For this reason, the gap which this research paper tries to cover is the improvement of technological progress evaluation in economic growth theories.

The main goal of this research is to construct a framework which would help to evaluate intersectoral technological spillover effects of sectors in Lithuanian manufacturing industry and analyze whether the results gained from created models coincide with the actual estimated values of technological progress measures.

Paper consists of literature review, where theoretical framework for performed research is depicted, methodology section, where empirical part of the research is shaped, findings, where results of performed research is presented and interpreted, and conclusions.

2. Literature Review

In the given context of the current degree of globalization, economic growth and expansion can be attributed to capacity of local production, extent of economic trade and foreign direct investment flows. Growth in manufacturing industries is a result of different factors: labor, science and technology, capital, policies, infrastructure and more (Zhang, Wu and Zhong 2018). Out of all the factors labor and capital are measurable, while others are hard to determine. For this reason, all of the intangible factors are grouped into science and technological progress indicators. There are a couple of factors which affect productivity growth: technological progress and technological efficiency (Shahabinejad, Yaghoubi and Mehrjerdi 2013). Technological progress is achieved when production frontier is shifted upwards due to technological improvements. Technological efficiency rises when the actual production of economy approaches potential production frontier value. In the long run growth of the economy is achieved because of technological progress.

Based on Solow neoclassical growth theory, long-run economic growth and increase in amount of production per labor unit depends only on technological progress (Acikgoz and Mert 2014). In the short-run economic growth can be determined by increasing capital accumulation, but long-run sustainable economic growth is believed to be essentially dependent upon increase in population and rate of technological progress (Yao, Hsieh and Hamori 2007). Technological progress at macro level can be estimated using Total Factor Productivity (TFP) measure, while at micro level research and development (R&D) expenses can be used as technological progress proxy. If R&D expenses cannot be obtained, annual number of patent applications can be used as indicator of research and development. According to Tan and Wei research (2019), increasing R&D expenses enhance companies' profitability measures, revenue growth rate, help to reduce production costs and improve market share. This leads to strengthened financial situation, although the effect is measured to be lagged. Investment into R&D and human capital also tends to reduce inefficiencies and bring produced output values closer to production possibility frontier (Chalk 2015). For R&D to be utilized efficiently, desirable external factors should be present. A research by Olayiwola (2014) indicated, that

in case of Nigerian manufacturing industry, increasing R&D expenses should be encouraged through effective policy frame by the government in order to maintain a sustainable technological progress growth. Akanbi, Padayachee and Bosch (2011) indicated that the ability to invest into capital and research depends on financial constraints of the market. With less developed financial markets it might be difficult to get the required funds for investment.

Equation 1, which is commonly used in analysis of economic growth sources, is presented here:

$$\ln \left(\frac{Y}{L}\right)_t = C + \alpha \ln \left(\frac{K}{L}\right)_t + u_t \quad (1)$$

In the given equation Y represents the level of output, while L is labor and K is capital stock. Coefficient α in the given context represents output elasticity of capital. According to Lin and Liu (2017) research, the output elasticity of capital in China between the years 1980-2014 varied between 0.5 and 0.6. C constant coefficient from equation 1 is decomposed in equation 2, where A depicts TFP value.

$$C = (1 - \alpha) \ln A \quad (2)$$

TFP helps to assess the efficiency of exploitation and utilization of resources, like manpower, material and financial resources (Zhang, Wu and Zhong 2018). TFP can be evaluated using two different methods: growth accounting and economic measurement. Growth accounting method is based on neoclassical growth theory. The estimation process using growth accounting method is relatively simple and the factors are less, but the main disadvantage is that the constraint is strong. Economic measure method uses various econometric models to evaluate TFP and includes more factors in a more comprehensive way, although estimation process is more complex.

In many economic growth models TFP is defined as a multiplicative technology term in the production function (Fernald 2014). Although under standard conditions statistical definition of TFP corresponds with multiplicative term, in a heterogenous model, under constant-returns restrictions and with perfectly competitive producers' market, definition of TFP can be interpreted as an outward shift in society's aggregate production possibilities frontier.

Besides capital and labor, some studies include energy into production function analysis (Yang et al. 2017). Inclusion of energy as a parameter in analysis of production function reflects the contribution of energy-saving technology to the improvement of total general technological progress development. Technological progress is also an indispensable factor in terms of importance for the environment (Pham, Huynh, Nasir 2020). In this case technological progress can be defined with a given function:

$$TC_{it} = \frac{\partial \ln f(x_{it}, \beta)}{\partial t} = \alpha_1 + \alpha_2 t + \alpha_3 \ln K_{it} + \alpha_4 \ln L_{it} + \alpha_5 \ln E_{it} \quad (3)$$

Technological progress, which is created through expanding global value chains, can also affect the utilization of energy resources. According to Wang et al. (2020), there exists an inverted U-type nonlinear relationship between China's manufacturing sector participation in global value chain and intensity of energy consumption in production. At first participation in global value chain leads to increasing energy intensity in production, while higher degree of participation leads to energy intensity reduction in manufacturing industries.

Tabuchi, Thisse and Zhu (2018) research suggests that technological progress inequality could be one of the main reasons for emergence of regional disparities. The results also indicate that workers in more technologically advanced countries have larger incentive to invest in human capital as price of an efficiency unit of labor is higher and this gives stronger impulsion to improve skills. Besides that, with free flow of labor workers tend to concentrate in regions where their work is rewarded with higher pay. Zhou and Lou (2018) also agree that investment into human capital is the driving force of social and economic development, while education is an important way for knowledge precipitation and accumulation. Increasing the education input can lead to gradual increase of high-quality human capital accumulation, which promotes technological innovation and progress. While neoclassical economic theories treat technological innovation as an exogenous variable, more modern growth theories recognize technological innovation as mainly being affected by factors, such as human resource accumulation and human resource level.

Satpathy, Chatterjee and Mahakud (2017) research concluded that in case of Indian manufacturing industry, technology, size and competition in form of raw material imports are the main sources of productivity growth. Estimations indicated that firm size had a positive effect on some of sectors in Indian manufacturing industry, while disembodies technological intensity and R&D expenses had a significant positive effect on technological progress development all throughout the industry.

International trade is also distinguished as a factor, which affects technological progress (Lin, Chen and Zhang 2018). If a manufacturing sector is export oriented, it encounters competition with local companies in the sectors. When trying to compete not only with internal market competition, but also with foreign companies, reduction of energy and other input recourse consumption can lead to reducing costs, which strengthens global competitive position. Higher levels of international trade can also slow down structural transformation of economies in high-income countries (Dauth et al. 2017). In case of Germany, a trend of secular decline in manufacturing and rising employment in service sector, which is usually perceived in technologically advanced countries, was impeded by increasing trade with low-wage countries. Foreign direct investment (FDI) is also one of the factors, which can highly influence development of technological progress. Increasing FDI can lead to creation of new jobs, enhancement of technological progress transfer and boost of economic growth in host countries (Belloumi 2013). The effect of FDI on host country can depend on different factors. If the technological gap is wide between two countries, then the effect of FDI to host country will be significant. Also, the effect of FDI is observable on the long-run basis.

According to Fernald (2014), TFP measure might end up being biased during recessions. For the measure to be suitable for technological progress measurement, it should control for labor composition. During economic downturns labor quality systematically rises as workers with lower skills and education are more likely to lose their jobs.

In order to assess cointegration between two time series, Granger causality can be used. Granger causality indicate, that if two time series are individually I(1) and cointegrated, causal relationship will exist at least in one direction (Oxley, Greasley 1998). If bivariate cointegration between parameters exists, then either unidirectional or bidirectional Granger causality must also exist, although in finite samples there is guarantee that the tests will identify it. Even if Granger causality is identified in a bivariate model, the relationship may not be Granger-causal in a larger model with more variables involved (Leutkepohl 2011). When additional variables are included in the model, bivariate causal structure may disappear. Despite of that, Granger causality can help to identify, whether one variable's lagged values can be included into vector autoregression (VAR) equation of another variable (Zhou and Luo 2018). Evaluation of Granger causality between two variables can be identified with the given equations:

$$X_t = \alpha + \sum_{i=1}^m \beta_i X_{t-i} + \sum_{j=1}^n \gamma_j Y_{t-j} + u_t \quad (4)$$

$$Y_t = a + \sum_{i=1}^q b_i Y_{t-i} + \sum_{j=1}^r c_j X_{t-j} + v_t \quad (5)$$

Vector auto-regression (VAR) econometric model is broadly used for analysis of dynamic impact and relationship between different variables (Zhou and Luo 2018). VAR model is based on statistical properties of data, where construction of model is carried out by considering endogenous variables as functions of hysteresis values of every other endogenous variable in the system. Therefore, VAR helps to explain multivariate set of endogenous variables uniquely, exploring and capturing the dynamics of linear interactions in multivariate processes (Damasio and Mendonca 2019). VAR model's basic mathematical expression is presented in 6 formula:

$$y_t = \alpha_1 y_{t-1} + \dots + \alpha_p y_{t-p} + Hx_t + \varepsilon_t \quad (6)$$

In the given expression y_t is the column vector of k-dimensional endogenous variable with lag intervals of p, while x_t represents values of exogenous variables. As presented in X equation, advantage of VAR is that the model can include other exogenous explanatory variables while still only describing interaction between endogenous variables in their lagging periods and their current

period. VAR model can be constructed with either I(1) or I(0) variables (Oxley and Greasley 2010). If the data is I(1) and not cointegrated, causality tests cannot validly be derived unless the data is transformed to induce stationarity.

VAR models are one of the best for evaluation of shock transmission among variables as they provide information on impulse responses (Effiom et al. 2011). With the help of VAR models impulse response functions can be obtained, which informs how and at what magnitude variables are affected by changes in other endogenous variables. Impulse response analysis studies the relations between variables and how the effects of nonzero residuals or shocks are traced through the system, propagating from one variable to another (Leutkepohl 2011).

3. Methodology

To assess which factors affect technological progress values of Lithuanian manufacturing sectors VAR model, presented in 7 equation, is used.

$$A_{i,t} = \alpha_i + \sum_{k=1}^3 \beta_{i,t-k} A_{i,t-k} + \sum_{k=1}^3 \beta_{j,t-k} A_{j,t-k} + \sum_{k=1}^3 \beta_{i,t-k} INV_{i,t-k} + \beta_{i,t} LP_{i,t} + \beta_{i,t} CR_{i,t} + \beta_{i,t} GP_{i,t} + \varepsilon_i \quad (7)$$

Separate models are designed individually for every sector operating in manufacturing industry. Technological progress values are represented by TFP measures, estimated based on Solow's neoclassical growth theory's methodology. Independent variables can be divided into endogenous and exogenous. Endogenous variables are included in models with their lagged values (t-k) compared to dependent variable, while exogenous variables – with equal time period to dependent variable (t). Endogenous variables in the given VAR models were chosen to be included with maximum lag value of 3. This maximum lag value was chosen for two reasons. Firstly, according to Verspagen and Loo (1999), intersectoral spillover effect reaches its peak after two-year period and after three years spillover effect starts to decline rapidly. For this reason maximum lag value of 3 years should be enough to establish intersectoral technological spillover effect. Secondly, annual data for sectors in Lithuanian manufacturing industry currently is available for only 19 years and larger lag values would firmly reduce degrees of freedom of the model thus potentially distorting results of the models.

Looking at endogenous variables of VAR model, $A_{i,t-k}$ represents lagged TFP values of the dependent variable while $A_{j,t-k}$ represents lagged TFP values of other manufacturing sectors, which potentially affect technological progress values of dependent variable. Out of all sectors in Lithuanian manufacturing industry the ones, which should be included in VAR model, were chosen with the help of Granger causality method. Last endogenous variable, presented as $INV_{i,t-k}$, depicts reinvestment ratio. It is estimated as annual amount spent on long-term tangible and intangible assets, divided by average annual book value of long-term capital.

Out of all the exogenous variables, included in VAR model, $LP_{i,t}$ depicts labor productivity ratio. It is estimated as prime cost of annually produced goods and worked hours per year ratio. $CR_{i,t}$ independent variable represents capital structure ratio (average annual foreign capital value divided by value of total annual capital employed). Lastly, $GP_{i,t}$ measure represents annual inflation adjusted gross profit values of sectors in Lithuanian manufacturing industry.

All of the information used in VAR models and utilized in evaluation of technological progress values of sectors in Lithuanian manufacturing sectors was gathered from Lithuanian Department of Statistics.

4. Findings

Table 1 presents results of all VAR models performed on technological progress values of Lithuanian manufacturing sectors. Out of 18 analyzed periods VAR models indicate that spillover effect does not exist in case of 3 sectors, which means that technological progress values of only 3 sectors are not significantly affected by changes in technological progress values of other sectors. The most common scenario is when technological progress value is significantly affected by TFP lagged value of one

other sector. This happened in case of 8 sectors out of 18. Technological progress values of 5 sectors in the analyzed period were jointly affected by changes of TFP in 2 other sectors, in case of 1 VAR model changes in technological progress values were jointly affected by TFP fluctuations in 3 other sectors and there was even a single occasion when technological progress value of a sector was jointly affected by changes in TFP values of 4 different sectors.

Looking at effect of exogenous variables on technological progress values in Lithuanian manufacturing industry, labor productivity had a significant effect on changes of technological progress in case of 10 out of 18 analyzed sectors, capital structure ratio affected changes in technological progress of 7 analyzed sectors, while inflation adjusted gross profit value has affected movement of technological progress value in case of 15 sectors.

Table 2 presents residual variance values of all 18 analyzed VAR models. The goal is to examine whether estimated technological progress values of VAR models with highest residual variance still fit actual values and can be used for analysis of technological progress fluctuations. VAR model for technological progress value of basic metals sector possesses largest residual variance value out of all analyzed sectors, 0.35, which is almost twice as large as the second biggest value, 0.18, measured for VAR model of beverage sector.

Table 1. VAR model of technological progress in Lithuanian manufacturing industry results.

Dependant variable	Independent variables						Dependant variable	Independent variables						
AC10, t	AC28, t-2	DN10, t	UKa10, t	GP10, t			AC23, t	AC23, t-2	AC10, t-1	AC18, t-1	AC27, t-3	AC30, t-2	DN23, t	GP23, t
	0.079 (0.017)	19.42 (0.0004)	2.451 (0.0000)	0.0004 (0.0120)				0.2413 (0.0052)	0.6975 (0.0054)	0.7522 (0.0016)	0.1773 (0.0002)	0.1201 (0.0006)	-59.72 (0.0006)	0.0016 (0.0000)
AC11, t	AC23, t-1	DN11, t	GP11, t				AC24, t	AC33, t-1	UKa24, t	GP24, t				
	0.4646 (0.0073)	29.36 (0.0128)	0.0014 (0.0010)					0.8302 (0.0000)	3.7872 (0.0000)	0.0314 (0.0000)				
AC13, t	AC13, t-1	AC22, t-1	AC22, t-2	INV13, t-2	DN13, t	GP13, t	AC25, t	AC25, t-1	AC25, t-3	AC15, t-2	GP25, t			
	0.1952 (0.0354)	0.2965 (0.0084)	0.3928 (0.0010)	0.0353 (0.0005)	56.2619 (0.0007)	0.0037 (0.0000)		0.4650 (0.0024)	0.4400 (0.0117)	0.1891 (0.0381)	0.0024 (0.0000)			
AC14, t	AC14, t-1	AC14, t-3	GP14, t				AC26, t	AC26, t-2	AC23, t-1	DN26, t	UKa26, t			
	0.5801 (0.0033)	0.4126 (0.0302)	0.0019 (0.0144)					0.5522 (0.0000)	0.2346 (0.0073)	32.4716 (0.0021)	-1.0775 (0.0003)			
AC15, t	AC15, t-2	AC14, t-1	GP15, t				AC27, t	AC27, t-3	AC14, t-2	AC22, t-1	INV27, t-1	INV27, t-3	UKa27, t	GP27, t
	0.3651 (0.0080)	0.3056 (0.0001)	0.0059 (0.0000)					0.4021 (0.0180)	1.5647 (0.0104)	0.7559 (0.0454)	-0.0437 (0.0006)	-0.0415 (0.0064)	4.0751 (0.0003)	0.0025 (0.0130)
AC16, t	AC16, t-1	INV16, t-2	DN16, t	GP16, t			AC28, t	AC28, t-3	AC18, t-1	DN28, t	GP28, t			
	0.4305 (0.0207)	0.0107 (0.0088)	27.35 (0.0039)	0.0006 (0.0008)				0.4094 (0.0000)	1.285 (0.0000)	57.32 (0.0080)	0.0045 (0.0002)			
AC17, t	AC16, t-1	AC27, t-2	AC28, t-3	UKa17, t	DN17, t		AC30, t	AC30, t-1	AC15, t-1	AC27, t-3	INV30, t-2	INV30, t-3	UKa30, t	
	0.3633 (0.0010)	0.0893 (0.0002)	0.0524 (0.0209)	0.8042 (0.0021)	22.9099 (0.0000)			0.6942 (0.0000)	1.9313 (0.0003)	0.8219 (0.0001)	0.1769 (0.0000)	-0.0476 (0.0028)	3.4750 (0.0004)	
AC18, t	AC18, t-2	AC18, t-3	AC11, t-2	AC15, t-3	GP18, t		AC31, t	AC31, t-2	AC11, t-3	AC24, t-3	DN31, t	UKa31, t	GP31, t	
	0.6484 (0.0061)	-0.6361 (0.0362)	0.3262 (0.0061)	0.4949 (0.0053)	0.0006 (0.0002)			0.5165 (0.0004)	0.2023 (0.0129)	0.1846 (0.0056)	66.2128 (0.0028)	-4.2949 (0.0133)	0.0018 (0.0009)	
AC22, t	AC22, t-3	DN22, t	GP22, t				AC33, t	AC33, t-1	AC26, t-1	AC30, t-1	GP33, t			
	0.5874 (0.0005)	22.90 (0.0027)	0.0012 (0.0035)					0.4419 (0.0204)	0.4403 (0.0268)	0.1167 (0.0145)	0.0021 (0.0072)			

Figure 1 compares actual TFP values of sectors operating in Lithuanian manufacturing industry and their estimated values from VAR models. Figure 1 depicts values of sectors which VAR models contain

largest residual variance values. Basic metals sector is the one with largest residual variance. During the period of 2003-2015 modelled TFP value follows the actual value closely, even echoing TFP drop during the economic crisis, which hit basic metals sector in the year of 2009. After 2015 a departure between actual and modelled TFP values can be observed. As actual values between 2015-2018 are larger compared to modelled values, there exists a variable which was not included in VAR model that leads to raising technological progress of the analyzed sector. Inclusion of the missing factor would reduce residual variance of the model.

Table 2. Residual variance values for VAR models of Lithuanian manufacturing sectors

Sector	Variance of residuals	Sector	Variance of residuals
AC24 (Basic metals)	0.3465	AC28 (Other machinery)	0.0326
AC11 (Beverage)	0.1807	AC31 (Furniture)	0.0296
AC30 (Other vehicles)	0.0912	AC25 (Metal products, excluding machinery)	0.0239
AC15 (Leather products)	0.0665	AC18 (Printing)	0.0134
AC27 (Electrical equipment)	0.0544	AC10 (Food)	0.0111
AC33 (Machinery repair and maintenance)	0.0436	AC23 (Other non-metal mineral products)	0.0098
AC26 (Computers, electronics and optical devices)	0.0414	AC16 (Wood and wood products)	0.0055
AC22 (Rubber and plastic)	0.0389	AC13 (Textile)	0.0026
AC14 (Clothing)	0.0330	AC17 (Paper and paper products)	0.0019

Second largest VAR model residual variance is witnessed in case of beverage sector technological progress value. Between the years of 2003-2009 fluctuations in actual and modelled values change in similar patterns. VAR model even manages to depict TFP changes during the period of economic crisis. After that changes in actual and modelled values started differentiating. Differently, then in case of basic metals sector, TFP modelled values diverge in both ways: during the years of 2010 and 2014-2015 modelled technological progress values are lower while in 2013 and 2018 modelled TFP values outgrew actual values. This indicates that VAR model smoothens TFP changes of beverage sector, not depicting the more rigid changes of technological progress measure, while still managing to convey the general movement of TFP values.

Third largest residual variance out of 18 constructed models is witnessed for other vehicles sector. Figure 1 indicates that modelled value follows actual TFP values accurately all throughout the analyzed period. Large residual variance can be attributed to high values of TFP. Technological progress measure in 2018 almost reaches a value of 10. For this reason, large residual variance value emerged not because modelled values of TFP deviated from actual values of technological progress, but due to high TFP level.

Modelled value of leather products sector deviated from actual values of technological progress due to a few reasons. Firstly, in VAR model value of technological progress in the year of 2003 is hugely understated. Actual TFP value is around 1.53 while modelled – 0.56. Secondly, peak TFP value, 1.83, which is reached in 2008, is understated in model (1.57). Other than these two years, deviation from actual TFP values can be witnessed on different time frames but general movement of technological progress is reproduced pretty well. After fixing departures of modelled technological progress values in the before mentioned years given VAR model can be used to analyze fluctuations of leather products sector technological progress variation.

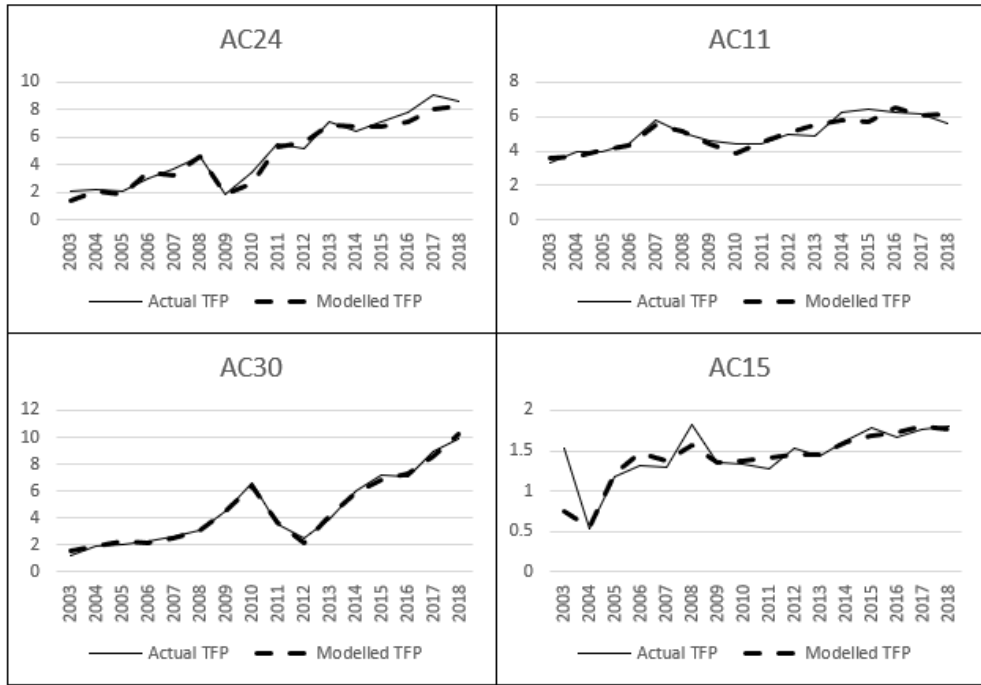


Figure 1. Technological progress actual and VAR modelled values of Lithuanian manufacturing sectors with largest residual variance values.

All in all, VAR models with even the highest residual variance measures represent changes of actual TFP values pretty closely. After some adjustments and inclusion of additional variables, which would increase the fit of given VAR models, obtained functions can be used for analysis of fluctuations in technological progress values.

Figure 2 presents residual values of VAR models with largest residual variance in order to analyze whether no trend exists in residuals. Non-staticity in residual values of technological progress models would lead to distortion of TFP measures. This would indicate that VAR models are inappropriate to analyze fluctuations of technological progress values.

Analyzing residuals of basic metals VAR model, it can be witnessed that in case of most periods residual values are positive, especially at the end of analyzed time interval. This means that actual values for the most part are larger than modelled values. Residual values of the sector could be diminished to an average value of 0 by including additional variables into the VAR model which would explain part of the actual TFP measure fluctuations not reflected in the model.

Beverage and other vehicles sectors residual values of constructed VAR models fluctuate around 0 value all throughout the analyzed period. In case of other vehicles sector increase in fluctuations of residual values can be witnessed at the later years of analyzed period, suggesting possible heteroscedasticity in the VAR model refuting assumption required for the model to be static. Despite of that the change in residual values seems to be random and no formation of trend can be perceived. More detailed tests are required to analyze whether VAR model of other vehicles sector can be classified as static.

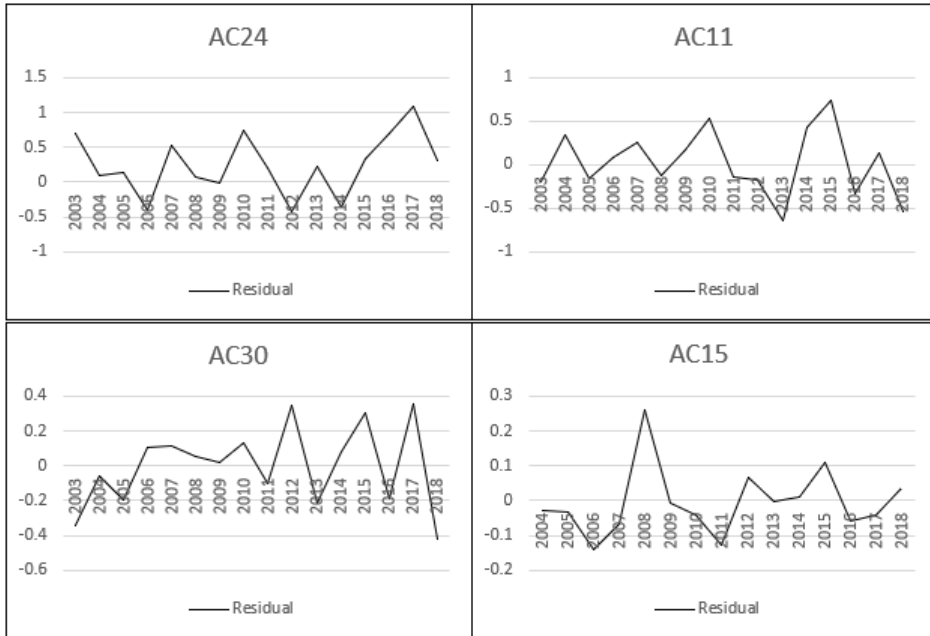


Figure 2. Residual values of VAR models with largest technological progress residual variance

For leather products VAR model a spike in residual values can be witnessed in the year of 2008. This means that the variables, which are included in VAR model, do not explain the rapid increase in technological progress value right before the economic crisis occurred. Besides the discrepancy in 2008 and before mentioned deviation at 2003, residuals all throughout the other years fluctuate around the value of 0 with no trends noticeably taking place.

Table 3 presents results of augmented Dickey-Fuller (ADF) test which evaluates cointegration (joint stationarity) of VAR models for each of the sector in Lithuanian manufacturing industry. ADF assesses error terms of VAR models in three different ways: with no intercept and no trend included into unit root evaluation equation, with intercept and no trend, with intercept and with trend. Most significant results of ADF tests was gained when estimation equations did not include no intercept and no trend. According to ADF test results only VAR model of basic metals sector is non-stationary. Other 17 VAR models possess cointegration thus making them jointly stationary. For these 17 VAR models estimated coefficient values are proper for assessment of technological spillover effect between sectors.

Table 3. Augmented Dickey-Fuller test statistic values of VAR model error terms

Sector	None	Intercept	Intercept and trend	Sector	None	Intercept	Intercept and trend
AC10	-2.086 **	-2.051	-2.245	AC23	-3.273 ***	-3.104 **	-2.961
AC11	-3.297 ***	-3.175 **	-3.067	AC24	-1.624 *	-2.192	-2.488
AC13	-4.827 ***	-4.596 ***	-4.441 ***	AC25	-2.465 **	-2.361	-1.871
AC14	-2.194 **	-2.085	1.810	AC26	-4.283 ***	-4.136 ***	-3.919 **
AC15	-3.878 ***	-3.715 **	-3.529 *	AC27	-2.999 ***	-2.859 *	-2.637
AC16	-2.587 **	-2.443	-2.634	AC28	-2.466 **	-2.394	-2.431
AC17	-4.130 ***	-3.955 ***	-3.759 **	AC30	-2.994 ***	-3.366 **	-2.902
AC18	-3.072 ***	-2.929 *	-2.751	AC31	-3.506 ***	-3.397 **	-3.043
AC22	-3.703 ***	-3.556 **	-5.07 ***	AC33	-2.663 ***	-2.555	-2.230

Represents significance levels: '***' – 0.01, '**' – 0.05, '*' – 0.10

5. Conclusions

Analysis of literature indicated that in order to assess how different factors affect fluctuation of technological progress values of companies in manufacturing industry, best option is to use vector autoregression model. In the case of Lithuanian manufacturing industry constructed VAR models have two different kinds of independent variables – endogenous, which are included in models with their lagged values, and exogenous, which are included in models with the same time period as dependent variables.

18 VAR models, one for each sector in Lithuanian manufacturing industry, were constructed in order to assess which factors and by how much affect changes in technological progress values. These models were also built to evaluate whether intersectoral spillover effect of technological progress takes place in Lithuanian manufacturing industry takes place. The analysis showed that in case of only three sectors out of analyzed 18 significant evidence of technological spillover effect was not witnessed.

Residual variance analysis of all 18 VAR models indicated that even in case of models with highest values of residual variance, modelled values echoed movement of actual technological progress values quite closely. No clear seasonality in residuals of VAR models was witnessed, which means that errors of the models did not distort tendencies of technological progress value changes. Augmented Dickey-Fuller test suggests that only in case of 1 sector out of 18 analyzed cointegration between evaluated parameters does not exist. Due to non-stationarity coefficients estimated from VAR model of basic metals sector are not suitable for evaluation of technological spillover effect between sectors. Results of other 17 VAR models are significant, and they suggest that technological spillover effect between sectors in Lithuanian manufacturing industry is observable.

References

- Acikgoz, S. & Mert, M. (2014). Sources of Growth Revisited: The Importance of the Nature of Technological Progress, *Journal of Applied Economics*, 17:1, 31-62, DOI: 10.1016/S1514-0326(14)60002-7.
- Akanbi, O. A., Padayachee, V. & Bosch, A. (2011). The macroeconomic determinants of technological progress in Nigeria. *South African Journal of Economic and Management Sciences*. 14. 282-297. 10.4102/sajems.v14i3.17.
- Burkett, P. (2006). Total Factor Productivity: An Ecological-Economic Critique. *Organization & Environment - ORGAN ENVIRON*. 19. 171-190. 10.1177/1086026606288744.
- Cardarelli, R. & Lusinyan, L. (2015). U.S. Total Factor Productivity Slowdown: Evidence from the U.S. States. *IMF Working Papers*. 15. 1. 10.5089/9781513520834.001.
- Crafts, N. (1995). Exogenous or Endogenous Growth? The Industrial Revolution Reconsidered. *The Journal of Economic History*, 55(4), 745-772.
- Damasio, B. & Mendonca, S. (2019). Modelling insurgent-incumbent dynamics: Vector autoregressions, multivariate Markov chains, and the nature of technological competition. *Applied Economics Letters*, 26:10, 843-849.
- Dauth, W., Findeisen, S. & Sudekum, J. (2017). Trade and manufacturing jobs in Germany. *DICE Discussion Paper*, No. 242, ISBN 978-3-86304-241-7, Düsseldorf Institute for Competition Economics (DICE), Düsseldorf.
- Effiom, L., Ubi, P., Okon, E. & Eyo, E. (2011). Trade Liberalization and Human Capital in Nigeria: a Vector Autoregressive Analysis. *European Journal of Economics, Finance and Administrative Sciences*.
- Fernald, J. (2014). A Quarterly, Utilization-Adjusted Series on Total Factor Productivity. *Federal Reserve Bank of San Francisco Working Paper 2012-19*.
- Jerzmanowski, M. (2007). Total Factor Productivity Differences: Appropriate Technology Vs. Efficiency. *European Economic Review*. 51. 2080-2110. 10.1016/j.euroecorev.2006.12.005.
- Lin, B., Chen, Y. & Zhang, G. (2018). Impact of technological progress on China's textile industry and future energy saving potential forecast. *Energy, Volume 161*, Pages 859-869, ISSN 0360-5442.
- Lin, B. & Liu, K. (2017). Energy Substitution Effect on China's Heavy Industry: Perspectives of a Translog Production Function and Ridge Regression. *Sustainability*. 9. 1892. 10.3390/su911892.
- Luetkepohl, H. (2011). Vector Autoregressive Models, *Economics Working Papers ECO2011/30*, European University Institute.

- Mounir, B. (2013). The relationship between trade, FDI and economic growth in Tunisia: An application of the autoregressive distributed lag model. *Economic Systems*, 38, 269–287. 10.1016/j.ecosys.2013.09.002.
- Olayiwola, O. (2014). Technical change and total factor productivity growth in Nigeria manufacturing sector: A malmquist index approach. *Sai Om Journal of Commerce and Management*, 1, 11-18.
- Oxley, L. & Greasley, D. (1998). Vector autoregression, cointegration and causality: testing for causes of the British industrial revolution. *Applied Economics*, 30:10, 1387-1397, DOI: 10.1080/000368498325002.
- Pham, N. M., Huynh, T. L. D. & Nasir, M. A. (2020). Environmental consequences of population, affluence and technological progress for European countries: A Malthusian view. *Journal of Environmental Management*, Volume 260, 110143, ISSN 0301-4797.
- Satpathy, L., Chatterjee, B. & Mahakud, J. (2017). Firm Characteristics and Total Factor Productivity: Evidence from Indian Manufacturing Firms. *Margin: The Journal of Applied Economic Research*, 11, 097380101667601.
- Shahabinejad, V., Mehrjerdi, M. & Yaqubi, M. (2013). Total Factor Productivity Growth, Technical Change and Technical Efficiency Change in Asian Economies: Decomposition Analysis. *Iranian Journal of Economic Studies*, 2, 47-69.
- Tabuchi, T, Thisse, J. F. & Zhu, X. (2018). Does technological progress magnify regional disparities? *International Economic Review*, 59, 10.1111/iere.12283.
- Tan, K. & Wei, S. (2019). An Empirical Study on R&D Investment and Financial Performance of Listed Companies in Liaoning Equipment Manufacturing Industry. *Proceedings of the 5th International Conference on Economics, Management, Law and Education*, 10.2991/aebmr.k.191225.049.
- Verspagen, B. & Loo, I. D. (1999). Technology Spillovers Between Sectors and Over Time. *Technological Forecasting and Social Change*, Volume 60, Issue 3, 1999, Pages 215-235, ISSN 0040-1625.
- Wang, L., Yue, Y., Xie, R. & Wang, S. (2020). How global value chain participation affects China's energy intensity. *Journal of environmental management*, 260, 110041.
- Yang, Z., Shao, S., Yang, L. & Liu, J. (2017). Differentiated effects of diversified technological sources on energy-saving technological progress: Empirical evidence from China's industrial sectors. *Renewable and Sustainable Energy Reviews*, Volume 72, Pages 1379-1388, ISSN 1364-0321.
- Yao, W. J., Hsieh, Y. C. & Hamori, S. (2007). An Empirical Analysis about Population, Technological Progress, and Economic Growth in Taiwan. *Economics Bulletin*, Vol. 15, No. 23 pp. 1-13.
- Zhang, H., Wu, J. & Zhong, N. (2018). An Empirical Analysis of the Effect of Total Factor Productivity on Manufacturing Performance. *Proceedings of the 2018 3rd International Conference on Modelling, Simulation and Applied Mathematics*, 10.2991/msam-18.2018.57.
- Zhou, G. & Luo, S. (2018). Higher Education Input, Technological Innovation, and Economic Growth in China. *Sustainability*, 10, 2615, 10.3390/su10082615.