DYNAMIC ANALYSIS OF THE ICTS USAGE IN THE SENSE OF PRODUCTIVITY GROWTH

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Abstract

The aim of this paper is to analyse productivity growth in the Czech manufacturing industry elicited by the ICTs use. We applied the vector autoregression (VAR) model, which allows us to examine time lags effects of the ICT-capital on the productivity growth. Available time series data are limited for the purpose of such analysis therefore we attempted to model additional data by using autoregressive (AR) model. We involved 14 industries which were observed in time period from 1990 to 2007. Our ambition is to study time delays effects between implementation of ICTs in the industry and the resulting productivity growth.

***Keywords*:** *ICT, VAR model, AR model, Productivity Growth, Czech Republic*

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1 INTRODUCTION

It is undeniable that ICTs present one of the key innovations of the last century. Many studies as well as the report of the European Commission from 2005 identify ICTs as an important driver of economic and employment growth. According to this report the ICTs contribute to more than 40% of the EU overall productivity growth (REDING, V., 2005).

Moreover, the new strategy “Europe 2020” emphasizes the importance and potential of ICTs in terms of removing negative effects of the crisis and preparing EU economies to the challenges of the next decade. The main objective is to find new methods and tools for measuring the digital economy, the development of global economy, the inflow of investment in the ICTs research and development, but also educated human capital and innovative ideas.

ICTs can be considered a new type of capital goods and increasing investment in ICTs could lead to the labour productivity and TFP (Total Factor Productivity) growth if ICTs include real technological change (Smith, 2001).

Subsequently, investment into ICTs could complement or substitute investment into other capital goods and so increase production capacity of sectors and industries using ICTs.

Despite of expectations that increasing computing power enhances productivity growth, many early studies in the 70th and 80th indicated negative effects of ICTs in relation to productivity. This concept is sometimes referred to as “Solow computer paradox”. Many authors have attempted to reveal the conflict between the expected and actual effects of the ICTs statistics. The results of their work provide several explanations of the negative ICTs impacts on the economic growth. For example, Brynjolfsson and Yang (1996) listed some possible explanations of the “productivity paradox” like measurement errors, time delay of pay-offs from information technology, the effect of the redistribution factor (which means that the competitive advantage obtained by the company due to pioneer introduction of ICTs is quickly absorbed by other companies or ineffective management of the ICT investments (including “maverick spend” etc.).

The aim of this paper is to focus on the problem of time inconsistency and try to reduce it by applying dynamic analysis of the ICTs impacts. We will examine the volatility of firm productivity depending on the ICTs use and try to find out how fast the productivity changes can occur by incorporating ICTs into use. For example, econometric study by Brynjolfsson et al. (1994) shows that the entire affect of ICTs becomes evident in a period of two to four years. Referring to this argument but regarding to limited data available we will test our analysis for maximum 3 years delays.

2 DATA

For the empirical analysis of the ICTs impacts, annual data of the Czech Republic from 1995 to 2007 have been used. They were obtained from the released data contained in the EU KLEMS database. We used time series data about the ICT-capital stock (coded in this analysis as *ictk*) in millions CZK, non-ICT capital stock input (*noictk*) in millions of CZK, total working hours of employees in millions (*hour*) and gross value added at current basic prices in millions CZK (*va*) for 14 manufacturing industry branches (Table 1. provides overview of analysed industries as well as their codes used in further analysis for simplification). We understand the ICT-capital as a whole amount of ICTs employed and used in the industry. For the purpose of our analysis we decided to use gross value added per hour (*vahour*) as measure of productivity growth in the industry. The quantity of value added is measured in the EU KLEMS research as a function of only capital, labour and time.

Table 1: Industries overview

INDUSTRIES OVERVIEW (with coding)	
FOOD , BEVERAGES AND TOBACCO	1 5a6
TEXTILES, TEXTILE , LEATHER AND FOOTWEAR	1 7t9
WOOD AND OF WOOD AND CORK	2 0
PULP, PAPER, PAPER , PRINTING AND PUBLISHING	2 1a2
CHEMICAL, RUBBER, PLASTICS AND FUEL	
- Coke, refined petroleum and nuclear fuel	2 3
- Chemicals and chemical	2 4
- Rubber and plastics	2 5
OTHER NON-METALLIC MINERAL	2 6
BASIC METALS AND FABRICATED METAL	2 7a8
MACHINERY, NEC	2 9
ELECTRICAL AND OPTICAL EQUIPMENT	3 0t
TRANSPORT EQUIPMENT	3 4a35
MANUFACTURING NEC; RECYCLING	3 6a7
ELECTRICITY, GAS AND WATER SUPPLY	4 0a1

Source: EU Klems, 2007

The aim of this analysis is to find out, whether the ICT-capital stock leads to higher productivity of examined industries as well as how long time after implementing ICTs we could observe impacts on productivity. To answer these questions we decided to apply the vector autoregression (VAR) model. With the VAR process we are able to examine lag values (*t-1, t-2* and *t-3*) of the ICTs time series and their impacts on current (in sense of time period *t*) productivity if occurred.

Available time series data do not provide a sufficient sample for the VAR model, therefore we have used autoregressive model (AR) to generate and model additional data and extend our time series. We have tried to estimate data for the time period from 1990 to 1994. To be honest, we have to admit that the estimated data for the ICTs time series could be biased. ICTs are relatively new technologies that are used massively in the last years and data estimates could be influenced by recent situation and not real state of the ICTs usage in 1990-1994.

3 METHODOLOGY

As mentioned in the previous chapter, in this paper the VAR model is used to ascertain possible lead-lag relationships between the time series. It is a natural extension of the univariate autoregressive model to dynamic multivariate time series. The VAR model has proven to be especially useful for describing the dynamic behaviour of economic and financial time series and for forecasting.[1]

The VAR(p) model is described by the formula:

$$y_t = \delta + \sum_{i=1}^{p} \Phi_t y_{t-i} + \varepsilon_t$$

Let $y_t = (y_{1t}, \dots ,y_{kt})'$, $t = 0, 1, \dots$, denote a k-dimensional time series vector of random variables of interest, p is the lag order of the system, δ is the vector of intercepts and ε_t the vector of white noise with zero mean and positive definite covariance matrix.

The most appropriate method for estimating the parameters of the VAR is a method of least squares. Important decisions in the VAR analysis are the selection of variables and determination of the appropriate length of the delay *p*. To select an appropriate length of the delay, the most commonly used information criterions like - Akaike's or Schwarz – are used.

For this type of model it is important to examine the stationarity of the time series. Stationarity (or the number of differences to obtain stationarity) determines what kind of data can be used for calculations. If the original time series are stationary, they can be directly used to estimate the unknown parameters and then to predict future developments. If the original time series are non-stationary (which occurs very frequently in macroeconomic variables), then in the models may be used only adjusted time series. Stationarity of the time series can be most commonly obtains by difference (or eventually logarithm).

There are several ways to determine the difference order like assessing the time series chart or assessing the shape of the selective autocorrelation function (VACF) and selective partial autocorrelation function (VPACF). But since these two methods of determining the order of differentiation are subjective in nature, it was gradually

[1] Vector Autoregressive Models for Multivariate Time Series

created several tests indicated as a unit root testes. The most commonly used is extended Dickeyov-Fuller test (Augmented Dickey-Fuller tests - ADF test), which was applied in our analysis as well.

The VAR process can be affected by other observable variables that are determined outside the system of interest - exogenous (independent) variables. They can be stochastic or non-stochastic. Naturally the process can also be affected by the lags of these exogenous variables. A model used to describe this process is called a vector autoregressive model with exogenous variables VARX(p,s), which we consider as the most suitable for running of our analysis.

The VARX(p,s) model is written as:

$$y_t = \delta + \sum_{i=1}^{p} \Phi_i y_{t-1} + \sum_{i=0}^{s} \Theta_i^* x_{t-i} + \varepsilon_t$$

Where $x_t = (x_{1t}, ,,,, x_{rt})'$ is an r-dimensional time series vector (of exogenous variables) and Θ^*_i is a $k\ x\ r$ coefficient matrix[2].

Analysing the ICTs impacts on productivity using the VAR model required longer time series than were available. Therefore our ambition was to apply appropriate process to model time series data necessary to construct the VAR model. In time series modelling, the prediction of values is based on the pattern of past values of the variable under study, but not generally on explanatory variables which may affect the system.

An effective procedure for building empirical time series models is the Box-Jenkins approach. We used autoregressive (AR) model for estimating further year of time series. The AR model is a type of random process which is often used to model and predict time series. The autoregressive model is one of a group of linear prediction formulas that attempt to predict an output of a system based on the previous outputs.

The notation AR(p) indicates an autoregressive model of order p. The AR(p) model is defined as:

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t$$

Where $\varphi_1, \ldots, \varphi_p$ are the parameters of the model, c is a constant (often omitted for simplicity) and ε_t is white noise.

4 EMPIRICAL RESULTS

Our analysis follows the Cobb-Douglas production function model, which is adjusted to this form:

$$\ln(vahour) = \ln(ictk) + \ln(noictk) + \ln(hour)$$

[2] SAS - Vector Autoregressive Process with Exogenous Variables

Application of the VAR process proves significant impacts of the ICT-capital on productivity growth on 3 (Coke, refined petroleum and nuclear fuel (23); Basic metals and fabricated metals (27a8); Electrical and optical equipment (30t) industry) out of 14 industry branches used in the analysis.

Coke, refined petroleum and nuclear fuel industry indicates significant impacts of ICTs in third year. These impacts are negative, which means that the use of ICTs decrease productivity of this industry. We can explain negative effects by the ICTs costs, time necessary to adapt new technologies in sense of employees training for instance etc. This industry is not taking advantage of the ICTs investment in examined period. Consequently, we can not consider this industry as flexible in adapting new technologies. But we assume that examination of a longer period would show positive results, which are not reached by our limited analysis. Descriptive statistics also shows that this industry has average use of ICTs about 881 millions CZK, which is 1/3 of the average use in for example Electrical and optical equipment industry (which we consider as the ICTs intensive industry). We have analysed only available industry aggregated data therefore we miss a lot of information about individual firms in this industry and their characteristics. We can look at this industry from two sides. Firstly, the usage of ICTs is lower because core processes in this industry do not necessarily require significant ICT support and increase in ICTs would not lead to higher productivity anyway. Or we can assume that higher increase in the usage of ICTs and improvement and modernisation of business processes would improve their productivity results.

On the other hand, Basic metals and fabricated metals industry shows significant positive impacts of ICTs on productivity immediately at the same time period. 1% increase (yoy[3]) in the ICTs use should lead to 83% productivity increase (yoy). It can mean that this industry can adapt new technologies fast or that there is used limited amount of new technologies necessary for their production, when it is easier for individual companies to adjust their internal processes and train employees in order to use them. Looking at descriptive statistics table of this industry we can observe high mean of the ICT-capital variable. It can mean that companies involved in this industry can be highly efficient in improving their computerization as well as business processes according to ICTs and have higher proportion of well ICT-skilled employees. Unfortunately, we do not have detailed characteristics about individual firms representing this aggregate statistics. For instance, how many companies are involved in comparison with other industries or if there are more larger companies than smaller in this sample. From our results and limited dataset we can only assume that probably they are able to use their resources more effective and more likely they have also good cost-reducing policy because there is significant increase in productivity. Significantly high percentage increase in productivity in this industry is partly

[3] yoy – year over year

disquieting. It can be result of omitted variables which are not involved in this regression but have significant effect on the productivity growth.

In the Electrical and optical equipment industry we can observe significant positive impact of the ICT-capital on increase of productivity in the third year at 5% significance level. 1% (yoy) increase in the ICTs use seems to affect 67% (yoy) increase in productivity. This industry can be considered as intensive user of ICTs and therefore we expected the positive ICTs impacts. Descriptive statistics also indicate that the average value of the ICT-capital is high in comparison to other examined industries (all industries in used sample). As we assumed the positive effects would not arise immediately but with three years time delays in this case. Regarding problems that were mentioned relating to other industries (e.g. insufficient dataset information) we can conclude that there is high potential of ICTs in sense of productivity growth. Tables 2.a) b) and c) present descriptive statistics for the three mentioned industries:

Table 2.a): Coke, refined petroleum and nuclear fuel (23) – Descriptive statistics

Variable	N	Mean	Std Dev	Minimum	Maximum
vahour	18	1105.770	936.850	237.813	3980.600
Ictk	18	881.283	647.784	249.000	2636.000
Noictk	18	24747.810	2363.220	22196.620	28481.000
Hour	18	8.220	5.665	1.725	23.000

Source: Authors, SAS output

Looking at means, Coke, refined petroleum and nuclear fuel industry shows relatively high proportion of non-ICT capital in comparison with ICT-capital. We can also see quite high value added per hour, which can be probably caused by the use of non-ICT capital (e.g. plant, machinery, buildings or vehicles). However, the size of the non-ICT capital of this industry could be biased by its relatively expensive elements, which prices can be incomparably higher than those of the ICT-capital. Industry also indicates small demand for total working hours of employees. Therefore, it seems that this industry is mainly capital-intensive and not labour-intensive. Standard deviation for every variable is quite high, which implies significant differences in their size for individual years of the time series. It may be result of the progressive ICT development, lower demand for labour, inflation, higher or lower number of companies in this industry in certain year etc.

Table 2.b): Basic metals and fabricated metals (27a8) – Descriptive statistics

Variable	N	Mean	Std Dev	Minimum	Maximum
vahour	18	199.625	71.536	39.230	344.759
Ictk	18	5532.800	2319.210	1048.700	9041.000
Noictk	18	186225.690	15301.600	170388.500	218433.000
Hour	18	397.781	36.366	343.000	460.000

Source: Authors, SAS output

In Basic metals and fabricated metals industry, the mean difference between the no-ICT and ICT-capital is slightly smaller but still significant. We can hold the same assumptions for the capital as in the previous case. We can see lower average value added per employee and higher labour intensity in this industry, which may be explained by the industry character or its lower efficiency in the use of available resources.

Table 2.c): Electrical and optical equipment (30t) – Descriptive statistics

Variable	N	Mean	Std Dev	Minimum	Maximum
vahour	18	168.640	71.378	31.871	265.417
Ictk	18	2780.180	2706.540	1035.100	9170.000
Noictk	18	75861.620	28456.760	37202.000	129612.000
Hour	18	268.339	41.098	222.133	347.000

Source: Authors, SAS output

Electrical and optical equipment industry shows smaller difference between average non-ICT capital and ICT-capital. This industry is probably less demanding in sense of expensive plant or machinery or non-ICT capital in general and requires higher proportion of ICTs. Alarming standard deviation of the ICT-capital may reflect significant ICT development and their progressive incorporation into the industry over time.

Following tables (Table 3.a), b) and c) show VARMAX results for these three individual industries:

Table 3.a): Coke, refined petroleum and nuclear fuel (23) – VARMAX results

Equation	Parameter	Estimate	Error	T Value	Pr > |t|	Variable
ldvahour	CONST1	-0.845	0.232	-3.65	0.068	1
	XL0_1_1	-3.074	0.958	-3.21	0.085	ldictk(t)
	XL0_1_2	48.112	13.950	16497.00	0.075	ldnoictk(t)
	XL0_1_3	-2.345	0.771	-3.04	0.093	ldhour(t)
	XL1_1_1	-2.662	0.823	-3.24	0.084	ldictk(t-1)
	XL1_1_2	2.873	6.288	0.46	0.693	ldnoictk(t-1)
	XL1_1_3	0.550	0.365	18264.00	0.271	ldhour(t-1)
	XL2_1_1	-1.691	0.426	-3.97	0.058	ldictk(t-2)
	XL2_1_2	7.768	6.009	47119.00	0.325	ldnoictk(t-2)
	XL2_1_3	-2.485	0.844	-2.95	0.099	ldhour(t-2)
	XL3_1_1	-1.434	0.326	-4.40	0.048	ldictk(t-3)
	XL3_1_2	1.732	1.162	17899.00	0.275	ldnoictk(t-3)
	XL3_1_3	0.073	0.500	0.15	0.898	ldhour(t-3)

Source: Authors, SAS output

For this table, we can conclude that most of regressors are significant at 10% level except first, second and third lag difference of non-ICT-capital logarithms and first and third lag difference of total working hours of employees logarithms. It means that these variables do not seem to have impact on productivity in this industry. By correlation matrix between regressors that explain total working hours of employees we examined multicollinearity problem. This can cause insignificance and high estimate values of the labour regressors. We focused our analysis on the ICTs impacts. Regression implies negative significant impact at 5% significance level in the third year.

Table 3.b): Basic metals and fabricated metals (27a8) – VARMAX results

Equation	Parameter	Estimate	Error	T Value	Pr > |t|	Variable
ldvahour	CONST1	0.678	0.455	1.49	0.275	1
	XL0_1_1	0.832	0.167	4.97	0.038	ldictk(t)
	XL0_1_2	-8.600	7.254	-1.19	0.358	ldnoictk(t)
	XL0_1_3	-1.275	3.023	-0.42	0.714	ldhour(t)
	XL1_1_1	-0.878	1.187	-0.74	0.536	ldictk(t-1)
	XL1_1_2	-15.853	9.813	-1.62	0.248	ldnoictk(t-1)
	XL1_1_3	-4.050	3.821	-1.06	0.400	ldhour(t-1)
	XL2_1_1	-2.669	2.128	-1.25	0.337	ldictk(t-2)
	XL2_1_2	-5.785	6.578	-0.88	0.472	ldnoictk(t-2)
	XL2_1_3	-1.387	2.537	-0.55	0.639	ldhour(t-2)
	XL3_1_1	-2.098	1.862	-1.13	0.377	ldictk(t-3)
	XL3_1_2	7.273	5.623	1.29	0.325	ldnoictk(t-3)
	XL3_1_3	-3.689	2.754	-1.34	0.312	ldhour(t-3)

Source: Authors, SAS output

In this case almost all the regressors are insignificant at 10% significance level. The only one explanatory variable in this model seems to be difference of the ICT-capital logarithms at the recent time *t*. We expect that there are other omitted variables, which were not included into our analysis or there can be also problem of multicollinearity between explanatory variables.

Table 3..c): Electrical and optical equipment (30t) – VARMAX results

Equation	Parameter	Estimate	Error	T Value	Pr > |t|	Variable
Ldvahour	CONST1	0.092	0.050	1.85	0.206	1
	XL0_1_1	-0.137	0.041	-3.33	0.080	ldictk(t)
	XL0_1_2	2.346	0.618	3.79	0.063	ldnoictk(t)
	XL0_1_3	-1.051	1.193	-0.88	0.472	ldhour(t)
	XL1_1_1	0.177	0.060	2.96	0.098	ldictk(t-1)
	XL1_1_2	2.449	0.691	3.54	0.071	ldnoictk(t-1)
	XL1_1_3	-12.590	1.252	-10.06	0.010	ldhour(t-1)
	XL2_1_1	0.120	0.058	2.05	0.177	ldictk(t-2)
	XL2_1_2	-4.902	0.680	-7.21	0.019	ldnoictk(t-2)
	XL2_1_3	7.812	1.380	5.66	0.030	ldhour(t-2)

XL3_1_1	0.673	0.048	14.07	0.005	ldictk(t-3)
XL3_1_2	1.493	0.574	2.60	0.122	ldnoictk(t-3)
XL3_1_3	-5.787	0.432	-13.39	0.006	ldhour(t-3)

Source: Authors, SAS output

Last model obtains three insignificant results in variables (recent, second and third difference of total working hours of employees logarithms) at 10% significance level. There is most probably problem of multicollinearity of variables, which explain total working hours of employees.

Apart from already mentioned problems there is necessary to point out on other issues of this analysis.

According to the small sample of industries, in which we could observe the ICTs impacts on productivity, we can not definitely conclude which lag of the ICT-capital usage improves profitability of the industry as we expected. We have to admit that analysis brought only one significant result in the Electrical and optical equipment industry. Negative results in the rest of the examined industries could be influenced also by shortage of year data in time series which did not allow us to provide analysis with more delays. It means that ICTs can affect productivity in these industries after longer period than only three years.

Another reason why there is not significant impact of ICTs in the rest of industries could be caused by inefficient computerization, obsolescence and low flexibility of business processes, low investment in ICTs, unqualified or insufficiently trained employees, wrong cost policy etc.

Moreover, we do not have detailed information about the concrete ICTs used in individual companies. In regard of several studies as for instance report about the ICTs impact "Information Society: ICT impact assessment by linking data from different sources", which examined that certain technologies are more contributional for certain industries. Inappropriate even huge investment in ICTs in the industry will not bring expected effects, which could also partly explain insignificant results in the examined industries of our research.

5 CONCLUSION

The main aim of this paper is to examine the ICTs impacts by employing dynamic analysis of the time series. Although the impact of ICTs on economic growth initially was not statistically proven, recent higher quality of data and methodologies as well as for instance taking into account the time factor allow us more precisely describe the ICTs impacts in sense of productivity growth.

Most of the current studies as well as the EC and OECD reports identified ICTs as an important driver of economic growth and employment. Therefore studying the ICTs impacts the macroeconomic and microeconomic level is highly discussed topic. Consequently there is high demand for relevant and reliable models which unable us to determine the effects of ICTs as well as to predict their future development.

This paper is focused on the ICTs impacts in Czech manufacturing industry branches. By application of the VAR model, we obtained statistically significant results for three out of 14 industries. In particular results show significant positive impacts for Electronic and optical equipment industry, when productivity growth is affected by third year lag of the ICT-capital.

This paper explains potential reasons of observed behaviour in the industries. We are also aware of the data problem and insufficient length of the time series in our analysis what can lead to biased results. Therefore we consider our analysis as eventual model or proposal for further research in this field more than explicit evaluation of the ICTs impacts. Our main ambition was to point out on inevitability to involve dynamic models into the ICTs impacts research because they can not be captured immediately. But they need some time to become evident.

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