WORK PRODUCTIVITY IN THE SECTOR OF KNOWLEDGE INTENSIVE SERVICES IN RELATION TO WORK PRODUCTIVITY IN THE MANUFACTURING INDUSTRY

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Abstract: The manufacturing industry represents the most important part of gross output in the Czech Republic. In the long run, it is necessary for the Czech industry to be competitive. At the same time, it can be assumed that foreign pressure on the Czech manufacturing industry will at least partially transform into pressure on professional and scientific activities. Science and research thus play a key role. The aim of the article is to analyse the impact of work efficiency in the branch of professional, scientific, technical, administrative and support service activities (i.e. sections M and N of the CZ NACE classification of economic activities) on the manufacturing industry (section C). Productivity is measured as gross value added to the labor. The quarterly data of the Czech Statistical Office for the period 1995-2020 are used for the analysis. Time series are processed using a Census X12 filter; all variables are tested using the ADF test in two variants for the presence of a unit root. The testing of the long-term relationship is conducted by means of the Johansen test. The results show that both productivity delays in sector C and sectors M and N have a statistically significant impact on productivity in sector C. However, a positive productivity shock in sector C has a negative impact on current productivity and, conversely, a positive shock in productivity in branch M + N in t-1 is positively reflected in branch C at time t.

Keywords: work efficiency, gross value added, time series, knowledge intensive services, Industry 4.0, manufacturing

JEL Classification: J24; O14; L84

INTRODUCTION

The paradigm of Society 4.0 and Industry 4.0 is considered worldwide to be a new phenomenon that brings enormous potential for individuals as well as entire economies (Hinke, 2019). Vochozka et al. (2020) add that these facts undoubtedly affect the so-called knowledge economy as well, the typical feature of which lies in the strong representation of industries that are characterized by a high intensity of research and development in their economic structure. Horák et al. (2019) note that this type of sector includes the technologically demanding sectors of the manufacturing industry as well as the knowledge intensive services sector. Although their uniform definition is internationally respected, there are several differences across the individual countries in these sectors regarding the ratio of science and research representation, i.e. the technological and knowledge intensity (Ludbrook et al., 2019).

Coric et al. (2017) characterize the manufacturing industry as a very important sector focusing on the production and processing of goods which is accompanied by the creation of new commodities or the creation of added value. The final products can take the form of finished goods intended for sale to customers or the form of intermediate products used in the production process. According to Dolourex and Shearmur (2012), in addition to the manufacturing industry, the knowledge intensive services (KIS) sector is also gaining in technological, social and economic importance in individual countries.

López and Ramos (2013) state that knowledge intensive services connect various segments, such as accounting and legal services, engineering, architecture, audio-visual technology, advertising, software, research and development or educational or healthcare services. Despite the existence of obvious differences in these segments, they all share a common feature, namely the employment of highly qualified human resources and being both users and producers of information and knowledge to provide services to their clients.

Piroozfat (2013) argues that the fundamental difference between processing and other types of enterprises is often very obvious, for example when it comes to differences in production and services. According to Olibe (2010), manufacturing companies differ from service companies in the tangibility of their output. Another difference is further reported by Kuruuzum et al. (2010) who state that service providers create a service only when requested by the customer, whereas processing companies produce goods for storage. Another difference may be that the provision of services is labor intensive and cannot be easily automated. On the contrary, processing companies have the possibility of automating their production processes in order to reduce labor demands.

According to Arsalan et al. (2014), business environment currently has a very strong support in the economy knowledge which is transforming knowledge workers as the main source for maintaining and supporting business competencies. As stated by Adriaensen et al. (2016), compared to manual work in the knowledge-intensive services sector, the number and share of workers is constantly growing, worldwide. The author adds that, however, very little is known about the factors of labor productivity that support this sector. Ruostela and Lónnqvist (2013) also believe that the success of today's businesses lies primarily in knowledge workers, with improving their performance and productivity being seen as a key factor in economic growth.

Ramirez and Nembhard (2004) state that measuring labor productivity is a very important activity that is carried out using a variety of effective measurement systems. These make it possible, for example, to monitor individual performance, identify unusual patterns, identify differences that can be attributed to an individual or a work system, or determine the impact of new technologies or a new management philosophy. It can also help improve the recruitment process, identify redundant skills, make forecasts, plan strategically, assign tasks, or create rewards and bonuses.

The term productivity is characterized by Tapasco-Alzate et al. (2020) generally as a relationship between the inputs used and the outputs generated. Specifically, labor productivity is related to the variation of yields depending on the labor needed to add value to the final product. The author further adds that labor productivity in the knowledge-intensive services sector is different (more complex) in comparison with labor productivity in traditional production, i.e. also in the manufacturing industry. These differences are reflected particularly in the high level of complexity involved in the large number and interrelationship of sub-tasks during the provision of services; in the uncertainty due to the limited availability of the required resources or in the variability of the probability of changes during the provision of services.

1. METHODOLOGY

In this paper, we test the influence of labor productivity in the sector Professional, scientific, technical and administrative activities NACE M + N (prod_(t-1)^MN) on labor productivity in the sector Manufacturing - NACE C (prod_t^c). We measure productivity as gross value added to the labor. According to Karabarbounis and Neiman (2014), it is quite common for the share of labor to be measured as compensation to labor relative to gross value added ("gross labor share"). This is caused mainly by the fact that gross value added is often measured more accurately and better than in the case of net value added.

The work is further based on the Czech Statistical Office quarterly data for the period 1995 Q1-2020 Q1. The data come from analyses of the performance of the economy and the labor market in the Czech Republic by the Czech Statistical Office for individual time periods representing a total of 101 data rows. The data file contains data on labor productivity for a given period, namely for sector M and N (i.e. the sectors of knowledge-intensive services standing in the focus of this paper) and sector C (representing

the most important part of gross output in the Czech Republic) of the CZ NACE classification of economic activities. Due to the presence of the seasonal component, all-time series were refined using a Census X12 filter, provided that the individual components have an additive character. In addition to the above-stated, the issue of appropriate procedures for seasonal adjustment of the time series began to receive considerable attention about half a century ago. In the 1950s, an agency called the U.S. Bureau of the Census was established in the United States for this purpose. The known methods that can be encountered in practice include, for example, Census X11 (or Census X11Q) and Census X12, which, as already mentioned, will be used for the purposes of this paper. A characteristic feature of this algorithm is mainly that it applies several specially taken moving averages on a specific time series, which forms a combined filter.

Furthermore, all variables were tested using the ADF test for the presence of a unit root. Two variants were tested. The first variant with intercept and the second variant with intercept and trend. For all variables, it was not possible to reject the null hypothesis of the absence of a unit root. The Augmented Dickey-Fuller (ADF) has been used mainly for its current popularity and ease of use. This fact is confirmed by Aylar et al. (2019), who state that the ADF test is one of the most widely used and well-known unit root tests, based on the first-order autoregressive process model. It can simply be characterized as a common statistical test used to test whether a time series is stationary or not.

In the next step, we tested the logarithmic differences. Differentiated variables are already stationary. We assume that productivity is governed by the I (1) process. To test a long-term relationship, we used the Johansen test (1991), which, however, did not support the presence of a cointegration relationship. The Johansen test is commonly used for general testing of cointegration between several type I (1) time series, admitting the existence of more than one cointegration relationship. It can be stated that in cointegration analysis, the Johansen test is one of the most used tests.

2. RESULTS

Hypothesis testing is based on an estimate of the following ARDL (1,1) model (Pesaran et al. 1998):

$$\Delta \ln prod_t^c = \beta_0 + \beta_1 \Delta \ln prod_{t-1}^c + \beta_3 \Delta \ln prod_{t-1}^{MN} + \epsilon_t, \tag{1}$$

where: $\epsilon_t \sim iid(0, \sigma^2)$.

The results of the estimate for Equation 1 are shown in Table 1. We obtained the residues for the presence of autocorrelation and next heteroskedasticity. The presence of autocorrelation and heteroskedasticity was not demonstrated in any of the tests. We assume that Equation 1 faithfully reflects the dynamics in the model.

Tab. 1: Equation estimates

Variable	Coefficient	Std. Error	p-value
Intercept	0.014	0.004	0.000
$\Delta \ln prod_{t-1}^c$	-0.246	0.095	0.012
$\Delta \ln prod_{t-1}^{MN}$	0.216	0.095	0.025

Note: R2 = 0,114.

Source: Authors.

It is clear from Table 1 that both productivity delays in Sector C and M + N have a statistically significant impact on productivity in Sector C at time t. However, a positive productivity shock in Sector C has a negative impact on current productivity. Specifically, a 1% increase in productivity at time t-1 means a 0.24% decrease in productivity at time t. This finding corresponds with the basic theoretical basis of returns to scale. The company thus collects lower revenues with an increasing production. In the following period, this phenomenon subsequently reduces its production.

Conversely, a positive productivity shock in sector M + N at t-1 will be positively reflected in sector C at time t. Specifically, a 1% increase in productivity in M + N at t-1 means a 0.22% increase in productivity in sector C at time t. This result may be due to the fact that companies from sectors M and N are in a way specific and these companies very often use companies from sector C to outsource their business activities. However, as the coefficient of determination (R2) shows, this relationship is not strong. Although these are aggregated data, only 11% of the variance of the dependent variable was explained.

CONCLUSION

If we monitor the performance of the whole economy, it is necessary to pay attention not only to the overall output of the economy, but also to the productivity of individual inputs. It is also necessary to monitor productivity in individual sectors of the national economy. From a general point of view, productivity can be seen as the ratio of output to input. The most common and simplest process here is the measurement of labor productivity, which can be characterized as gross value added (GVA), hours worked or gross output per worker. The fundamental difference in the assessment of labor productivity lies in fact in the role of work. Sometimes the work is understood in the context of the primary tool designed to achieve the final product, other times it can be the main source, such as technological progress. Countries with high labor productivity have a noticeable gradual increase and modernization of technical equipment. This is a long-term development.

There is no doubt that productivity growth, whether it is the growth of factor productivity, capital productivity or labor productivity, is a necessary prerequisite for ensuring the competitiveness of business entities, but also of the entire national economy. It can be argued that the new EU Member States usually show high labor productivity growth compared to the long-term Member States. In these post-communist economies, the effects of innovation and restructuring processes are manifested.

The aim of this paper was to analyze the impact of work efficiency in the professional, scientific, technical, administrative and support activities on the manufacturing industry. The results of the analysis show that both productivity delays in sector C and sectors M and N have a statistically significant impact on productivity in sector C, but a positive shock in productivity in sector C has a negative impact on current productivity and, conversely, a positive shock. In productivity in sector M + N in t-1 will be positively reflected in sector C at time t. Productivity strengthens the competitiveness of enterprises in the given sectors. Business owners and self-employed persons increase profits, employees can legitimately demand an increase in their wages and salaries. It is therefore clear that thanks to the increase in productivity in the M + N sector, the productivity of one of the most important sectors - the manufacturing industry - is also growing automatically.

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