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CREATIVE DESTRUCTION AND LABOR PRODUCTIVITY IN POLISH MANUFACTURING INDUSTRIES

Agnieszka SZCZEPKOWSKA-FLIS

Kazimierz Wielki University, Bydgoszcz; agnieszka.szczepkowska-flis@ukw.edu.pl,
ORCID: 0000-0003-3946-426X

Purpose: The aim of the study was to determine the impact of creative destruction on labor productivity, with the level of technology in industries as a factor modifying this impact.
Design/methodology/approach: The econometric analysis was conducted for 24 manufacturing industries in Poland in 2018-2021. Employment turnover rates were used as measures of creative destruction. In modeling changes in labor productivity as a function of creative destruction, a classification of manufacturing industries into technical sectors based on the intensity of R&D was used. It was also tested whether the relationship between the examined categories has changed during the COVID-19 pandemic. Regression equations were estimated using the panel OLS.
Findings: The results of the analysis showed that creative destruction had a positive impact on changes in labor productivity, but inter-industry labor reallocation was not pro-efficient. These regularities, both in terms of direction and strength of impact, did not differ during the COVID-19 pandemic. These conclusions apply only to high and medium technology industries. The lack of relationship between job creation, job destruction, labor reallocation and productivity in low-tech industries suggests that there is a threshold of R&D intensity ($I_{R\&D} > 1\%$) required for creative destruction to play an active role in economic processes.
Research limitations/implications: The categories and classification of industries used in the analysis are only approximate measures of creative destruction and technological level, so the further research is required. Especially, it is needed to confirm the thesis about the existence of a threshold of R&D intensity and the impact of creative destruction on labor productivity.
Originality/value: Incorporating the level of technology as a factor modifying the impact of creative destruction on labor productivity allowed to connect two research areas: 1) the effects of technological progress on job destruction/job creation and 2) their impact on labor productivity. The regularities noted in the study may explain, at least in part, the divergent research results regarding the effects of creative destruction measured by employment turnover rates on labor productivity observed at the level of industries, sectors and regions.
Keywords: job creation, job destruction, labor productivity, manufacturing industry.
Category of the paper: Research paper.

1. Introduction

The concept of creative destruction comes from the Theory of Economic Development of J.A. Schumpeter (1960), according to which the source of development processes are innovations, and the mechanism responsible for moving the economy to higher growth paths is based on two different in nature, but interrelated phenomena: the creation of qualitatively different, new elements of the economic system (enterprises, processes, products, technologies, etc.) – creation; elimination of old, ineffective elements of the economic structure – destruction. The consequence of creative destruction is the reallocation of production factors (labor, capital) from less to more effective uses, leading to a change in the economic structure combined with improved efficiency.

Numerous empirical studies concerning efficiency and industry structure which take into account the entries/exits of enterprises, as well as the effects of resource reallocation within incumbent entities (within effect) and between companies (between effect) have generally confirmed the positive impact of creative destruction on productivity and economic growth (Kozłowska, 2010, p. 61-70; Metcalfe, Ramlogan, 2006). Firms turnover and related competition, market selection and reallocation of production factors have been recognized as the basic sources of growth in aggregate productivity (Dachs et al., 2016; Masso et al., 2004). It was also found that the conditions existing in the enterprise environment (structural and technological features of the industry, institutional factors) influence the intensity of creative destruction (firms turnover) and its effects on productivity changes (Kozłowska, 2010, p. 70).

Analogous conclusions are provided by the results of research on the labor market, in which employment turnover rates expressed in terms of job creation and job destruction are used as measures of creative destruction[1]. It has been noted that:

- job creation and job destruction are continuous phenomena, they are an immanent feature of economic processes (Caballero, Hammour, 2000), and the intensity of job creation/destruction and labor reallocation are strongly related to the business cycle (Graves, 2023; Näf et al., 2022; Rembert, 2017),
- more labor flows take place within narrowly defined industries than among them (Caballero, Hammour 2000; Vainiomäki, Laaksonen, 1999), and inter-industry differences in the intensity of job creation and job destruction are a derivative of differences in the technological level (technological intensity and expenditure on R&D), saturation of production processes with human capital (Dachs et al., 2016; Santos et al., 2023; Vainiomäki, Laaksonen, 1999), the nature of technological changes (embodied/non-embodied technological progress) (Dosi et al., 2021; Santos et al.,

[1] The basic premise for using job turnover rates as measures of creative destruction results from the fact that the effect of firms turnover is labor reallocation taking place at the level of companies, industries/sectors, as well as regions (De Loecker, Konings, 2006; Rembert, 2017).

2023), as well as the adaptation of firms to these changes resulting from differences in the costs of adapting new solutions to the skills and technical equipment of employees (Irandoust, 2023; Mortensen, Pissarides, 1998).

Moreover, research results have shown that the effects of job creation, job destruction and labor reallocation on productivity growth are characterized by significant diversity at the level of industries, sectors (Caballero, Hammour, 2000; De Loecker, Konings, 2006) and regions (Kuźmar, 2019). Although these differences may be the result of several factors (research method, analytical perspective, institutional factors), it cannot be ruled out that the complexity of the relationship between technology and employment dynamics plays an important role in this respect.

The results of an empirical study presented in this article for the manufacturing industries in Poland in 2018-2021 are consistent with this view in the sense that the aim of the analysis was to determine the impact of creative destruction, measured by employment turnover rates, on labor productivity, with the level of technology in industries as a factor modifying this impact. Hence, in modeling changes in labor productivity as a function of job creation, job destruction and labor reallocation, a classification of manufacturing industries into technical sectors based on the intensity of R&D was used. Moreover, it was tested whether the economic disruptions and institutional solutions introduced during the COVID-19 pandemic have distorted the relationships between the examined categories.

2. Data and Method

In the study annual data published by the Central Statistical Office for 24 manufacturing industries in Poland in 2018-2021 was used[2]. In line with the research goal, labor productivity was modeled, assuming that it is a function of creative destruction and the accompanying labor reallocation. Gross value added at constant prices from 2018 per employee (variable PP_L) was used as a measure of labor productivity. Referring to many studies on the labor market in the context of creative destruction (Ahmadiani et al., 2022; De Loecker, Konings, 2006; Kuźmar, 2019; Vainiomäki, Laaksonen, 1999), categories describing the movement of employees were used as approximate measures of creative destruction (job creation and job destruction)[3]:

[2] The data was taken from the Statistical Yearbooks of Industry. The latest Statistical Yearbook of Industry 2022 published by the Central Statistical Office contains information for 2021.

[3] The hire (termination) rate is calculated as the ratio of the number of hires less the number of persons returning to work from childcare (the number of terminations less the number of persons granted childcare) during a surveyed year to the number of full-time paid employees as of 31st December from the year preceding the surveyed year (GUS, 2022, p. 199).

- hire rate – job creation (variable *WP*), expressing the share of new employees in employment;
- termination rate – job destruction (variable *WZ*), reflecting the share of dismissed employees in employment.

According to Schumpeter's views, creative destruction is two inseparably connected phenomena: creation and destruction. Therefore, the interaction between *WP* and *WZ* variables was added to the model to fully reflect the impact of creative destruction on labor productivity. It was assumed that the interaction of variables *WP* and *WZ* (*WP*WZ*) in the regression model reflects intra-industry labor reallocation processes.

The basic equation describing the relationship between labor productivity and creative destruction in manufacturing industries was a linear regression model in the form:

$$PP_{L\,jt} = \alpha_0 + \alpha_1 WP_{jt} + \alpha_2 WZ_{jt} + \alpha_3 WP_{jt} * WZ_{jt} \tag{1}$$

Due to the fact that the time scope of the study covers the period of the COVID-19 pandemic and related legal solutions (lockdown, anti-crisis shields) aimed at preventing the spread of the virus and protecting enterprises and jobs, it cannot be ruled out that the creative destruction and its impact on labor productivity were subject to disruptions. Hence, the binary variable *DCOV* was included in the regression equation (1), the value of which was 1 for observations for 2020, and 0 for the remaining years (2018, 2019, 2021). The form of the regression equation is described by the formula:

$$\begin{aligned} PP_{L\,jt} = \alpha_0 + \alpha_1 WP_{jt} + \alpha_2 WZ_{jt} + \alpha_3 WP_{jt} * WZ_{jt} + \alpha_4 DCOV * WP_{jt} + \alpha_5 DCOV \\ * WZ_{jt} + \alpha_6\, DCOV * WP_{jt} * WZ_{jt} \end{aligned} \tag{2}$$

The statistical significance of parameter estimates α_4, α_5, α_6 implies that the impact of the job creation, job destruction, and labor reallocation, respectively, on labor productivity in 2020 differed from the impact recorded for the remaining years. In such a case, the strength of the influence of the variables *WP*, *WZ* and their interaction (*WP*WZ*) on the PP_L variable in 2020 is determined by the sum of the coefficients, respectively: $\alpha_1 + \alpha_4$; $\alpha_2 + \alpha_5$ i $\alpha_3 + \alpha_6$. The lack of statistical significance of parameter estimates α_4, α_5, α_6 means that the impact of the examined categories on labor productivity was identical throughout the research period.

Moreover, assuming that the level of technology is a factor modifying the impact of creative destruction on labor productivity, the GUS classification of manufacturing industries into technical sectors was applied. Based on the intensity of R&D ($I_{R\&D}$), four sectors are distinguished: high technology ($I_{R\&D}$ > 7%), medium-high technology (2.5% < $I_{R\&D}$ < 7%), medium-low technology (1% < $I_{R\&D}$ < 2.5%) and low technology ($I_{R\&D}$ < 1%) (GUS, 2023, pp. 159, 202-203).

Among 24 manufacturing industries only two were classified as high technology. Therefore, instead of four technology sectors, three sectors were distinguished: the high technology sector (*WT*) (including industries from the high and medium-high technology sectors), the medium technology sector (*ST*), identical to the medium-low technology sector, and the low technology sector (*NT*).

In the econometric study, the division of industries according to technology levels was used by including two binary variables in the regression equation (1):

- the *DWT* variable, for which the value of 1 in each year of observation was assigned to industries belonging to the *WT* sector, and the value of 0 to other industries,
- the *DNT* variable, for which the value of 1 in each year of observation was assigned to industries belonging to the *NT* sector, and the value of 0 to other industries.

The estimated regression equation was of the form:

$$PP_{L_{jt}} = \alpha_0 + \alpha_1 WP_{jt} + \alpha_2 WZ_{jt} + \alpha_3 WP_{jt} * WZ_{jt} + \alpha_4\, DWT * WP_{jt} + \alpha_5 DWT * WZ_{jt} + \alpha_6\, DWT * WP_{jt} * WZ_{jt} + \alpha_7\, DNT * WP_{jt} + \alpha_8 DNT * WZ_{jt} + \alpha_9\, DNT * WP_{jt} * WZ_{jt} \tag{3}$$

The interpretation of the regression parameters for the *DWT* and *DNT* variables is analogous to that presented for the binary variable *DCOV*, but in this case the reference point are the results recorded for the sectors classified as medium technology: statistical significance of the parameter estimates α_4, α_5, α_6 (α_7, α_8, α_9) implies that the impact of the *WP*, *WZ* variables and their interactions on the PP_L variable in the *WT* sector (in the *NT* sector) differed statistically from the impact recorded for the *ST* sector. The strength of its impact in the *WT* (*NT*) sector is determined by the sum of the coefficients corresponding to a given category of the independent variable: $\alpha_1 + \alpha_4$; $\alpha_2 + \alpha_5$ and $\alpha_3 + \alpha_6$ ($\alpha_1 + \alpha_7$; $\alpha_2 + \alpha_8$ and $\alpha_3 + \alpha_9$).

Before estimating the regression equations, the PP_L, *WP* and *WZ* variables were logarithmized. Due to the two-dimensional nature of the data (spatial-temporal data), panel regression was used. Due to the differences between individual manufacturing industries, panel models with fixed effects were used. Regression equations were estimated using the panel OLS. The validity of including fixed effects in the model was tested using the test for differentiation of the intercept between groups (Welch's test). The assumption of normality of distribution of regression residuals was tested using the Doornik-Hansen test. The Wald test was used to verify the assumption of homoscedasticity of regression residuals, while the hypothesis of the lack of autocorrelation of the residual component was tested using the Wooldridge test. If autocorrelation and/or heteroscedasticity of the residual component were found, the OLS with heteroskedasticity and autocorrelation consistent standard errors (HAC) was used. The statistical significance of the sums of regression coefficients was tested using the Student t-test. The level of statistical significance of the tests was set at $\alpha = 0.05$.

3. Results

Based on the results of regression equation (2) (Table 1), it can be concluded that in 2018-2021, job creation, job destruction, and labor reallocation had a statistically significant impact on labor productivity in the Polish manufacturing industries. It should be noted, however, that while the impact was positive in the case of job creation (measured by the hire rate) and job destruction (measured by the termination rate), the opposite was observed with respect to the interaction of these variables. The negative value of the coefficient with the interaction of the *WP* and *WZ* variables means that the labor reallocation accompanying creative destruction were not pro-efficient and weakened the positive effects related to job creation and job destruction. The observed relationships, both in terms of the direction and strength of the impact, were the same during the COVID-19 pandemic and in the remaining years examined – none of the regression coefficients for the interactions of variables with the *DCOV* variable met the conditions for statistical significance.

Table 1.
Estimation results of the regression equation (2)

Method: Panel OLS with fixed effects. HAC; number of observations: 96				
Variable	**Coefficient**	**Standard Error**	**t statistics**	**p value**
const	−1.5898	2.7133	−0.5859	0.5636
WP	2.6453	0.8508	3.1090	0.0049
WZ	2.1226	1.0107	2.1000	0.0469
*WP*WZ*	−0.8450	0.3131	−2.6980	0.0128
*DCOV*WP*	−0.1223	0.0819	−1.4940	0.1487
*DCOV*WZ*	0.0450	0.1346	0.3341	0.7413
*DCOV*WP*WZ*	0.0248	0.0366	0.6763	0.5056
LSDV R^2 = 0.9791; Within R^2 = 0.3105; F statistic F(6, 23) = 5.2794; p = 0.0015; Welch test value F(23, 25.9) = 9.5419; p = 0.0000; D-H test value χ^2 = 0.4436; p = 0.8011.				

Source: own calculations.

The validity of the assumption that the level of technology is a factor modifying the impact of creative destruction on labor productivity is partially confirmed by the regression results (3) (Table 2).

Table 2.
Estimation results of the regression equation (3)

Method: Panel OLS with fixed effects. HAC; number of observations: 96				
Variable	**Coefficient**	**Standard Error**	**t statistic**	**p value**
const	−1.1099	2.3706	−0.4682	0.6441
WP	4.3445	0.3944	11.0100	0.0000
WZ	3.6208	0.2163	16.7400	0.0000
*WP*WZ*	−1.3591	0.1164	−11.6800	0.0000
*DWT*WP*	0.0545	2.5818	0.0211	0.9833
*DWT*WZ*	−0.4336	2.3756	−0.1825	0.8568
*DWT*WP*WZ*	−0.0670	0.8970	−0.0747	0.9411
*DNT*WP*	−3.6569	0.9836	−3.7180	0.0011

Cont. table 2.

*DNT*WZ*	−3.5935	1.0747	−3.3440	0.0028
*DNT*WP*WZ*	1.2122	0.3527	3.4370	0.0022
LSDV R^2 = 0.9834; Within R^2 = 0.4517; F statistic F(9, 23) = 773.035; p = 0.0000; Welch test value F(23, 25.9) = 7.2170; p = 0.0000; D-H test value χ^2 = 1.2936; p = 0.5237.				

Source: own calculations.

Based on the results, it was found that the relationship between the job creation, job destruction, labor reallocation and labor productivity in industries classified as medium technology and high technology did not differ significantly – none of the regression coefficients for the interaction of variables with the *DWT* met the conditions of statistical significance. However, the results for industries of the low-technology sector lead to a different conclusion. The statistical significance of the regression coefficients (3) α_7, α_8, α_9 implies that the impact of the *WP*, *WZ* variables and their interactions on the PP_L variable in the *NT* sector was different from that observed in the medium and, indirectly inferring, high technology sectors. This conclusion is confirmed by the results of the regression equation (3), from which the binary variable *DWT* was removed (Table 3).

Table 3.
Results of estimating the regression equation (3) excluding the binary variable DWT

Method: Panel OLS with fixed effects. HAC; number of observations: 96				
Variable	**Coefficient**	**Standard Error**	**t statistic**	**p value**
const	−1.3587	1.6515	−0.8227	0.4191
WP	4.3313	0.6980	6.2060	0.0000
WZ	3.6417	0.6942	5.2460	0.0000
*WP*WZ*	−1.4105	0.2421	−5.8250	0.0000
*DNT*WP*	−3.6437	1.1277	−3.2310	0.0037
*DNT*WZ*	−3.6145	1.2461	−2.9010	0.0081
*DNT*WP*WZ*	1.2637	0.4071	3.1040	0.0050
LSDV R^2 = 0.9811; Within R^2 = 0.3747; F statistic F(6, 23) = 12.2216; p = 0.0000; Welch test value F(23, 25.9) = 7.3820; p = 0.0000; D-H test value χ^2 = 0.4043; p = 0.8170.				

Source: own calculations.

The results presented in Table 3 lead to two basic conclusions:

- the positive impact of job creation, job destruction and the negative impact of labor reallocation on the PP_L variable characteristic of industries in the medium and high technology sectors are consistent with the results obtained for the entire group of industries, i.e., without their division into technical sectors (Table 1),
- in low-technology sector, neither job creation nor job destruction nor labor reallocation were statistically significant factors influencing labor productivity. Although the regression coefficients for all interactions of variables with the binary variable *DNT* meet the condition of statistical significance, the sums of the coefficients determining the direction and strength of the impact of the *WP*, *WZ* variables and their interactions on the PP_L variable were not statistically significantly different from zero (Table 4).

Table 4.
Results of the significance test of the sum of coefficients in the regression equation (3) excluding the binary variable DWT

Variables	Sum of coefficients	Standard errors	t statistic	p value
WP; *DNT*WP*	0.6875	0.8857	0.7763	0.4455
*WZ; DNT*WZ*	0.0272	1.0348	0.0263	0.9792
*WP*WZ; DNT*WP*WZ*	–0.1469	0.3273	–0.4487	0.6578

Source: own calculations.

4. Conclusions

The results of the study revealed that in the manufacturing industries in Poland in 2018-2021, creative destruction, measured by the hire rate and the termination rate, had a positive impact on labor productivity, although this effect was weakened by the negative impact of labor reallocation – the reallocation of labor taking place in industries was not pro-efficient. The effect of reallocation, inconsistent with expectations, can be interpreted in the context of labor market regulations and frictions, which inhibit the effective flow of labor and lead to incorrect allocation of labor resources (Ahmadiani et al., 2022; Elfayoumi, 2022). The productivity "wedge" between the existing and optimal allocation of resources reflects the scale of institutional and market distortions (entry/exit barriers, transaction costs, regulations aimed at protecting enterprises and jobs, costs of hiring/firing employees) that cause Schumpeter's selection and reallocation are not working properly (Bennett, 2021; Irandoust, 2023).

The results obtained for the period of the COVID-19 pandemic are also inconsistent with expectations. The impact of job creation, job destruction and labor reallocation on labor productivity recorded in this period did not differ from the impact of these categories in the remaining years included in the study. The results of S. Graves (2023) for the US economy based on the simulation of a theoretical model indicate that the rate of job destruction in the second quarter of 2020 was twice as high as usual, while the rate of job creation almost did not change. In this context, it can be assumed that the legal solutions introduced in Poland in 2020 (anti-crisis shields) prevented the intensification of job destruction, leaving its effects on productivity unchanged.

It should be emphasized that the conclusions apply only to industries of medium and high technology sectors. This result is to some extent consistent with that reported by B. Dachs et al. (2016) for 26 European countries in the years 1998-2010, according to which the intensity of job creation and job destruction increases with the increase in the technological intensity of industries/sectors. The higher the level of technology, measured e.g. by R&D intensity, the more important the features typical of high-technology industries become in economic processes (short life cycle of products and processes, rapid diffusion of innovations, large share of highly qualified employees) (Comporek, 2014), and thus the more important Schumpeterian (innovative) dynamism based on the ability to innovate and efficiency (Ahmadiani et al., 2022; Spencer, Kirchhoff, 2006). Moreover, taking into account the criterion of the classification of industries according to levels of technology used in the study, the lack of relationship between the job creation, job destruction, labor reallocation and labor productivity in low-technology sector may lead to the conclusion that there is a threshold level of intensity of R&D ($I_{R\&D}$ > 1%) required for creative destruction to play an active role in economic processes. Confirmation of this thesis undoubtedly requires further research, especially since the categories and classification of industries used in the analyzes are only approximate measures of creative destruction and technological level.

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