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Technical change and wage premium shifts among task-content groups in Poland

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ABSTRACT

The article examines shifts in the wage premium between respective task-content groups of the labour force in Poland. The parameters of a microeconometric, multilevel model are estimated, and wage premiums for task-content occupation groups are calculated. Individual data from the 2004 to 2016 editions of Structure of Earnings by Occupation (S.E.O.) survey are used. A positive wage premium is reported in the group of non-routine jobs and a negative wage premium in the case of routine jobs, which is in line with the hypothesis of labour market polarisation. We find that labour market processes in Poland have not led to growing wage dispersion between task-content groups, but they enhanced changes in the wage premium within these groups.

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1. Introduction

In previous technological revolutions, technology replaced the physical effort performed by animals and then by people. Currently, Information and Communication Technologies (I.C.T.) are replacing not only physical strength but also mental abilities and the human senses. I.C.T. has entered areas that were once the exclusive domain of people, where human superiority over technology was associated with those dimensions where advanced mental or communication skills are required (Brynjolfsson & McAffe, 2011, p. 26). It turned out, however, that this domain is also subject to automation, and I.C.T.-driven technical change leads to far-reaching shifts in the employment and wages structure. These processes have been examined within the framework of the theory of Skill-Biased Technical Change (S.B.T.C.) and the relatively new concept of Routinisation-Biased Technical Change (R.B.T.C.).

The validity of these hypotheses has been studied mainly in the most developed countries (Green & Sand, 2015, p. 638; Hershbein & Kahn, 2018, p. 1749; Woods, 2017, p. 754). Studies devoted to the impact of technical change on wage premium

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shifts in post-transition economies, including Poland, seem to be scarce. If we assume that countries have access to technologies at a comparable level, technical change in the labour market should have a similar trajectory, and trends of productivity, employment and wage structures should be comparable between developed and developing countries in the long run. Therefore, we can potentially expect an acceleration of technology-driven structural changes in the Polish labour market in the near future, leading to changes in wage premiums among the respective task-content groups.[1] Analysis of the impact of technical change on wage premium shifts seems to be especially interesting in the case of a country that is on the path of dynamic growth characterised by the dynamic growth of employment in knowledge-intensive business services.[2] Testing the validity of the S.B.T.C. and R.B.T.C. hypotheses, as well as understanding the impact of technical change on wage premium shifts in a fast-growing country seems to be important for a few reasons. Firstly, changes in the relationship of wages between different occupational groups may reflect changes in the ratio of labour demand between different groups and the productivity shifts among them. This should result in better recognition of labour market needs and provide recommendations for education policy. Secondly, knowledge about the dispersion of wages across professions informs individuals which skills are growing in demand. Thus, individuals know which traineeship programmes may be useful to improve their position in the labour market. In addition, enterprises are better informed about which employee development programmes they should support, and central and local governments receive feedback on which training services within the Active Labour Market Policy scheme should be enhanced. Thirdly, analysis and extrapolation of current trends make it possible to forecast income diversification in the future. This knowledge may help the government to introduce policies better tailored to reducing income inequalities.

The article contributes to the economic literature in three ways. Firstly, it provides a methodological contribution. To the best of the authors' knowledge, this is the first attempt to use a multilevel model to test the validity of hypotheses associated with the impact of technical change on the labour market. Alternative approaches to testing the validity of the S.B.T.C. and polarisation hypotheses have been applied so far. Secondly, the proposed model extends previous empirical approaches used for the analysis of factors affecting wages in Poland. There have been no studies, to our knowledge, which analysed factors that shape wages in Poland in terms of occupational and task-content groups. Thirdly, a new method for translating occupational groups into task-content groups is presented.

The main aim of the article is to identify the magnitude and trajectory of wage premiums among occupational and task-content groups in Poland. Additionally, we indicate key determinants which drive wage premium discrepancies at the individual and company levels. The research hypothesis states that wage premium distribution in Poland exhibits R.B.T.C. patterns. However, we assume that these patterns have unique features stemming from the fact that Poland still lags behind the E.U. leaders in I.C.T. implementation. In the course of our study, auxiliary hypotheses which link wage premium to individuals' and companies' characteristics are also verified.

The empirical approach is based on the micro-data from the 2004 to 2016 editions of the Structure of Earnings by Occupation (S.E.O.), provided by the Polish Central Statistical Office. We estimate the parameters of a microeconometric mixed-effects model and predict random effects for different task-content and occupational groups. The use of the multilevel model enables the relationship between an individual's and an enterprise's characteristics and wages to be identified more precisely. If there are significant random wage differences in different groups, and these differences are not taken into account, sample selection bias may arise. It should be stressed that the analysis of wage differences between different groups is possible without advanced econometric techniques. However, estimating the parameters of well-specified micro-econometric model makes it possible to analyse the differences, *ceteris paribus*. By testing the hypothesis of the equality of random effects between 2004 and 2016, we are, in fact, testing whether the changes in wage distribution among task-content groups follows S.B.T.C. or R.B.T.C.

The article is structured as follows: Section 2 provides a literature review on the technical changes in labour markets in developed and developing countries. Section 3 describes the methodology and data sources used for the empirical analysis. In Section 4, the results and findings for the Polish labour market are discussed. Section 5 concludes.

2. Technical changes in the labour market – a literature review

Rapid advances in computerisation and automation have resulted in many existing skills becoming increasingly redundant. Evidence shows that technology is the most important driver of current shifts in employment structure, and it outperforms international trade as an explanation of job polarisation and the rise in inequality. In the modern literature, there are two dominant streams of analysis regarding how technical change influences the labour market: upgrading skills and labour market polarisation. They are described by two theories: S.B.T.C. and R.B.T.C.

S.B.T.C. is a phenomenon related to the implementation of new technology, changes in production methods, or changes in work organisation. These things lead to an increase in demand for highly qualified labour compared to low-skilled labour, provided that relative wages are constant (Katz, 2002, p. 6). It implies that in the decade of the microelectronics revolution, there is an increase in demand and relative wages for highly-skilled labourers, while less skilled workers must face decreased income or even unemployment as their jobs succumb to automation and relocation (Moore & Ranjan, 2005, p. 401). In particular, I.C.T. capital seems to affect positively the wages of people who use computers in the workplace (DiNardo & Pischke, 1997, p. 296). Studies by Acemoglu (2002, p. 64), Card and DiNardo (2002, p. 742) or Blankenau and Cassou (2011, p. 3136) have confirmed the existence of S.B.T.C. in developed countries.

However, Richter (2014, p. 383) showed that if the assumption of equal capital shares (in the two-sector model) is removed, the increase in the skill premium in the U.S. may be explained by a reallocation of capital and neutral or unskilled-biased technical change. There are also other arguments raised, e.g., inequality is not an inevitable by-product of S.B.T.C. (Huhne & Herzer, 2017, p. 1350). According to Goldin and Katz (2008, p. 94–101), changes in the relative wages of workers with different educational attainments are determined by the 'race' between the demand for skills – driven by S.B.T.C., and the supply of skills – driven by changes in the educational attainment of the workforce. As a result, wage inequality between more- and less-educated workers occurs only to the extent that the relative demand of more skilled workers exceeds supply. Another argument pointing to the negative impact of S.B.T.C. on inequality is based on the spillover of technology between highly- and less-skilled labourers (Fang, Huang & Wang, 2008, p. 139). As Das (2008, p. 74) argues, an increasing number of highly-skilled labourers benefits less-skilled workers with superior learning capabilities as they receive support to develop and apply their talents to their work.

The results of empirical studies indicate that there are large differences in the evolution of wage inequality across countries. While Huhne and Herzer (2017, p. 1348) identified a long-term upward trend in the relative wage of tertiary-educated workers compared to less educated ones for Germany and the U.S. over the period 1970–2005, a declining pattern was observed over almost the entire sample period in the case of Finland and South Korea. These findings indicate that using education policy for social equalisation, as well as abolishing highly competitive university entrance examinations, results in a negative relationship between innovation and inequality.

Autor and Price (2013, p. 9) revealed that the share of employees performing non-routine tasks in the U.S. has increased substantially since the 1970s, while the share of the labour force employed in routine-intensive tasks has declined significantly – which is in line with S.B.T.C. It also turned out that the share of the labour force performing non-routine manual tasks declined for five decades, but the trend reversed in 2000. This observation provided the basis for the argument that I.C.T. complements rather than substitutes low-end interpersonal service jobs.

This argument has been developed within the R.B.T.C. theory, which questioned the validity of the S.B.T.C. approach and which explained labour market polarisation. The theory of labour market polarisation refers to the results of empirical observations which indicated that the change in the structure of labour demand driven by I.C.T. favours not only highly-skilled labour but also low-skilled employees, while medium-skilled labour is the biggest loser.[3] R.B.T.C. is rooted in the model presented by Autor et al. (2003, p. 1310), referred to as the A.L.M. model. In the A.L.M. approach, five types of tasks ('task-content groups' in our approach) are usually defined: non-routine analytical, non-routine interpersonal, non-routine manual, routine cognitive, and routine manual tasks. The potential impact of I.C.T. on these tasks depends on the ability to provide algorithms to be performed by a computer. As a result, I.C.T. could potentially replace routine tasks, be complementary to non-routine analytical and interpersonal tasks, and provide ambiguous conclusions about non-routine manual tasks. Because routine tasks are concentrated in the middle of the skills distribution, the relative share of employees in occupations requiring high and low skills, as well as the wage premium in these occupations, should grow, leading to labour market polarisation and growing wage inequalities. Technology-induced employment polarisation seriously threatens many routine jobs in back offices and administration, e.g. secretaries or bank tellers (Peugny, 2019, p. 5). Such white-collar occupations have faced much less pressure from offshoring and international trade. A large part of routine jobs requires certain skills and training. These skills were used to secure the mid-range wages of white-collar workers and thus provided for a relatively comfortable standard of living. Therefore, it is argued that digitalisation and automation jeopardise upward social mobility for medium-skilled routine workers.

Job polarisation has been considered in different contexts in the modern literature. Autor and Dorn (2013, p. 1559) relate job polarisation to the combination of non-neutral technological progress and the preferences of consumers who favour variety over specialisation. Non-neutral technological progress reduces the costs of routine tasks since cheaper machines replace labour input. As a result, the relative price of goods with respect to services decreases. If goods and services are complementary, the demand for the outputs of service occupations will go up, leading to an increase in wages and employment in these occupational groups.

Moreno-Galbis and Sopraseuth (2014, p. 45) hypothesised that population ageing explains the labour market polarisation phenomenon. They proposed a model making it possible to estimate the elasticity of substitution between services and goods by age group. This model made it possible to analyse the combined impact of technological progress and population ageing on demand for labour input in the personal services sector. The results suggested that personal services and goods are complements for older workers and substitutes for young ones. Labour market polarisation has also been explained in the context of increasing demand for personal services by wealthy households in developed countries (Autor & Dorn, 2013, p. 1558). Gains at the top of the distribution of wages have resulted in an increase in the opportunity cost for high-skilled workers in buying home services. The problem of the heterogeneity in job polarisation across industries has also been considered in the labour economics literature (Goos, Manning & Salomons, 2014, p. 2524; Shim & Yang, 2018, p. 143). These studies indicate that the persistent structure of interindustry wage differentials explains the different degrees of changes in employment share over time. This phenomenon was explained by the heterogeneity of the production function across industries and the fact that routine and non-routine workers are valued differently by industries. Shim and Yang (2018, p. 142) also argue that firms in a high-value industry are more likely to substitute I.C.T. capital for routine employees than enterprises in low-wage industries, leading to different degrees of job polarisation across industries. Last but not least, the role of the declining middle in political changes has been discussed in the modern socio-economic literature (Kurer & Palier, 2019, p. 3). It is argued that in times of job polarisation, routine cognitive workers face economic stagnation compared with highly skilled and highly specialised individuals of non-routine professions that benefit from technological complementarities. Therefore, routine white-collar workers are perceived as being a large and electorally relevant group with the capacity to actively voice dissatisfaction in the political arena.

The results of empirical studies confirm the validity of the polarisation hypothesis for labour markets in developed countries. Autor et al. (2003, p. 1311) uncovered job polarisation in the U.S. A sharp drop in the fraction of the population employed in middle-skilled occupations in the U.S., and the disappearance of some routine occupations, was identified by Cortes, Jaimovich and Siu (2017, p. 86). Meanwhile, job polarisation in the U.K. was found by Goos and Manning (2007, p. 132), and evidence of the job market polarisation for Germany was provided by Dustmann, Ludsteck, and Schönberg (2009, p. 869), among others. Though the results obtained by Fonseca, Lima and Pereira (2018, p. 328) indicate that Portugal has also experienced job polarisation since the mid-1990s, specific features of this phenomenon for Portugal have been identified. While a sharp decline in routine manual employment was uncovered, the decline of routine cognitive employment turned out to be modest and coupled with a higher wage premium. The labour market in northern European countries was identified as polarised by Asplund et al. (2011, p. 94–95) and by Adermon and Gustavsson (2015, p. 911), while evidence of job polarisation for several O.E.C.D. countries was provided by Michels, Natraj and Reenen (2014, p. 74) and for Europe as a whole by Goos et al. (2009, p. 62, 2014, p. 2524).

Some findings emphasise that the timing and extent of job polarisation may differ across countries (Fonseca et al. 2018, p. 319). Countries with a large public sector may present an occupational (and wage) structure which is less permeable to market forces. Moreover, some institutional aspects in wage setting (e.g. collective bargaining agreements) could act as counteracting forces in the distribution of wages, which may affect the employment growth of different types of jobs. In countries with significantly lower levels of G.D.P. per capita, hiring routine workers is still more profitable than investing in I.C.T. in some industries. This is due to the fact that while the price of computer capital is the same in all countries, the level of wages in routine task-intensive occupations is correlated with the income of the economy.

Unfortunately, changes in employment and the wage structure described by S.B.T.C. or R.B.T.C. are rarely analysed in the group of Central and Eastern European (C.E.E.) countries. The results obtained by Hardy, Keister and Lewandowski (2018, p. 209) showed that the changes in task distribution in this region are generally in line with trends which are characteristic of developed countries, with one exception – routine cognitive tasks. The results of the study conducted by Arendt (2018, p. 318) revealed an employment increase instead of a decline in the middle of the skill/wage distribution. Moreover, the results proved to be inconsistent with the S.B.T.C. hypothesis. The relationship between the level of routinisation of jobs and wages was studied for the Polish economy by Parteka (2018, p. 83). Her regression results showed that occupations with higher routine content experienced stronger downward pressure on wages.

3. Data and methodology

In this empirical study, we took advantage of individual data from seven editions of the Polish S.E.O., covering biannual data from the period 2004 to 2016.[4] The dependent variable we constructed is based on comparing the wage[5] of an individual worker with the median wage in the edition. Such normalisation tackles the problem of an increase in nominal wages which may be due to inflation or a labour productivity increase. The proposed measure can be interpreted as the logarithm of the relative wage of the *i*-th worker in year *t*, depending on the median wage:

$$WAGE\_REL_{it} = log\left(\frac{WAGE_{it}}{med(WAGE)_t}\right). \tag{1}$$

According to the S.B.T.C. and R.B.T.C. hypotheses, the wage of a worker should depend on the skill requirements of the individual's profession and on the task content of the performed job, respectively. As the S.E.O. database contains information on occupations,[6] not job-related tasks, we had to categorise specific occupations into task-content groups. We followed the approach proposed by Hardy et al. (2018, p. 208), who classified all three-digit code occupations in E.U. countries within five task-content groups according to the dominant task content of the jobs: non-routine cognitive analytical, non-routine cognitive personal, routine cognitive, routine manual and non-routine manual physical. This approach is consistent with the methodology presented by Autor et al. (2003, p. 1293).

However, our thorough analysis of the task content of jobs in Poland led us to introduce a modification to Hardy's et al. (2018, p. 208) categorisation. Firstly, we decided to classify the minor occupational group 'Dieticians and nutritionists' into the non-routine analytical category. Secondly, we created a new task-content group: non-routine cognitive analytical and personal, allocating to this group those occupations which require both analytical and personal skills: Medical doctors, Dentists, University and higher education teachers, Real-estate professionals, Authors, journalists and linguists, and Regulatory government associate professionals. Table 1 presents the concept of the six task-content groups used in our study.

In our approach, each worker belongs to one of 131 three-digit code occupational groups, and each three-digit code group belongs to one of the six task-content groups defined in Table 1. As a result, our data has a hierarchical structure; thus, a hierarchical model should be used in order to explain individuals' wages. Theoretically, individuals belonging to the same three-digit code occupational group should have similar wages, *ceteris paribus*. If large differences between workers' wages from the same occupational group exist, workers with lower wages may quit and start working for enterprises offering higher wages. The wages of workers from the same task-content group may differ slightly more, but we expect that between-group variation exceeds the within-group variation. Therefore, a multilevel model seems to be appropriate. We propose the estimation of the parameters of the following multilevel model:

Table 1. Method of classifications of occupational groups into task-content groups.

Group	Acronym	Examples of professions within the group[9]
Non-routine cognitive personal	*NRCP*	Business services managers
Non-routine cognitive analytical	*NRCA*	Physicians
Non-routine cognitive analytical-personal	*NRCAP*	Medical doctors
Non-routine manual-physical	*NRMP*	Telecommunication technicians
Routine cognitive	*RC*	General office clerks
Routine manual	*RM*	Craftsmen

Source: Own elaboration.

$$WAGE\_REL_{it} = \boldsymbol{x}_{it}\boldsymbol{\beta} + \boldsymbol{z}_{it}\boldsymbol{u} + \varepsilon_{it}, \tag{2}$$

where $\boldsymbol{x}_{it}$ denotes the vector of control variables and $\boldsymbol{\beta}$ is the vector of consecutive parameters. Vector $\boldsymbol{u}$ consists of random effects. Two kinds of elements are included in this vector. u_{ddd}^{y} is a random effect for year y (y = 2004, 2006, 2008, 2010, 2012, 2014, 2016) and the three-digit code occupational group *ddd*. u_{ta}^{y} is a random effect for year y and task-content group *ta* (*ta*= N.R.C.P., N.R.C.A., N.R.C.A.P., N.R.M.P., R.M., R.C.). These random effects can be interpreted as an occupational wage premium or a task wage premium. Vector $\boldsymbol{z}_{it}$ takes on values 0 and 1 depending on whether an observation belongs to a cluster defined by year and occupational (task-content) group or not.

In order to verify the validity of the research hypothesis, the following statistical hypothesis should be tested:

$$H_0 : u_{ta1}^{2016} - u_{ta1}^{2004} = u_{ta2}^{2016} - u_{ta2}^{2004}, \tag{3}$$

$$H_1 : u_{ta1}^{2016} - u_{ta1}^{2004} > u_{ta2}^{2016} - u_{ta2}^{2004},$$

If hypothesis H_0 is rejected, it means that changes in wages were more advantageous for individuals from the first group than from the second one. Moreover, if *ta1* relates to non-routine tasks and a task-content group *ta2* relates to routine tasks, polarisation occurs.

The choice of control variables constituting vector $\boldsymbol{x}_{it}$ depends on the availability of data in the S.E.O. database as well as the results of other studies. Table 2, based on literature, summarises all explanatory variables used in the specification with the expected sign of the estimate.

Table 3 presents descriptive statistics for continuous variables as well as fractions for discrete variables.

4. Results and discussion

The estimation procedure started by estimating the most general model, which took into account the variables considered in Table 2. It turned out that all variables included in vector $\boldsymbol{x}_{it}$ had a statistically significant impact (at the 0.05 level of significance) on the dependent variable. Next, we tested the presence of fixed and random effects and conducted the Hausman (1978) test in order to choose one of two models assuming the presence of effects. The results of testing are presented in Table 4 and indicate that the model with random effects should be used in order to explain wages.

Table 5 presents the estimates of the parameters for explanatory variables without regional or industry dummies. Estimates of the parameters for industry sectors and regional dummies are included in Tables 6 and 7.

Our results confirmed the gender wage gap in the Polish economy, which is in line with the findings of other studies (Kompa & Witkowska, 2018, p. 265). Women with the same level of education and experience, and who work in the same industry

Table 2. List of explanatory variables.

Variable	Definition	Justification
EDU_k[10]	1 for individuals with *k*-th level of education, *k* = *basic, vocational, secondary technical, tertiary* Secondary, general education is used as a base category	Mincer (1974) argued that individual wages grow as the number of years of schooling increases.
FEMALE	1 for females and 0 for males	Extensive economic literature indicates that the problem of the gender wage gap exists in labour markets in developing as well as developed countries (Jones Makepeace & Wass, 2018)
INDEF	1 if a respondent is employed for an indefinite period and 0 otherwise	Workers with permanent job contracts have a stronger position within an enterprise. Their wages should be higher (Aleksynska, 2018, p. 724)
SIZE_l	1 for individuals employed in enterprises of size *l*, *l=50–249 workers*, *250–499 workers*, *over 500 workers* Enterprise employing 10–49 workers is used as a base category	As Idson and Oi (1999, p.106) argue, big firms pay efficiency wages to deter shrinking and adopt a discretionary wage policy to share profits
PRIVATE	1 for workers employed in a private firm and 0 for individuals employed in a public enterprise	Private and public sector jobs differ in several dimensions. The hedonic theory of wages can explain wage differentials arising from these different dimensions (Emilio, Ponczek, & Botelho, 2012, p. 72)
REG_m	1 for individuals employed in a firm located in region *m; m* = *Kujawsko-Pomorskie, Lubelskie, Lubuskie, Lodzkie, Malopolskie, Mazowieckie, Opolskie, Podkarpackie, Podlaskie, Pomorskie, Slaskie, Swietokrzyskie, Warmińsko-Mazurskie, Wielkopolskie, Zachodniopomorskie Dolnoslaskie* is used as a base category	According to the New Geography approach, there is a correlation between wages and the economic potential of the region (Cieślik & Rokicki, 2016, p.674)
SEC_n	1 for individuals employed in a firm from industry section *n; n* = *A,B,D,E,F,G,H,I,J,K,L,M N,O,P,Q,R,S* Section C is used as a base category	Different industries are characterised by different productivity levels. Moreover, the strength of trade unions may differ across industries (Papapetrou & Tsalaporta, 2017)
EXP_GEN	Experience of the worker (number of years) in all firms that the individual had worked in before the poll was conducted	Mincer (1974) also argued that individual wages grow with the level of experience

Source: Own elaboration.

and region, earn less than their male counterparts. The results of the analysis regarding the education wage premium are in line with the Mincer hypothesis of positive returns to education. Estimates of the parameters for the remaining variables are also in line with expectations. Employees in private and larger firms, on permanent contracts, earn more, *ceteris paribus* (Aleksynska, 2018, p. 733) (Table 4).

Significant inter-industry differences in wages[7] have been revealed (Table 6). High wages in the Scientific and IT industries are determined mostly by the demand-side of the labour market, while relatively high wages in the Polish mining industry are historically determined by the strong position of trade unions in this industry sector, dating back to the times of the centrally-planned economy (Jonek-Kowalska, 2015, p. 33)

Wage differences in the regional dimension clearly point to the dominant position of the Mazowieckie region. This result stems from the leading role of Warsaw, the capital city, which cumulates the economic and social potential of the country. The lowest wages are expected in those regions which are classified as the least developed Polish regions with low innovation potential. These results are in line with the New Economic Geography approach (Cieślik & Rokicki, 2016, p. 674).

Table 3. Descriptive statistics for continuous variables and fractions for discrete variables.

Regions				
Region	Dolnośląskie	Kujawsko-Pomorskie	Lubelskie	Lubuskie
Fraction	0.08	0.05	0.04	0.02
Region	Łódzkie	Małopolskie	Mazowieckie	Opolskie
Fraction	0.06	0.08	0.19	0.02
Region	Podkarpackie	Podlaskie	Pomorskie	Śląskie
Fraction	0.05	0.02	0.05	0.13
Region	Świętokrzyskie	Warmińsko-Mazurskie	Wielkopolskie	Zachodniopomorskie
Fraction	0.03	0.03	0.10	0.04
Sections				
Section	A	B	C	D
Fraction	0.01	0.02	0.25	0.02
Section	E	F	G	H
Fraction	0.01	0.04	0.11	0.06
Section	I	J	K	L
Fraction	0.01	0.02	0.04	0.02
Section	M	N	O	P
Fraction	0.03	0.03	0.07	0.15
Section	Q	R	S	
Fraction	0.09	0.01	0.00	
Educational attainment				
basic	vocational	secondary general	Secondary technical	tertiary
0.06	0.24	0.10	0.31	0.29
Size				
	10–49	50–249	250–499	500 and more
	0.24	0.29	0.17	0.30
Other binary variables				
FEMALE	INDEF	PRIVATE		
0.49	0.75	0.55		
Descriptive statistics for continuous variables				
	WAGE_REL – mean	WAGE_REL – standard deviation	EXP_GEN - mean	EXP_GEN – standard deviation
	0.054	0.563	17.90	11.78

Source: Own elaboration.

Table 4. Results of testing for the presence of effects and choice between a model with random and fixed effects.

Testing	H0 hypothesis	p-value	Decision
no effects or fixed effects	No effects	0.00	Rejected
no effects or random effects	No effects	0.00	Rejected
fixed effects or random effects	Random effects	0.37	Not rejected

Source: Own elaboration.

Table 8 consists of the predictions of random effects for consecutive task-content groups for all years, calculated in line with equation (2). This creates a basis to test whether the changes in wage distribution along task-content groups in the Polish labour market are in line with the R.B.T.C. hypothesis, as random effects inform us about differences in wages which cannot be explained by the other characteristics analysed and presented in Tables 5–7. In other words, a positive or negative wage premium must be a result of how much the occupations belong to the respective task-content groups. A positive wage premium, within the whole time-span of the analysis, was recorded only in two task-content groups: non-routine cognitive personal and non-routine manual physical. Since NRCP is the group with a stable and large wage premium (ranging from 0.30 to 0.43), it tells us about the importance of soft skills in the Polish labour market. This group of skills is usually categorised as universal or transversal, and is perceived as being important in modern labour

Table 5. Estimates of parameters for explanatory variables.

Variable	Estimate	Variable	Estimate	Variable	Estimate
Cons	−0.343***	*FEMALE*	−0.114***	*INDEF*	0.162***
EDU1	−0.062***	*EXP_GEN*	0.006***	*PRIVATE*	0.043***
EDU2	−0.061***	*SIZE2*	0.124***	*Number of observations*	4,835,366
EDU4	0.005***	*SIZE3*	0.207***	*Likelihood ratio statistic for testing the presence of random effects*	p-value = 0.000
EDU5	0.194***	*SIZE4*	0.255***		

Note: *** denotes significance at the 0.01 level of significance. *Source:* Own elaboration.

Table 6. Estimates of parameters for industry sectors.

Variable	Estimate	Variable	Estimate	Variable	Estimate
SEC_A	0.000	*SEC_H*	−0.047***	*SEC_N*	−0.201***
SEC_B	0.351***	*SEC_I*	−0.093***	*SEC_O*	−0.163***
SEC_D	0.218***	*SEC_J*	0.167***	*SEC_P*	0.081***
SEC_E	−0.093***	*SEC_K*	0.259***	*SEC_Q*	−0.120***
SEC_F	−0.013***	*SEC_L*	0.019***	*SEC_R*	−0.263***
SEC_G	−0.032***	*SEC_M*	0.039***	*SEC_S*	−0.093***

Note: *** denotes significance at the 0.01 level of significance. *Source:* Own elaboration.

Table 7. Estimates of parameters for regions.

Variable	Estimate	Variable	Estimate	Variable	Estimate
REG_Kujawsko-Pomorskie	−0.08***	*REG_Mazowieckie*	0.16***	*REG_Slaskie*	−0.02***
REG_Lubelskie	−0.13***	*REG_Opolskie*	−0.05***	*REG_Swietokrzyskie*	−0.12***
REG_Lubuskie	−0.06***	*REG_Podkarpackie*	−0.13***	*REG_Warminsko-Mazurskie*	−0.08***
REG_Lodzkie	−0.06***	*REG_Podlaskie*	−0.12***	*REG_Wielkopolskie*	−0.03***
REG_Malopolskie	−0.03***	*REG_Pomorskie*	0.02***	*REG_Zachodniopomorskie*	−0.03***

Note: *** denotes significance at the 0.01 level of significance. *Source:* Own elaboration.

markets (Heckman & Kautz, 2012, p. 462). Labour market studies conducted in Poland show there is a shortage of such skills (Strawiński, Majchrowska & Broniatowska, 2018, p. 46), which translates into an even higher wage premium for white collar workers who have these skills and who perform jobs in which non-routine cognitive personal tasks dominate. The wage premium for individuals performing non-routine manual physical tasks is much lower, ranging from 0.01 to 0.06. In fact, it is below the wage premium of the non-routine cognitive analytical task-content group, if we exclude observations from 2008 and 2010. In general, our results point to the disturbance which took place on the Polish labour market as a result of the world financial crisis, and which had unfavourable effects lasting from 2008 to 2010. In 2008, at the beginning of the crisis, wage premiums in all non-routine task-content groups decreased or became negative (N.R.C.A. and N.R.C.A.P.), and then started to recover. The non-routine cognitive personal and analytical task-content group is the exception to this rule – from 2014, we witnessed a negative wage premium in this group, which is hard to explain, taking into account the polarisation hypothesis. It appeared that the financial crisis did not have a negative impact on the relative wages of individuals performing routine jobs. Nevertheless, in the case of both cognitive and manual routine jobs, empirical relative wages were lower than theoretical ones, taking into account socio-demographic, sectoral and regional features (Table 8).

Table 8. Random effects in wages for task-content groups (2004–2016) (standard errors in brackets).

Task-content group/Year	2004	2006	2008	2010	2012	2014	2016
NRCP	**0.43 (0.08)**	**0.43 (0.07)**	**0.30 (0.07)**	**0.34 (0.05)**	**0.34 (0.06)**	**0.37 (0.05)**	**0.36 (0.04)**
NRCA	0.03 (0.14)	0.04 (0.11)	−0.04 (0.07)	−0.00 (0.08)	0.02 (0.06)	0.06 (0.05)	**0.10 (0.04)**
NRCAP	0.06 (0.18)	0.08 (0.11)	−0.05 (0.10)	0.02 (0.08)	0.01 (0.07)	−0.01 (0.09)	−0.02 (0.08)
NRMP	0.02 (0.11)	0.03 (0.10)	0.02 (0.08)	0.02 (0.06)	0.01 (0.05)	0.01 (0.06)	0.06 (0.07)
RC	−0.19 (0.11)	**−0.21 (0.09)**	**−0.20 (0.08)**	**−0.16 (0.07)**	**−0.21 (0.07)**	**−0.21 (0.06)**	**−0.24 (0.07)**
RM	**−0.36 (0.05)**	**−0.32 (0.07)**	**−0.22 (0.05)**	**−0.21 (0.04)**	**−0.18 (0.04)**	**−0.17 (0.03)**	**−0.17 (0.04)**

Note: Bold numbers indicate significance at the 0.05 level.

Regarding routine cognitive jobs, there is no clear pattern; however, since 2010, we can see a downward trend – the negative wage premium has increased. This phenomenon may be explained by two simultaneous processes taking place in the Polish labour market. The first one – from the demand-side – stems from the fact that Poland has become one of the top destinations for offshoring business in the C.E.E. region (Reijnders & de Vries, 2018, p. 418). Still, many tasks processed in 1st–4th generation offshoring centres are of a routine cognitive nature. As a result, many offshoring centres report a high demand for skilled labour to perform these routine cognitive tasks (clerical jobs). The negative occupational wage premium for workers performing routine cognitive tasks is also in line with the results obtained by Parteka (2018, p. 83).

The declining value of the 'negative' wage premium is observed in the group of workers performing routine manual tasks. This phenomenon may be due to the rapid decline of the vocational education system in Poland, stemming from the relatively low quality and potential of vocational schools, and the eagerness among the youth to acquire a university degree. These tendencies led to a sharp drop in the supply of individuals professionally prepared to perform routine manual tasks, although the demand for such a labour force has been stable (many international corporations moved assembly lines to Poland because of labour cost competitiveness). Since routine manual tasks are mainly done by vocational education graduates, analysis of the performance of wages of workers with vocational education in Poland should explain the observed phenomenon. As Strawiński et al. (2018, p. 43) noticed, though the wages of vocational education graduates are lower than those who had received a secondary general education, the decreasing number of graduates of vocational education has contributed to reducing this gap. The reduction of the wage gap between workers performing routine cognitive and routine manual tasks may also be associated with the effects of urbanisation and migration to large agglomerations. As Acceturo, Dalmazzo, and de Blasio (2014, p. 263) showed, when demand for a highly qualified workforce who perform managerial and professional jobs in cities grows, this growing 'professional' class creates a demand for services provided by low-skilled workers. Another explanation for the reduction in the negative wage premium for routine manual workers, especially in 2016, may be associated with the social transfers of the Polish government after 2015. The introduction of the '500 plus family' benefit by the new government elected in 2015 resulted in a decrease in the labour supply in Poland. This drop was especially noticeable in the group of low-skilled workers performing routine-manual tasks.

Table 9. Random effects in wages for selected occupational groups between 2004 and 2016.

Task-content group	ISCO 3-digit code	Name of occupation	Random effect 2004	Random effect 2016	Random effect Diff
NRCP	112	Managing Directors and Chief Executives	−0.177	1.455	1.632
	121	Business Services and Administration Managers	1.673	0.329	−1.344
NRCA	211	Physical and Earth Science Professionals	−0.307	−0.231	0.076
	242	Administration Professionals	0.925	−0.053	−0.978
NRCAP	221	Medical Doctors	−0.398	0.512	0.910
NRMP	314	Life Science Technicians and Related Associate Professionals	2.150	−0.033	−2.183
	315	Ship and Aircraft Controllers and Technicians	−0.351	1.381	1.732
RC	331	Financial and Mathematical Associate Professionals	0.455	0.033	−0.422
RM	613	Mixed Crop and Animal Producers	−0.080	0.075	0.155
	815	Textile, Fur and Leather Products Machine Operators	0.169	−0.062	−0.231

The results presented in Table 8 are generally in line with the R.B.T.C. hypothesis in terms of shifts in wage distribution. However, taking into account the scale of the wage premium – positive in the case of non-routine jobs, and negative for routine task-content groups – the polarisation pattern cannot be fully explained by technical progress, as in the case of the Canadian labour market (Green & Sand, 2015, p. 639). Moreover, the usual prediction of the R.B.T.C. hypothesis posits growing wage inequalities. Our study did not confirm this phenomenon. The massification of higher education – a supply-side factor – which has taken place in Poland since the 1990s, has created an over-supply of highly-qualified individuals with a university degree who are theoretically prepared to perform non-routine tasks (Strawiński et al., 2018, p. 45). Moreover, a possible explanation for reducing the wage gap captures changes in the relative demand for highly-skilled versus medium-skilled, and highly-skilled versus low-skilled labour that are due more to international trade. Given that Poland has a comparative advantage in medium- and low-skill labour-intensive industries, the low demand for highly-skilled workers results in a decrease in their relative wages.

We should keep in mind that the wage premium for task-content groups stems from internal dynamics regarding wage changes in certain occupations belonging to the same task-content group. These inter-group dynamics appeared to be quite significant in some cases. In Table 9, we present the changes in relative wages for selected occupational groups at the I.S.C.O. three-digit level to show how heterogeneous the task-contents groups are. In most task-content groups, we may find cases of three-digit occupational groups which underwent a transition from a perceptibly negative to a positive wage premium (and vice versa) between 2004 and 2016. The most extreme examples are Life science technicians and related associate professionals, whose relative wage dropped from 2.150 in 2004 to −0.033 in 2016; conversely, Ship and aircraft controllers and technicians noted an increase in relative wage by 1.732 (both occupational groups are within the N.R.M.P. task-content group).

Business services and administration managers, and Managing directors and chief executives are similar examples in the N.R.C.P. task-content group, but with slightly smaller changes in relative wages. The shift from a negative to a positive wage premium in the group of Medical doctors (N.R.C.A.P.) is an obvious consequence of the growing supply shortage and generation gap in this occupational group in the Polish labour market. It is worth noting that the lowest 'extreme' changes in wage premium, relatively speaking, were recorded in the case of routine task-content occupations. This may imply that the biggest shifts in relative wages are concentrated in the high and low-paying occupations, while shifts in middle-wage occupations are quite stable.

Table 10 depicts the results of testing the changes of wages for different pairs of task-content groups, making it possible to identify the relative winners and losers of technical change in the Polish labour market with regard to relative wage. '+' means the task-content wage premiums of workers in the task-content group listed in rows increased compared with the task-content wage premiums of workers from the task-content group listed in the column. '-' reflects the opposite situation, while '0' means the difference was statistically insignificant. From this perspective, it seems the biggest winners are individuals working in N.R.C.A. as well as R.M. jobs, as their wage premiums increased between 2004 and 2016 in relation to almost all other task-content groups, while the biggest losers are individuals performing R.C. jobs. This is in line with the previously discussed unique features of the Polish labour market. Interestingly, wage premiums in NRCAP jobs decreased in comparison to other task-content groups, except for R.C. jobs, while N.R.M.P. jobs gained position (in terms of the wage premium) in relation to N.R.C.A.P. and R.C. task-content groups (Table 10). These results correspond to the R.B.T.C. hypothesis, to a large extent, with divergence related to the relative wage position of non-routine cognitive analytical and personal, as well as routine manual task-content groups.

The heteroscedasticity of the error term was tested. Average residuals were then calculated for each three-digit occupational groups in all periods. Autocorrelation of these residuals was tested on the basis of the test proposed by Bera, Sosa-Escudero, and Yoon (1999). The results from Table 11 indicate there was neither heteroscedasticity nor an autocorrelation problem. Moreover, the goodness of fit turned out to be high. As a robustness check, the parameters of the quantile regression model with

Table 10. Changes in wage premiums among task groups between 2004 and 2016.

Task-content group	NRCP	NRCA	NRCAP	NRMP	RC	RM
NRCP	X	–	+	0	+	–
NRCA	+	X	+	+	+	0
NRCAP	–	–	X	–	+	–
NRMP	0	–	+	X	+	–
RC	–	–	–	–	X	–
RM	+	0	+	+	+	X

Table 11. Results of diagnostic tests and measuring goodness of fit.

R-squared = 0.81					
Distribution of residuals					
Range for residuals	Lower than −0.5	Between −0.5 and −0.1	Between −0.1 and 0.1	Between 0.1 and 0.5	Larger than 0.5
Fraction	0.04	0.08	0.75	0.09	0.04

Testing autocorrelation and heteroscedasticity		
Testing	p-value	Decision
Autocorrelation	0.37	No autocorrelation
Heteroscedasticity	0.51	No heteroscedasticity

fixed effects for task-content groups were estimated. Similar peculiarities were revealed. The results are available upon request.

5. Conclusion

This article provides new insights into labour market processes in Poland by focusing on wage premium differences between six task-content groups since 2004, when Poland joined the E.U. The study finds that relative wages in the Polish labour market are driven by the characteristics of the individual and the company. We reported significant sectoral, inter-industry and inter-regional differences in relative wages. Most importantly, we argue that wage premium distribution between respective task-content groups reveals the existence of polarisation processes in the Polish labour market, which have some unique features compared to highly developed economies. There are a few specific conclusions stemming from this study.

Firstly, although there has been a positive wage premium in the group of non-routine jobs and a negative wage premium in the case of routine jobs, it is evident that relative wages in routine manual jobs are too high to be in line with the standard R.B.T.C. hypothesis. This phenomenon is, to a large extent, explained by educational upgrading and the stigmatisation of vocational education in Poland. Thus, we found that the technical change in the Polish labour market is driven not only by demand-side factors but also by the interplay of the supply-side. This seems reasonable since our analysis is of a medium rather than a long-run character. Secondly, although the technical change in Poland has not led to growing wage dispersion between the top and bottom task-content groups, there have been significant changes in wage premiums within the task-content groups. There are examples of occupations which, within 12 years, transformed from high positive to negative wage premiums, and vice versa. This means that even if changes at the level of task-content groups seem not to be revolutionary, there are high internal dynamics within the groups. Thirdly, the study finds that the processes of technical change in the Polish labour market depend significantly on the economic situation, e.g., in the case of an economic slowdown, or the crisis we witnessed in 2008–2010, the development paths of relative wages drift away from the long-run trend. Thus, we may assume that shifts in wage premiums, which stem from R.B.T.C. processes in Poland, would have been faster if there had been no global financial crisis in the first decade of the twenty-first century.

Even though Poland is not a leader in terms of economic development and technology absorption, the socio-economic conditions improved sufficiently to translate the effects of technical change and globalisation into the polarisation of wages. However, this wage-polarisation pattern is unique in the sense that the hollowing out effect in the middle of the skills distribution is relatively weak in comparison with highly developed countries.

A limitation of the study is related mainly to the fact that in the S.E.O. survey important variables, which may affect wages (e.g. marital status, size of town of an enterprise) are not available.[8] Moreover, the S.E.O. database is a result of a sample survey of enterprises which employ at least nine people. This may influence the results of the analysis. In the future, we plan to use a harmonised data set and conduct a comparative study among V.4. or C.E.E. countries to test for discrepancies in wage premiums among task-content groups in these countries. This would provide more insight into wage setting processes related to labour market polarisation in a group of countries facing similar problems and sharing a similar history as post-transition economies.

Notes

1. The task-content groups approach we applied refers to the Autor, Levy and Murane (2003, p.1291) categorisation of jobs according to routine/non-routine and cognitive/manual intensity of tasks performed in certain job. We decided to use the term ‘task-content group’ to emphasise that different jobs can be categorised into groups according to the dominant content of the tasks.
2. In 2009, Poland was promoted to the group of high income economies and it significantly reduced its distance to the richest E.U. countries between 2004 and 2016.
3. More recently, I.C.T.-driven technical change, perceived as the primary reason for labour market polarisation, was augmented by the impact of offshoring on the wage-occupation distribution (Zlate, 2016, p.42).
4. To ensure stability of institutional background within the whole sample period, we decided to start the analysis in 2004, when Poland joined European Union. The latest available S.E.O. data set covers the year 2016.
5. Full-time employment wages were used in our study.
6. To tackle the problem of changes in occupation classification between 2004 and 2016, all data sets were harmonised in line with the I.S.C.O.-08 classification.
7. We used the Polish Classification of Activities P.K.D. 2007, which is consistent and comparable with N.A.C.E. rev. 2 classification. Data sets related to 2004 and 2006, which were originally coded in line with the P.K.D. 2004 classification, were recoded into P.K.D. 2007.
8. These variables are available in the Labour Force Survey database, which is characterised by the high percentage of non-responses
9. The list of occupational groups according to five task-groups used by Hardy et al. (2018, p.208) is available at: http://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-isco-to-kzis/. The exact categorisation of all three-digit code occupations into six task-groups is available upon request.
10. We are aware that this variable may be treated as endogenous. However, there is no family background information in the L.F.S. data. Therefore, we experienced the parameter identification problem. We treat variables associated with education level as exogenous.

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