PERCEPTION OF WORK PROCESSES AUTOMATION AND REMUNERATION EXPECTATIONS. SURVEY ON STUDENTS IN CRACOW

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Introduction

New technology stimulates changes in a large scope of social and economic phenomena (Avant, 2014), such as: economy sectors (Godin, 2006), product and processes innovations, business process and models (Blaschke et al., 2017), as well as corporate structures (Brown et al., 2014; Snow et al., 2017). These technologies, which include digital technologies, robotics and artificial intelligence, refer to automation of both mass production and office processes. For instance, Hindle et al. (2017, p. 5) shows that robotic process automation (RPA) experienced in 2016 a 68% growth rate on the global market, and by 2024 it will be valued 8.75 billion USD. Similarly, other studies suggest that global shared services centres are the sector where such solutions are introduced to the highest extent (Deloitte, 2017, p. 16; Lacity, Willcocks, 2016; Accenture, 2005; Lacity, Willcocks, 2012).

Poland presently holds the third place (ex aequo) with China and Mexico, among the most frequently indicated countries for locating shared services centres, after the United States (14% of the indications) and India (12%) (Deloitte, 2017, p. 6). Business services in Poland are typically located in Cracow, Warsaw or Wroclaw, as indicated by maturity and employment statistics (ABSL, 2019, p. 6). This sector is particularly important for the population covered by the study, in particular students of the city of Cracow, who constitute the labour supply for shared service centres.

The paper investigates whether the risk of automation of professions assigned to particular fields of study is considered by the future labour market entrants and reflected in their remuneration expectations. The research was conducted among students of universities and other higher education institutions in Cracow[1]. So, the research indirectly refers to potential employees of shared service centres as well as factors of creative class spatial distribution. In particular, we are attempting to answer the question, if remuneration expectations of students, e.g. future employees, react to the ongoing and forthcoming processes of automation.

The structure of the paper is as follows. The following point reviews the related literature. In the next part we present the data and method employed in the study, which is followed by the presentation of the calculation results. The paper closes with the conclusions.

Literature review

Technological progress determines many changes in work processes. It stimulates the growing demand for new employee skills (OECD, 2016) by favouring cognitive and social skills (Deming, 2017), which also result in changes in demand for specific types of jobs. Scholars indicate that the demand for experts and talented employees increases, especially in the field of artificial intelligence and information analysis. Simultaneously, there is a decrease in demand for employees with basic skills, since their work can easily be replaced by computers, robots, and other digital technologies (Brynjolfsson, McAfee, 2014, p. 10). As a result, modern technologies, or more precisely automation penetrate production processes in many countries (Acemoglu, Restrepo, 2016). It is generally accepted that automation drives up wages, create employment, some jobs become more interesting, increasing employee satisfaction and boosting companies' ability to attract a skilled workforce (Deloitte 2016, p. 1–2). In particular, scholars showed a relative increase in the productivity of employees with high skills, performing work based on abstract thinking, creativity, problem solving (skill-biased technical change) (Autor, Acemoglu, 2011), as well as an increased demand for experts and talented employees, especially in the field of artificial intelligence and information analysis (talent-biased technical change) (Brynjolfsson, McAfee, 2014). Precisely, *„wage gains went disproportionately to those at the top and at the bottom of the income and skill distribution, not to those in the middle"* (Autor, 2015, p. 5).

In response to the observed tendencies scholars developed an approach to estimate the scope of automation (Autor et al., 2003), and the risk of automation of professions (Frey, Osborne, 2013). In particular, Autor, Levy and Murnane have developed the methodology for estimating the potential scope of work that could be automated (Autor et al., 2003), so-called routinisation hypothesis, which is also argued towards a more distinctive impact of ICT (Terzidis et al., 2017). In particular, this approach allows to distinguish routine and non-routine tasks of each occupation[2] (Autor et al., 2003). Routine tasks typical for blue collars, refer to sequential, structured, rule-based and procedure-based activities and have a relatively high automation potential. In turn, non-routine tasks, such as cognitive (abstract) and manual tasks covering issues related with problem solving, creativity, require interpersonal and environmental adaptation to specific situational variables and information assessment. Therefore, non-routine tasks depend on specific, managerial and technical posts in fields such as: law, medicine, sciences, engineering, design and management. Consequently, these tasks are not subject to automation, as it is difficult to code such tasks as the instructions for multi-variant ways of machine operation (Autor, Acemoglu, 2011, pp. 1076–1079). Following Autor and Acemoglu (2011), scholars have investigated how routine and non-routine tasks react to changes in production as a result of ongoing automatization. For instance, empirical studies show that the share of jobs with non-routine work increased, while with routine work – decreased in the past decades in the USA (Michaels et al., 2014; Autor, 2015), Germany (Dustmann et al., 2009), Denmark (Terzidis et al., 2017), Australia (Coelli, Borland, 2016), Canada (Green, Sand, 2015), Japan, and selected groups of high-income countries (Wang et al., 2015; Goos et al., 2009; Terzidis et al., 2017, p. 5).

Moreover, Frey and Osborne (2013) developed a methodology to identify the risk of automation of individual professions. In particular this approach is based on two stages. The first stage is about identifying factors and variables constituting barriers to automation. In the second stage, the factors identified in the first stage are used to classify occupations with the risk of automation. It is worth emphasising that Frey and Osborne (2013, p. 31) suggest that it is difficult to automate occupations requiring a relatively high level of: (a) perception and manipulation of objects and information, (b) creativity, and (c) social intelligence.

Frey and Osborne (2013) showed that in the following two decades 47% of all employees in the US economy will be in the high-risk group related to automation. In other countries, the proportion of high-risk occupations to automation is relatively high, e.g. Finland: 35%, Norway: 33% (Pajarinen et al., 2015), Europe: 54% (Bowles, 2014), Singapur: 25% (Lee, 2017). Some examples of occupations most exposed to automation are telemarketers – 99%, accountants and auditors – 94%, retailers – 92%, real estate agents – 86%, text editors and typists – 81%, and agricultural workers. The lowest risk of automation face occupations like policymakers and senior officials, life sciences and health professionals (Frey, Osborne, 2013, p. 68–72). In turn, it is estimated that up to 5% of all jobs in the US economy can be fully automated using up-to-date technology, while approximately 60% of all jobs have at least 30% of the tasks that can be automated[3] (Maryika et al., 2017, p. 8).

Methodology of Frey and Osborn were employed to identify the risk of automation of office processes, with special focus on financial sector, including the so-called shared service centres. For example, the number of bankers, traders and other employees on the Wall Street (front office employees) decreased by 16% in the period 2010–2014. KPMG forecasts indicate that up to 100 million employees in this group will be replaced by automated processes by 2026 (Cline et al., 2016, p. 14). Automation poses a threat to many professions in the financial sector, e.g. accountants. Deloitte's studies have identified occupations in the financial function with: low, medium and high risk of automation (Nagarajah, 2016). The low probability of automation applies to work requiring higher competences, consisting in strategic planning and consulting, financial analysis and controlling, including positions like specialists in business and financial project management, financial directors and managers. The average probability of automation is related to the following positions: Managers and purchasing directors. Finally, the high probability of automation refers to relatively simple work in the area of accounting, related to: settlement of transactions, receivables and payments, including positions: payroll manager, financial administrator, credit controller, financial account manager, financial and accounting technicians, financial manager (Nagarajah, 2016).

The latter group of positions, which is assigned the highest risk of automation, relates to the majority of work carried out in shared service centres, in particular those located in Cracow. Until now, the view has been popularised that automation in this sector eliminates, first of all, simple work with information that requires low competences, but currently there is also a noticeable decline in employment among professionals in the financial sector.

Considering the results of the above discussed studies, we attempt to answer the question how remuneration expectations of students, e.g. future employees, react to the ongoing and forthcoming processes of automation. In this context, one may look into the choices of the field of studies which have become popular in the recent years. Yet, having in mind, that the choice of educational path is a complex decision we do not expect to find any relationship between the automation and the popularity of different academic tracks. In turn, we aim to study the relationship between students' awareness of the automation of work processes and students' remuneration expectations. In particular, we test the following hypothesis: students, as the sample of future labour market entrants, are able to incorporate the risk of automation in their remuneration prospects. It is worth emphasising that although research on remuneration expectation has a long tradition (Attanasio, Kaufmann, 2009; Kaufmann, 2014; Delavande et al., 2011; Major, Konar, 1984; Major et al., 1984), the studies combining remuneration expectations and any issues related with risk are rare.

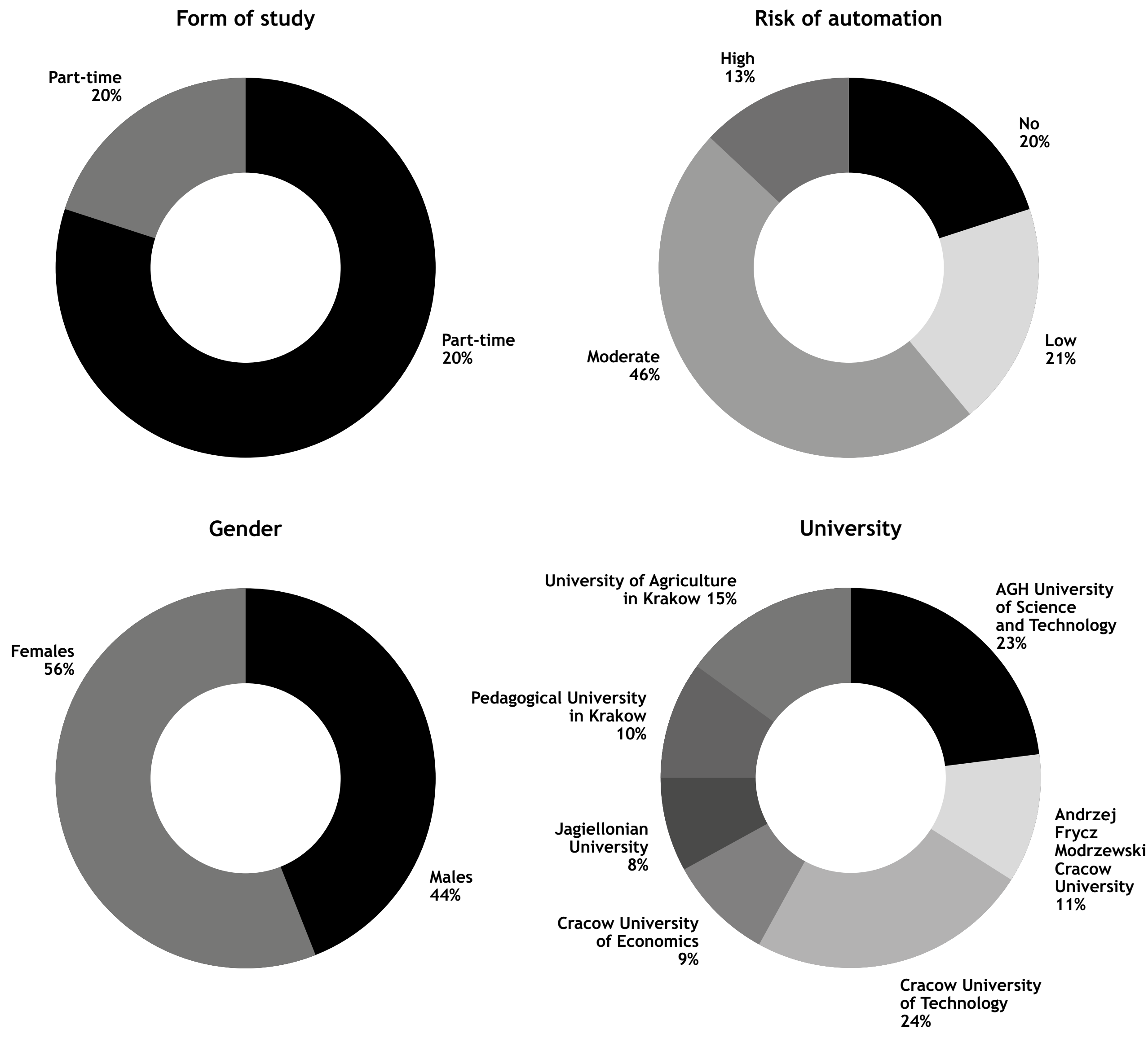

Figure 1. Sample structure
Source: own elaboration

Methods, research sample and data

We rely on primary and secondary data sources. The former one is a survey which was conducted at the turn of 2018 and 2019 on the convenience sample of students of 46 different field of studies in the city of Cracow, a major academic centre in Poland (n = 1180, see Figure 1 for the structure of the sample). The latter one is data retrieved from ELA database, a nationwide system to track careers of higher education graduates in Poland.

The main aim of the survey was to collect information on expected remuneration and the attitudes towards automation. To do so, we followed the literature on the methodology of measuring subjective expectations (for literature review, Delavande et al., 2011). In particular, we designed our survey to elicit individual distribution of future earnings similarly to Kaufmann (2014)for example, about career opportunities, translating into different expected returns to college. Poor people might expect low returns and thus decide not to attend or they might face high (unobserved. The data employed in the study was gathered using paper questionnaires with both open and closed questions given to the target group. We asked each individual to state the minimum (Y_{min}) and the maximum (Y_{max}) earnings he/she expected to earn after the completion of his/her current university-level faculty. Then, each respondent assigned the probability (π) of earning at least the midpoint of the Y_{min} and Y_{max}. These values were sufficient to derive measures of given percentiles of subjective distribution. Following Attanasio and Kaufmann (2009; 2014) and Kaufmann (2014)[4] we assumed that distribution was triangular and we calculated its first moment (Expected Remuneration – ER), with the following formula ((Guiso et al., 2002) for detailed explanations):

$$ER = \frac{1-\pi}{3}\,(2Y_{min} + Y_{max}) + \frac{\pi}{3}\,(Y_{min} + 2Y_{max})$$

From our secondary data source (ELA) we used the information on the earnings received by Polish graduates. On the basis of administrative data, ELA provides information on earnings of University graduates aggregated by form of studies (regular vs part-time), university, and field of studies. In particular, we used the information on the mean earnings of graduates of a given track, in the first year after graduation for the latest available year (2017). We combined this information with our individual-level survey based data, to calculate our main variable of interest – RRE (Relative Remuneration Expectation). We define RRE as:

$$RRE_i = \frac{ER_i - RR_j}{RR_j} \times 100\%$$

where:

RRE_i – Relative Remuneration Expectations of respondent i;

ER_i – Expected Remuneration of respondent i;

RR_j – Average remuneration received by graduates of track j.

Therefore, our dependent variable indicates remuneration expectations in relation to the real remuneration observed among students that graduated the same track of studies in a year 2017 (2 years prior to our survey).

Among the set of the right-hand side variables we included the risk of automation, and few controls to check the implication of personal and demographic characteristics of respondents, such as: gender, place of living, form of study (full-time versus part-time), and self-assessed probability of employment in automation-intensive service sector.

The division of studies into risk groups was made on the basis of the methodology of estimating the risk of automation of individual professions by Frey and Osborn (2013). This methodology is used in many studies (Maryika et al., 2017; Nagarajah, 2016). Such research approach was adopted to ensure internal validity of empirical evidence through observational and interpretational replicability (Stake, 1995).

Results

Data on the expected earnings, grouped by the level of automation risk, reveals that expected remuneration is, on average, lower among those students who face the lowest likelihood of automation of their profession (Figure 2).

These results, although surprising at the first sight, can be easily explained with the observed earnings of professionals assigned to the *lowest risk* category. Our sample of no-risk category consists of university tracks, whose graduates earned in 2017, on average, only 1542 PLN (as compared to 2152 PLN, 2266 PLN and 2379 PLN for low, moderate and high risk category, respectively). A significant number of students in this group are likely to look for a job in the public sector or are studying humanities/art. In both cases, professions of these graduates are at no risk of automation and are traditionally under-paid in Poland. In this context, the low expectations of these students can be treated as an expression of rationality. Indeed, we observe this kind of rational expectations in the whole of our sample – students tend to bind their expectations with the remuneration observed among graduates of their track (Figure 3). On average, students whose real earnings prospects are higher state higher remuneration expectations.

On the other hand, we observe a tendency of overestimating future remuneration and expecting to earn much more than the average value observed in reality. As presented in Figure 4 the vast majority of respondents estimated their future remuneration to be higher than average earnings of the respective graduates. The median of RRE indicates that over 50% of the surveyed students expect earnings higher by 66.9% than the average remuneration in their profession. These results were rather expectable, and can be explained with:

- the interpolation of positive trends on the labour market observed at the time the survey was conducted;
- and the phenomenon of *over-optimism* – a well-documented general tendency of humans to overestimate future successes and underrate the likelihood of negative events (Sharot, 2011).

On the basis of Figure 4 we can also conclude that over-optimism, although persistent among all subgroups, is smaller for students who face a higher risk of

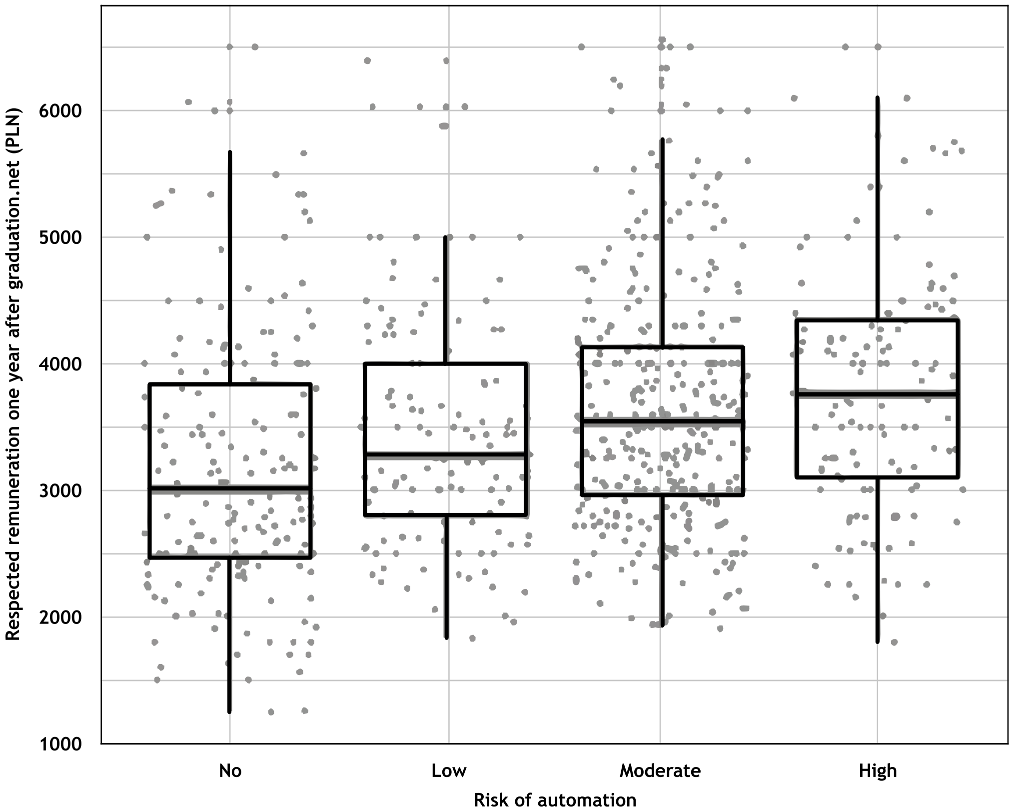

Figure 2. Expected remuneration, one year after graduation, net (in PLN) by category of risk of automation
Source: own elaboration

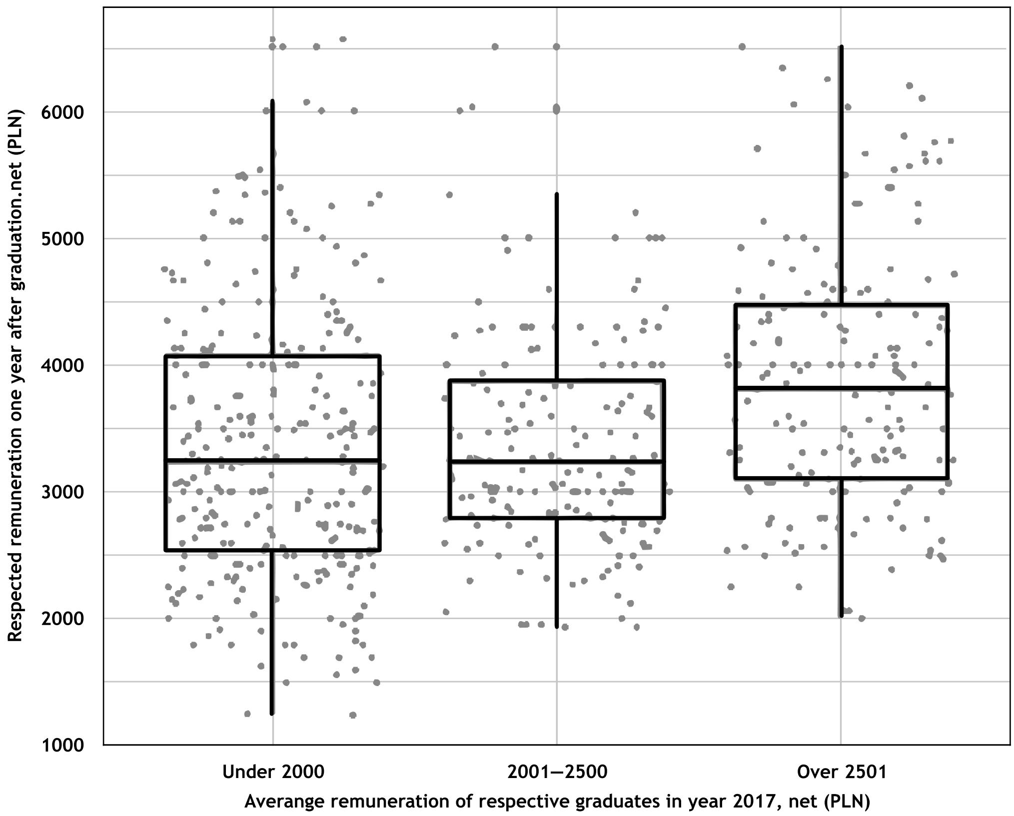

Figure 3. Expected remuneration of students (net, PLN) and real remuneration of the respective graduates (net, PLN)
Source: own elaboration

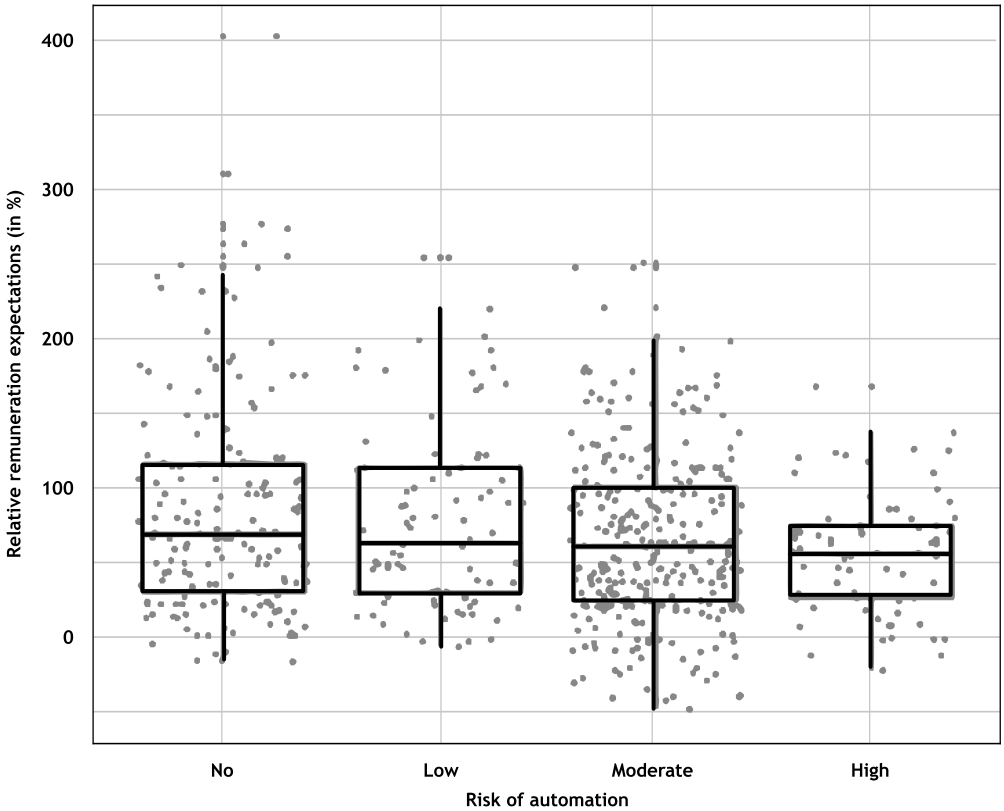

Figure 4. Relative remuneration expectations by category of risk of automation
Source: own elaboration

job automation. Such observation relates positively to our hypothesis that students adjust their expectations to the processes of jobs automation.

To verify if students' remuneration expectations reflect the risk associated with automation we ran a number of OLS regressions. In the regression No. 1, the only independent variable is the one that describes the risk of automation. In the result, column 1 (Table 1) presents differences in means of the dependent variable between group of respondents with no risk of automation and other risk groups. In line with data presented in Figure 4, we find out, that students who face at least some risk of automation (low, moderate or high) tend to have lower relative expectations than students whose jobs are not at risk of automation.

Furthermore, we include a set of control variables to our regression, namely: gender, place of living, form of study, and self-assessed probability of employment in automation-intensive service sector. The results reported in columns 2 and 3 do not differ substantially from the baseline model, indicating that students who face the highest risk of their job being automated, tend to formulate the smallest relative remuneration expectations. Counterintuitively, we observe that the group at moderate risk of automation has higher expectations that the group with low likelihood of automation. We expect this result may be a reflection of non-ideal categorisation of the automation risk. Still, these two group form significantly lower expectations that students at no risk of automation.

In the next set of regressions we look into the problem of different perception of automation and its impact on expected earnings (Table 2). We questioned students, if they agreed that automation of the office processes was a threat to job seekers in the institutions that implement such technologies. Responses to this question (labelled as „Perception of automation") were included in the regression of the relative remuneration expectations. As an additional control variable we included self-assessed probability of being employed in the institutions that automate office processes (SAPE). As reported in column 1, the obtained coefficients (except the variable *Risk of automation*) were not statistically significant. However, one should not conclude, that perception of automation is not important for the expected earnings prospects. A closer look at the problem discloses a rather more nuanced relationship. As documented in columns 2 and 3, the interaction between SAPE and perception of automation is an important factor to consider. When interaction term is included among the set of the independent variables, we obtain statistically significant coefficients for the variables of interest. On the basis of the reported results, we conclude, that a negative perception of automation leads to lower relative remuneration expectations. Moreover, the results show that the higher the SAPE variable, the smaller the remuneration expectations. At the same time, a positive coefficient of interaction term indicates that the effects of the negative perception of automation are suppressed by higher SAPE. In other words, respondents who simultaneously state that automation endangers employment prospects and who believe that their chances to become employed despite extensive automation are high, expect relatively high earnings.

Table 1. OLS regression of relative remuneration expectations

	Dependent variable: Relative Remuneration Expectations		
	(1)	(2)	(3)
In risk of automation = low	-20.713***	-26.620***	-24.941***
	(6.729)	(7.043)	(7.269)
In risk of automation = moderate	-29.771***	-19.242***	-17.770***
	(5.935)	(6.521)	(6.764)
In risk of automation = high	-39.548***	-33.089***	-32.084***
	(7.736)	(8.294)	(8.496)
Form of study = full-time		4.865	5.541
		(6.790)	(6.865)
Male		12.654***	12.667***
		(4.203)	(4.328)
Living in Krakow		8.332	9.383
		(6.459)	(6.598)
Living in small city (< 50k inhabitants)		8.258	9.999
		(6.953)	(7.172)
Living in the countryside		1.134	3.144
		(6.063)	(6.234)
Self-assessed probability of being employed in institutions that automate office processes			0.034
			(0.084)
Constant	89.866***	77.184***	72.294***
	(5.678)	(9.736)	(10.971)
Observations	777	769	736
R^2	0.022	0.039	0.037
Adjusted R^2	0.018	0.029	0.025
Residual Std. Error	56.500 (df = 773)	56.223 (df = 760)	56.513 (df = 726)
F Statistic	5.827*** (df = 3; 773)	3.883*** (df = 8; 760)	3.079*** (df = 9; 726)
Note: *p <0.1, **p<0.05, ***p<0.01, standard errors in parentheses			

Source: own elaboration

We find this attitude fairly justified, as students may expect that institutions which invest heavily in office work automation may suppress employment. At the same time, the same institution will be eager to offer remuneration higher wages to highly-skilled employees whose work is not easily automated, or/and is needed to support automation processes.

Conclusions

The paper reports the findings coming out from the data and information extracted from the survey conducted at the turn of 2018 and 2019. In particular, it includes a discussion of data and information that investigates whether the risk of automation of professions assigned to particular fields of study is recognised by the future labour market entrants and reflected in their remuneration expectations. The data and information employed in the study were collected among the students of higher educational institutions in Cracow, which is one of the leading centres for shared service in the world. Our findings relate to two main arguments.

Firstly, the empirical study shows that the expected remuneration is, on average, lower among those students who face the lowest likelihood of their profession automation. Consequently, the respondents whose real earnings prospects were higher, formulated higher remuneration expectations,

Table 2. OLS regression of relative remuneration expectation on the perception of automation

	Dependent variable: Relative Remuneration Expectations		
	(1)	(2)	(3)
In risk of automation = low	-25.988***	-26.869***	-27.911***
	(7.263)	(7.225)	(7.297)
In risk of automation = moderate	-18.035***	-17.490***	-18.815***
	(6.701)	(6.662)	(6.778)
In risk of automation = high	-30.346***	-31.271***	-33.164***
	(8.447)	(8.399)	(8.529)
Perception of automation = neutral	-3.018	-20.159	-18.741
	(6.892)	(14.565)	(14.548)
Perception of automation = negative	2.487	-34.450***	-33.016**
	(6.325)	(13.152)	(13.125)
Self-assessed probability of being employed in institutions that automate office processes (SAPE)	0.097	-0.349*	-0.342*
	(0.082)	(0.181)	(0.180)
Male			9.593**
			(4.262)
Perception of automation = neutral:SAPE		0.305	0.268
		(0.239)	(0.238)
Perception of automation = negative: SAPE		0.669***	0.642***
		(0.210)	(0.209)
Constant	83.907***	108.491***	104.877***
	(8.346)	(12.157)	(12.186)
Observations	737	737	732
R^2	0.024	0.039	0.044
Adjusted R^2	0.016	0.028	0.032
Residual Std. Error	56.397 (df = 730)	56.042 (df = 728)	55.851 (df = 722)
F Statistic	2.947*** (df = 6; 730)	3.647*** (df = 8; 728)	3.700*** (df = 9; 722)
Note: *p <0.1, **p<0.05, ***p<0.01, standard errors in parentheses			

Source: own elaboration

compared to students with lower expected salaries in a future career. Moreover, it has been was evidenced that over-optimism in anticipating the future earnings is more typical for respondents whose field of study is related with a profession that is more likely to be challenged by the automation. In result, our study supports the hypothesis that students adjust their expectations to the processes of jobs automation.

Secondly, our study demonstrates that students who face the highest risk of their job being automated, tend to formulate the smallest relative remuneration expectations. It means that students who believe their future profession is likely to be triggered by automation, anticipate on the one hand a high chance to be employed, on the other hand – relatively higher future earnings. It means that these students discount high risk of automation of the professions where they might be hired after graduation.

However, it is worth emphasizing that the findings of the study and conclusions formulated therein before have to be taken cautiously. Firstly, the research target group consists of students in Cracow only. Thus, the research sample covers only a fraction of future labour market entrants. Consequently, the remuneration expectations of the students illustrated in the study do not reflect the situation of other groups of future labour market entrants, such as secondary school graduates, new-entrants coming from the external labour market. Secondly, due to the convenience sampling issues, the opinions gathered through the survey cannot be treated as fully representative to the whole population of students.

Thirdly, the survey was conducted before the breakout of the COVID-19 pandemic. Therefore, it does not reflect the implications of pandemic on remuneration expectation of the research target group. However, the pandemic and a corresponding lockdown in a number of industries might have a huge impact on how future labour entrants (i.e. students) evaluate their remuneration prospects.

The research problem is of economic nature. However, its conclusions might be related to the management context. In particular, few aspects seems to be of a special interest, i.e. identification of major technological trends, speed of their implementation, main factors influencing automation in particular sectors as well as organisational and structural changes are and might be identified within automation-prone sectors, considering that the automation offers an alternative to outsourcing and offshoring. Deep sector-based understanding and internal assessments, as the result of research studies might enable enterprises to benefit from automation. The changing landscape of technology-prone sectors challenges the status quo for enterprises in terms of the way they function, their employment and human resource development needs (Chang, Huynh, 2016, p. 23). Expected buoyant demand for some but not all professional occupations, reflects the forecasts of continued growth of service industries, where specially crucial are: interpersonal skills, higher-order cognitive skills and systems skills (Bakhshi et al., 2017, pp. 14–15).

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Endnotes

1) Questionnaire survey covered the students in following fields of study: Public Safety, Medical Analytics, Architecture, Biology, Biotechnology, Construction, Chemistry, Dietetics, Economics, Ethics, Pharmacy, Finance, Geodesy, Informatics, Electronics and Telecommunication, Biomedical Engineering, Civil Engineering, Environmental Engineering, Material Engineering, Cosmetology, Logistics, Painting, Mathematics, Gardening, Pedagogics, Law, Psychology, Chemical Technology, Food Technology, Human Nutrition Technology, Commodity Science, Transport and Logistics, Electrotechnics and automatics, Geodesy, Geography, Mining and Geoengineering, Ceramics and Material Engineering, Robotics, Production and Energy Engineering, Land Science, Mechanics Science, Management, Agricultural Economics, Management and Production Engineering, Zootechnics at the higher educational institutions such as: Jagiellonian University, Cracow University of Economics, Cracow University of Technology, Pedagogical University of Krakow, AGH University of Science and Technology, University of Agriculture in Krakow, Andrzej Frycz Modrzewski Krakow University.

2) This typology conceptualized each occupation as a series of tasks, which determine the necessary skills possessed by employees. Therefore, the terms „tasks" and „skills" are used interchangeably, depending on whether referred to an occupation or an employee.

3) For example, data collection (64% potential for automation and 17% of working time in the economy) and its processing (69% potential for automation and 16% of working time in the economy) are carried out in almost all sectors, and consists in: administration of human resources, payroll and transaction data, placing data in the forms of insurance, credit, banking and health institutions (Maryika et al., 2017, p. 44).

4) Kaufmann argues, that triangular distribution suits the probability distribution of future earnings well because it gives relatively small weight to the earnings further away from the mid-point.

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Postrzeganie automatyzacji procesów pracy a oczekiwania płacowe. Badanie wśród studentów Krakowa

Streszczenie

Automatyzacja procesów pracy jest dynamicznie rozwijającym się zjawiskiem wpływającym na procesy społeczno-gospodarcze w ramach: sektorów gospodarki, innowacji produktowych i procesowych, modeli biznesowych oraz struktur przedsiębiorstw. Dynamicznie rozwija się również w obszarze centrów usług wspólnych. W artykule zbadano, czy ryzyko automatyzacji zawodów przypisanych do poszczególnych kierunków studiów jest dostrzegane przez przyszłych uczestników rynku pracy i znajduje odzwierciedlenie w ich oczekiwaniach płacowych. Badania przeprowadzono wśród studentów uczelni wyższych i innych krakowskich uczelni. Badanie opiera się na pierwotnych i wtórnych źródłach danych. Pierwsze z nich to badanie przeprowadzone na przełomie 2018 i 2019 roku na próbie studentów reprezentujących 46 kierunków studiów w Krakowie (n = 1180). Drugie źródło danych to dane pozyskane z bazy danych ELA, ogólnokrajowego systemu śledzenia karier absolwentów szkół wyższych w Polsce. Przeprowadzone badania wykazały, że studenci zwykle wiążą swoje oczekiwania z wynagrodzeniem obserwowanym wśród absolwentów ich kierunku. Średnio studenci, których realne perspektywy zarobków są wyższe, mają wyższe oczekiwania płacowe. Badanie ujawniło nadmierny optymizm, choć utrzymujący się we wszystkich podgrupach, jest mniejszy w przypadku studentów, którzy są narażeni na większe ryzyko automatyzacji pracy. Dodatkowo studenci, którzy są narażeni na największe ryzyko automatyzacji swojej pracy, zwykle formułują najmniejsze względne oczekiwania płacowe. Ponadto negatywne postrzeganie automatyzacji prowadzi do niższych względnych oczekiwań płacowych.

Słowa kluczowe

automatyzacja, postrzeganie automatyzacji przez studentów, oczekiwania płacowe, centra usług wspólnych