DO ENTRANTS TAKE IT ALL? THE EVOLUTION OF TASK CONTENT OF JOBS IN POLAND

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Wojciech **Hardy**

Roma **Keister**

Piotr **Lewandowski**

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INSTYTUT BADAŃ STRUKTURALNYCH

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The evolution of task content of jobs in Poland

Wojciech Hardy[♠], Roma Keister[♣], Piotr Lewandowski[♦ ♥]

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Abstract

In this paper we analyse the changes in task content of jobs in Poland between 1996 and 2014. We follow the approach taken by Autor, Levy & Murnane (2003) and Acemoglu and Autor (2011) of using the O*NET 2003 and 2014 data and the Polish LFS data, with a4-digit occupation classification. We find an increasing intensity of both non-routine and routine cognitive tasks, and a decreasing intensity of both routine and non-routine manual tasks, mainly due to shifts in the employment structure between occupations. Cohorts born after 1970 underwent large shifts in the task intensity structure and contributed most to the overall changes in task contents, while almost no adjustments occurred in cohorts born before 1970. The growth of non-routine cognitive tasks among workers born after the 1970 was largely driven by the tertiary education boom in Poland, although in some cohorts the rising supply of tertiary graduates was accompanied by a relative reduction of the non-routine content of jobs.

Keywords: task content of jobs, routinisation, intergenerational divide

JEL: J24, J23, I25

[♠] Institute for Structural Research, Warsaw, Poland and Faculty of Economics, University of Warsaw. E-mail: wojciech.hardy@ibs.org.pl.

[♣] Institute for Structural Research, Warsaw, Poland. E-mail: roma.keister@ibs.org.pl.

[♦] Institute for Structural Research, Warsaw, Poland. Corresponding author. E-mail: piotr.lewandowski@ibs.org.pl.

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Introduction

Since the early 1990s, the transition economies in Central Eastern Europe have joined the global networks of production and trade and their economic structures have largely converged to those of the most developed countries. The share of services in GDP and employment has increased, while the share of agriculture has declined. New types of services and businesses have emerged and grown. Industry has remained an important source of jobs, but its structure has changed as the comparative advantages of CEE countries evolved: heavy industry and textiles declined while vehicles, machinery, home appliances and electronics, as well as furniture and chemical production rose. These developments changed the demand for labour and its structure in terms of occupation and skills (IBS, 2014). Moreover, technological progress has influenced the nature of jobs in particular industries (Acemoglu and Autor, 2011; Goos et al., 2013; Autor, 2015), as well as the task content of particular occupations (Spitz-Oener, 2006; Levy and Murnane, 2013) around the world. Together, these processes have shaped the requirements faced by workers in CEE. Economic and productivity growth have increased wages, but the employment gains were often modest, even in the countries that made reforms early and joined the EU in 2004 or 2007. Arias et al. (2014) show that as late as 2010, CEE countries suffered from many years of lost employment potential, especially among older workers and women.[1] The demographic dimension was of crucial importance as the participation of older workers in the labour market was relatively low, and the participation in life-long learning remained limited in CEE. Nevertheless, the CEE workforce has remained relatively young, enrolment in education has been high and has risen especially at tertiary level. Having said that, according to the EBRD–World Bank Business Environment and Enterprise Performance Surveys (BEEPS), since 2005 skilled labour shortages have become one of the most commonly reported constraints on company growth in the region (Sondergaard et al., 2012).

In this paper we focus on Poland, which from a macroeconomic viewpoint has been one of the most successful CEE economies, but its labour market has embodied most of the developments and challenges described above. We apply the "skills and tasks" approach popularised by Autor et al. (2003) and Acemoglu and Autor (2011) to shed new light on the parallel developments of labour demand and supply in Poland between 1996 and 2014. We follow Aedo et al. (2013) and Arias et al. (2014) and utilise (US) O*NET data to quantify the task content of jobs by occupation.[2] We use Polish LFS data and apply a 4-digit occupation classification (approx. 400 occupations) which permits a much more detailed measurement of task contents than the earlier work based on 3-digit or 2-digit occupations. We utilise the widest range of O*NET data possible (including both 2003 and 2014) which allows us to quantify the role of between-occupation and within-occupation shifts on the evolution of task content of jobs. To the best of our knowledge, this has only been done once so far in the context of task content – Spitz-Oener (2006) showed that the task structure in Germany followed similar patterns to those in the US, and that substantial within-occupation changes occurred in the last few decades of the 20th century.

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[1] Arias et al. (2014) calculate years of potential employment lost as employment rates by age group minus the total potential working life.

[2] Assumption of task content equivalence between Poland and US is rather strong, but Handel (2012) shows that US occupation-based and non-US skill-survey based measures lead to very similar outcomes for European countries. Recently two surveys based on O*NET questionnaires were conducted in the EU Member States (*Indagine sulle professioni* in Italy and *Kvalifikace 2008* in the Czech Republic). Cedefop (2013) shows that correlations of their results with O*NET are high, mostly around 0.8, and argues that it is methodologically valid to use O*NET data to construct occupational measures in European countries.

Our analysis extends beyond this scope by considering the evolution of the task content structure of various birth cohorts. We are able to identify inter-generational divisions in the job content and its evolution over time which so far have been overlooked in the literature. Finally, we analyse how have changes in the educational structure contributed to the evolution of tasks. Other than considering general task-intensity differences between workers of different education levels, few authors have analysed the role of education in the overall task structure changes. Autor et al. (2003) showed that although the task content changes might be the same at all education levels, the demand for particular education levels may change as jobs become more computerised, as confirmed later by Spitz-Oener (2006). Although this undermines the necessity to decompose the overall changes to those at various educational levels (as the changes are comparable), it also raises new questions, namely: how are the changes in education attainment related to the future (task-described) career paths of workers? Is there an age cohort task-effect connected to the evolution of education attainment? We try to answer these questions for Poland by decomposing cohort-specific changes in the task content of jobs into factors driven by education, task content of occupations and labour matching.

The paper is structured as follows. The first section outlines the evolution of the labour demand and labour supply structure in Poland between 1996 and 2014. The second section introduces the data and methodology. The third section presents our findings. The final section provides conclusions.

1. The evolution of labour demand and supply in Poland

After the transition shock and the decline in employment,[3] since the middle of the 1990s labour demand in Poland has been affected by short-term (cyclical) and medium-term developments typical for emerging economies. Between 1996 and 2014 employment in agriculture declined by 1.49 million people and its share of total employment dropped from 22.1% to 11.5%. Industrial employment decreased by 170,000 people (equivalent to 2.5 pp. reduction in the total employment share),[4] while the composition of industry evolved. In this period Poland lost its comparative advantage in the production of apparel and textile goods, as well as fertilisers and minerals, while it gained advantages in many branches of agricultural and food production, as well as production of paper, rubber, consumer chemicals and cosmetics (IBS, 2014). Meanwhile the production of furniture, wood, boats and yachts as well as copper mining held firm. In 1996, the four branches of Polish manufacturing with the highest share in employment were: food and beverages (16.0%), machinery and equipment (12.2%), clothing and apparel (7.2%) and textiles (6.7%), while in 2014 they were: food and beverages (17.2%), basic metals and fabricated metal products (13.3%), motor vehicles (10.8%) and furniture (7.5%). Employment in services grew by 2.25 million people between 1996 and 2014 (an increase of 11.7 pp. in the total share of employment). The largest employment growth was recorded in professional, scientific and technical activities, administration and support services, IT and communication, finance and insurance, accommodation and food service activities, especially after the EU accession in 2004. The sector structure of employment converged to that in the EU15, although not entirely. In 2014 the share of

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[3] According to ILO, between 1988 and 1992 employment in Poland fell from 18.5 million to 15.5 million, mainly in manufacturing, mining and construction (by 1.62 million).

[4] In 2014, the industry employment share in Poland was 23%, similar to the Czech Republic, Slovakia and Hungary, and above the EU average of 15%. In the EU 15, only Germany and Italy had industry shares close to 20%.

agriculture and industry were both higher in Poland than in EU15, while the share of services was lower, especially of professional, scientific, technical, administrative and support services.

Figure 1. Employment by sector in Poland 1996-2014 (thousands of people).

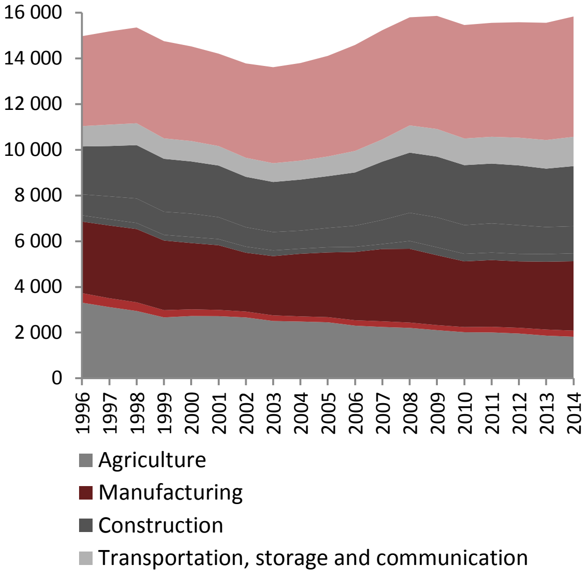
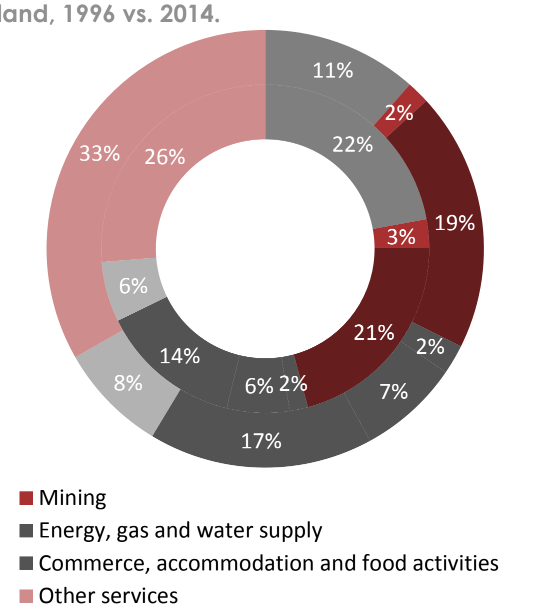


Figure 2. Sector structure of employment in Poland, 1996 vs. 2014.



Note: Some changes in employment by sector may result from changes in classifications: ISIC Rev. 3 since 1994, changed to ISIC Rev. 4 in 2008.

Note: The inner circle represents the structure in 1996, the outer circle in 2014.

Source: Own elaboration based on LABOURSTA, ILO and Eurostat data.

Changes in the structure of economy influenced the demand for occupations and skills (Arias et al., 2014; IBS, 2014), while the demographic and educational structure of the workforce changed dramatically. Numerous cohorts born in the 1970s and 1980s graduated and entered the labour market.[5] Compared to older generations, these cohorts increasingly went on to pursue higher education (see Figure 3).[6] The share of people with basic vocational education (which does not allow them to apply to universities) decreased from 34.2% of the workforce in 1996 to 26.2% in 2014. High schools (which allow university application) became the most popular type of secondary school. The share of individuals only obtaining general secondary or secondary vocational education remained stable, whereas the enrolment in tertiary education of 20-24 year-olds doubled between the late 1990s and 2010s. The share of people with tertiary education in the workforce rose from 11.4% in 1996 to 20.3% in 2004 and to 32.4% in 2014, the highest increase in the EU.[7] Progress was also noticeable in ICT-related skills. According to the European Commission's Digital Agenda Scoreboard, between 2005 and 2012 the

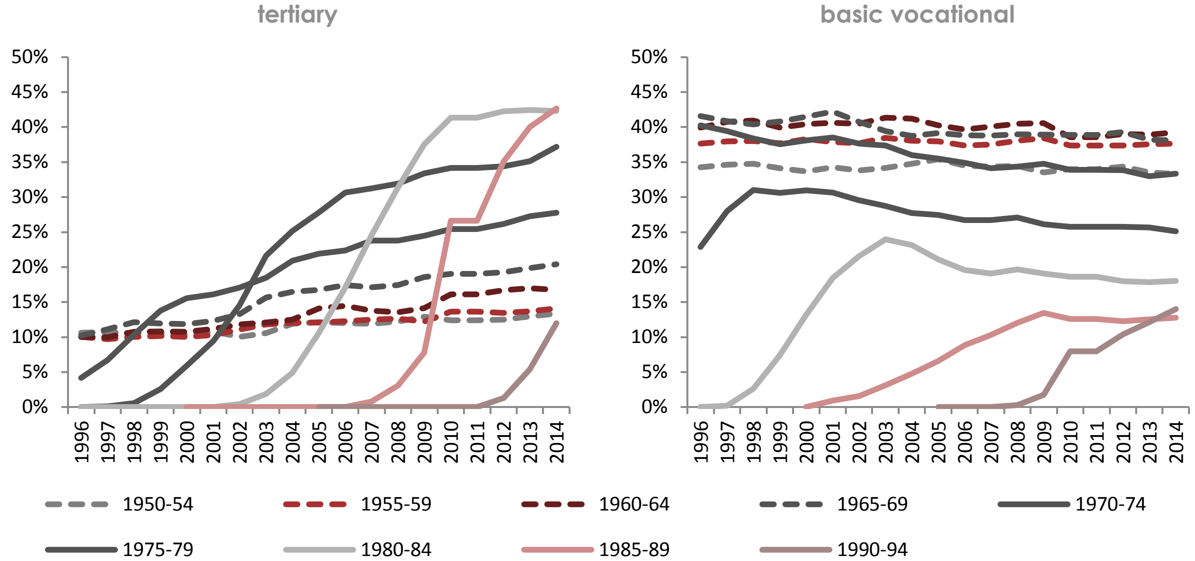
[5] The share of individuals aged 15-29 in the working age population amounted to 22-23% between 1996 and 2003, but later declined to 17% in 2014.

[6] We focus on tertiary and basic vocational education as the attainment of these two levels of education changed most. In other levels (junior high, primary or without primary; general secondary; post-secondary and secondary vocational) the changes were much smaller, for details see IBS (2014).

[7] An improvement in educational attainment has also been experienced by other countries in the region (particularly Lithuania, Latvia, Czech Rep., Slovakia and Slovenia), but it was not as pronounced as in Poland.

share of workers with medium or high computer skills in Poland rose from 40.6% to 50.3% and that of workers with medium or high internet skills from 18.6% in 2005 to 52.2% in 2013.[8]

Figure 3. Educational attainment by cohort in Poland, 1996-2014 (share of people with a given level of education)



Note: The legend shows the year of birth of the cohort. Minor fluctuations may result from the selection bias.
Source: Own elaboration based on LFS data.

Since the middle of the 1990s, the share of skilled workers in total employment in Poland has increased, mainly due to the rising share of professionals (from 9% in 1996 to 19% in 2014, see Figure 4). The share of managers and officials has remained stable at around 6%, as has the share of technicians at around 11%. The share of workers in low or medium-skilled non-manual occupations has also increased: the share of office clerks remained at around 7% from 1996 to 2014 (it was higher but has been declining in the EU15), whereas the share of people working in personal services rose from 9% in 1996 to 14% in 2014 (similarly to other EU countries). On the other hand, employment in manual jobs (agricultural workers, plant and machinery operators, assemblers and elementary occupations) has been falling, from 49% of total employment in 1995 to 37% in 2012 (a comparable decrease of 12 pp., to 18% in 2012, was recorded in the EU15). These patterns were especially pronounced for cohorts who entered the labour market after the transition, as illustrated by the 1970-1974 cohort (Figure 4). In general, the evolution of the occupational structure in Poland was consistent with the polarisation hypothesis (Goos et al., 2009). Moreover, structural and technological factors contributed to the vanishing of some occupations and the emergence of others. For instance, some engineering occupations (e.g. transportation and wood technology engineering) or weaving and knitting machine operators no longer constitute separate categories in the Polish classification of occupations, and were grouped into broader categories in 2002, while nuclear facilities operators became a separate occupation in 2002, as did mechatronics fitters in 2004. Many previously pooled IT-related occupations were recognised as stand-alone categories in 2010 – for example, computer systems designers and analysts were disaggregated into eight more specific occupations. In the next section we present the methodology to cope with the challenge of evolving occupational definitions and focus on the task content of jobs expressed with comparable measures.

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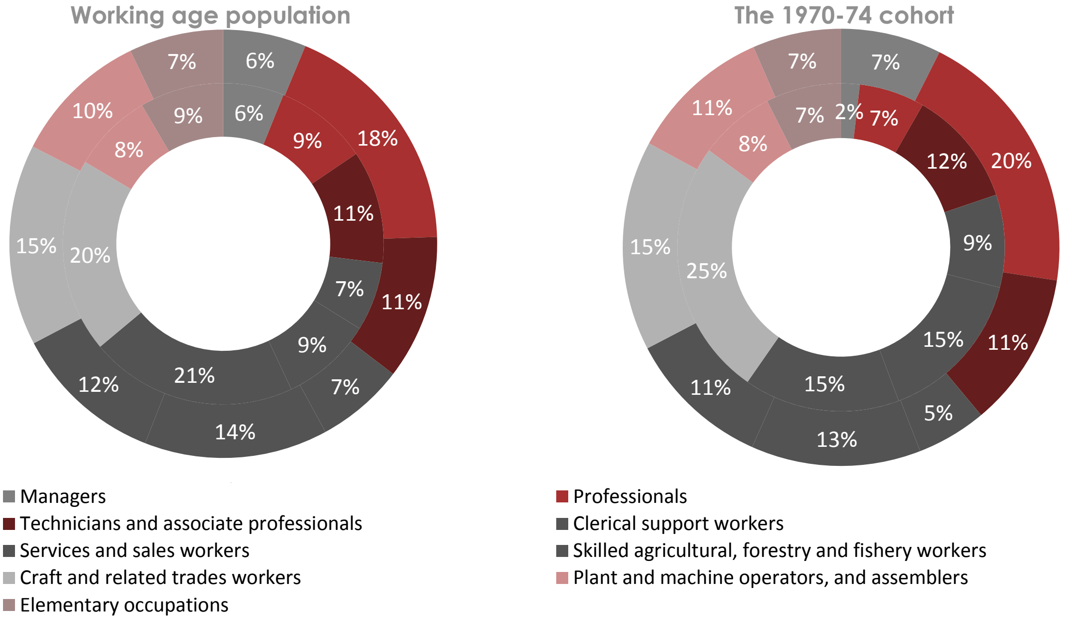
[8] For each Digital Agenda Scoreboard indicator we report the latest and earliest data available for Poland.

Figure 4. Occupational structure of employment in Poland, 1996 vs. 2014.



Note: The inner circle represents the structure in 1996, the outer circle in 2014.
Source: Own elaboration based on Eurostat data.

2. Data & methodology

2.1. O*NET data sets

We use the Occupational Information Network (O*NET) database as a source of information for the task content of occupations. Since 2003, O*NET data has been collected in the US for approximately 1000 occupations based on the Standard Occupational Classification (SOC), and by July 2014 has been updated fifteen times.[9] In line with the approach of Acemoglu and Autor (2011), we utilise four O*NET datasets: skills, work activities, work context and abilities. Each of them contains descriptors which are measured by scales such as the importance, level or extent of the activity.[10] Since the importance and level scales are highly correlated (0.92 in O*NET 2003 and 0.96 in O*NET 2014), we follow the approach of Acemoglu and Autor (2011) and only apply the importance scale. We use the earliest (2003) and the latest (2014) datasets available to capture the within-occupation change of task content over time. Table 1 summarises the datasets used.

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[9] O*NET is the successor of DOT (the Dictionary of Occupational Titles) which is no longer being updated. O*NET was launched in 1998 on the basis of the BLS Occupational Employment Statistics codes. In 2003 it was changed to SOC, meaning that consistent task content measures can be calculated since 2003.

[10] The scales have different ranges (e.g. the importance scale has values from 1 to 5, the level scale from 0 to 7).

Table 1. O*NET datasets used

O*NET dataset	No. of descriptors	No. of scales per descriptor	Types of scales	Data source
Skills	35	2	Importance and level	Analysts
Generalized work activities	41	2	Importance and level	Job incumbents / Experts
Work context	57	1	Importance	Job incumbents / Experts
Abilities	52	2	Importance and level	Analysts

*Source: Own elaboration based on the O*NET website.*

The number of occupations surveyed in O*NET has increased and changed over time as occupation classifications have been modified. For some datasets the number of descriptors measured in 2003 was lower than in 2014. In particular, the "structured vs. unstructured work" descriptor in the work context dataset, which is essential for measuring the routine cognitive task content, was only available for 54 SOC occupations in 2003, compared with 941 in 2014. Consequently, for all occupations lacking this descriptor in the O*NET 2003 database, we have assigned the earliest value available. The 2005 values provided almost 50% coverage, 2006 provided more than 80% and 2008 almost 100% (see Table 2).

Table 2. Numbers of occupations with complete information in 2003 O*NET, after imputation from subsequent O*NETs

Imputation from:	Number of complete occupations	Percent of complete occupations
Only O*NET 2003	54	6%
O*NET 2004	266	30%
O*NET 2005	441	49%
O*NET 2006	752	83%
O*NET 2007	877	97%
O*NET 2008	900	~100%

*Source: Own elaboration based on the O*NET data.*

2.2. Connecting O*NET tasks to the Polish LFS

To estimate the task content of jobs in Poland, we mapped O*NET task items to the corresponding four-digit occupations in Polish Classifications of Occupations and Specialisations called KZiS (*Klasyfikacja Zawodów i Specjalności),* and combined them with individual data of the Polish Labour Force Survey from 1996 to 2014,[11] so that all the individuals in the LFS were assigned task items corresponding to their occupation. The Polish LFS contains KZiS, a Poland-specific version of the International Standard Classification of Occupations (ISCO), while O*NET follows a modified version of the Standard Occupational Classification (ONET-SOC). To ascribe appropriate occupational attributes to the LFS data it was necessary to develop a link between these two classifications. Both ONET-SOC and KZiS have been modified over the years. ONET-SOC has undergone three revisions since 2000, the main one of which took place in 2010 (following the replacement of SOC2000 by SOC2010). KZiS underwent three revisions since 1995 which affected the 4-digit level codes: two smaller ones (in 2002 and 2004) and one major one in 2010 (following the replacement of ISCO-88 by ISCO-08). For the transition of ONET-SOC2000 into KZiS we implemented the following steps:

[11] The Polish LFS started in 1992, but until 1995 the occupational classifications were only reported at 3-digit level, and were not entirely comparable with the relevant international classifications. As a result, we began our analysis in 1996. The Polish LFS is conducted on a quarterly basis. Between 1996 and 2009, 45,000 individuals were surveyed each quarter, and since 2010 – 100,000 individuals per quarter.

1) Changing the ONET-SOC2000 data to simple SOC2000,
2) Linking the resulting SOC2000 data to ISCO-88 data,
3) Linking the resulting ISCO-88 data to KZiS 2004 data (LFS 2005-2010),
4) Linking the resulting KZiS 2004 data to KZiS 2002 data (LFS 2003-2004),
5) Linking the resulting KZiS 2002 data to KZiS 1995 data (LFS 1996-2002),
6) Mapping ONET-SOC2000 to ONET-SOC2010 using the O*NET crosswalk,
7) Changing the ONET-SOC2010 data to SOC2010,
8) Linking the resulting SOC2010 data to ISCO-08 data,
9) Linking the resulting ISCO-08 data to KZiS 2010 data (LFS 2011-2014).

Similar steps were taken for ONET-SOC2010, the only difference here was the starting point. The full list of crosswalks used to link the O*NET data (both with ONET-SOC2000 and ONET-SOC2010) to the evolving KZiS codes is available in the Appendix.

In some cases crosswalks do not provide unambiguous mapping between the two classifications. Four situations can be distinguished here. Firstly, one original occupation code (i.e. from a source or already-compiled classification) is only linked to one target occupation code (i.e. in a target classification) – in this case we inputted the original values of attributes to the target code. Secondly, one occupation code is linked to several target occupation codes – in this case we inputted the same original values of attributes to each target code. Thirdly, several occupation codes are just linked to one target occupation code – in this case we inputted the mean values of each attribute within the original codes to the single target occupation code. Fourthly, several occupation codes are linked to several target occupation codes – in this case we inputted the mean value of each attribute among the original codes to each target linked code. Table 3 presents the numbers of occupations for which we were able to assign O*NET attributes within each step.

Table 3. The resulting numbers of occupations in each classification, by starting points

To: Occupation classification	From: ONET-SOC 2000	From: ONET-SOC 2010
ONET-SOC 2000	902	-
ONET-SOC 2009	-	940
ONET-SOC 2010	748	942
SOC 2000	679	757
SOC 2010	680	770
ISCO-88	359	371
ISCO-08	399	422
KZiS 1995	**349**	**356**
KZiS 2002	**358**	**368**
KZiS 2004	**359**	**370**
KZiS 2010	**407**	**424**

Note: It was not necessary to map ONET-SOC 2010 into ONET-SOC 2000 because the transition between ONET-SOC 2000 and SOC 2000 is the same as for ONET-SOC 2009. Therefore we chose the more detailed ONET-SOC 2009 for the crosswalk.

*Source: Own elaboration based on O*NET, ISCO, KZiS and LFS.*

2.3. Calculating task contents

Having assigned the task items to the LFS data, we then standardised values of each task item *t* to make the data comparable over time (in accordance with Acemoglu and Autor, 2011), using the formula:

$$\bigwedge i \bigwedge j \in J \quad t_{i,j}^{std} = \frac{t_i - \mu_j}{\delta_j}, \qquad (1)$$

whereby J is the set of 16 task items listed in Table 4 for i observation in the LFS data and μ_j and δ_j are, respectively, the weighted average and standard deviation of j task item in 1996-2014, calculated as:

$$\bigwedge j \in J \;\; \mu_j = \frac{\sum_{i=1}^{N} t_{i,j} w_i}{\sum_{i=1}^{N} wi}, \qquad (2)$$

$$\bigwedge j \in J \;\; \delta_j = \left(\frac{\sum_{i=1}^{N} w_i (t_{i,j} - \mu_j)}{\sum_{i=1}^{N} w_i}\right)^{1/2}, \qquad (3)$$

whereby w_i is an ascribed weight of i observation in the LFS data.

Following Acemoglu and Autor (2011), we constructed five main task content measures: non-routine cognitive analytical and personal, routine cognitive and manual and non-routine manual physical. Each of these measures was created by adding up the appropriate standardised task items (listed in Table 4) and a subsequent standardisation of each of the resulting (five) task content measures.

Table 4. Construction of task contents measures

Task content measure (*T*)	Task items (*J*)
Non-routine cognitive analytical	Analysing data/information Thinking creatively Interpreting information for others
Non-routine cognitive interpersonal	Establishing and maintaining personal relationships Guiding, directing and motivating subordinates Coaching/developing others
Routine cognitive	The importance of repeating the same tasks The importance of being exact or accurate Structured vs. unstructured work
Routine manual	Pace determined by the speed of equipment Controlling machines and processes Spending time making repetitive motions
Non-routine manual physical	Operating vehicles, mechanized devices, or equipment Spending time using hands to handle, control or feel objects, tools or controls Manual dexterity Spatial orientation

Source: Own elaboration based on Acemoglu and Autor (2011).

Slight shifts in the estimated task structures were recorded following the KZiS revisions in 2002 and 2010. Rescaling was applied to correct the impact of these revisions. We standardised the task content measures separately in each of three sub-periods between the major classification changes (1996-2002, 2003-2010 and 2011-2014), according to the formulas (1)-(3). We then rescaled the 2003-2010 data so that the mean and standard deviation of each task content in 2003 was the same as in 2002. We rescaled the 2011-2014 data in the same way, equating the 2011 moments to those in the (rescaled) 2010 sample. This approach eliminated any potential heteroscedasticity resulting solely from classifications changes and allowed the trends to be analysed over the entire period studied.[12]

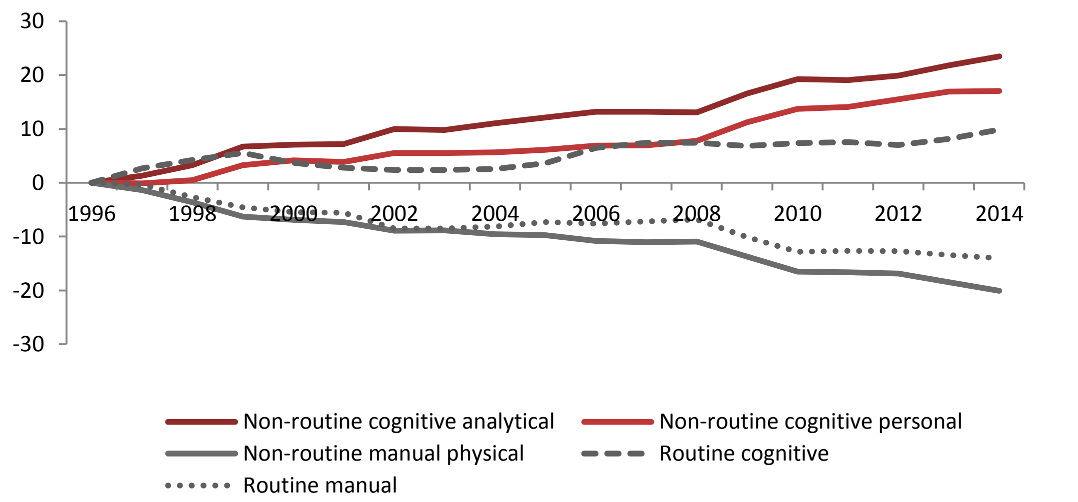
[12] We ran panel OLS regressions to validate this approach. We applied the means and standard deviations of task contents as dependent variables and dummies, indicating whether the observation was made after each of the years in the period 1996-2014 as explanatory variables. For the uncorrected data we found a shift in both the means and standard deviations after 2010 (significant at 1%), and no significant shift in the rescaled data.

3. Task content of jobs in Poland between 1996 and 2014

3.1. Overall trends

Our results show a general trend of increasing intensity (the number of tasks performed by an average worker) of non-routine cognitive tasks between 1996 and 2014 in Poland, mostly in line with the findings for the US (Acemoglu and Autor, 2011; Autor et al., 2003) or Germany (Spitz-Oener, 2006). The relative increase in analytical tasks was higher than for personal tasks (see Figure 5).[13] The gap between the growth in non-routine cognitive analytical and personal tasks emerged relatively early – in 2003 the average intensity of analytical tasks per worker had already accounted for more than 40% of the 2014 value, while for personal tasks it was 30%. Manual tasks, both routine and non-routine, declined in the period 1996-2014. The observed drop was 1.4 times greater for non-routine tasks. We also find that the intensity of routine cognitive tasks has gradually increased in Poland, except for the period 2001-2003. The relative increase in the intensity of routine cognitive tasks between 1996 and 2008 was comparable to that of non-routine cognitive personal tasks, but was much slower in 2009-2014. Results regarding routine cognitive tasks differ from the previous findings of declining routine cognitive tasks in countries like the US or Germany (Autor et al., 2003; Spitz-Oener, 2006), although Jaimovich and Siu (2012) and Acemoglu and Autor (2011) show that the trend in routine cognitive tasks might be dependent on the analysed period and the gender of workers.

Figure 5. Evolution of task content intensities in Poland from 1996 to 2014 (multiplied by 100).



*Note: A moving average was used to combine the derived mean task content measures from the 2003 and 2014 O*NET data sets. To make the results comparable the task indices were rescaled so that the initial value of them all was 0.*
*Source: Own calculations based on LFS & O*NET data.*

[13] We used the moving average to combine the task content intensities obtained from 2003 and 2014 O*NET. From 1996 to 2003 we used task indices based on O*NET 2003, for any year t in the period 2004-2014 we assigned a weight $\frac{2014-t}{11}$ to task indices based on O*NET 2003, and a weight $\frac{t-2003}{11}$ to task indices based on O*NET 2014. To make the results comparable we rescaled the task indices so that the initial value of them all was 0.

In the next step, for every task i we decompose the change (between 1996 and 2014) of the average task intensity per worker, T_i, into three factors: (i) the contribution of the between-occupation changes, i.e. changes in the (occupational) structure of employment, BO_i; (ii) the contribution of shifts in the task content intensities within particular occupations over time, WO_i;[14] and (iii) the contribution of the interaction between changes in the employment structure and shifts in task intensities, INT_i,[15] according to the formulas below:

$$\bigwedge i \in T \;\; (T_i^{2014} - T_i^{1996}) = (\sum_{j \in E} t_{i,j}^{14} e_j^{14} - \sum_{j \in E} t_{i,j}^{03} e_j^{96}) = BO_i + WO_i + INT_i, \qquad (4)$$

$$\bigwedge i \in T \;\; BO_i = \sum_{j \in E} t_{i,j}^{03} (e_j^{14} - e_j^{96}), \qquad (5)$$

$$\bigwedge i \in T \;\; WO_i = \sum_{j \in E} e_j^{96} (t_{i,j}^{14} - t_{i,j}^{03}), \qquad (6)$$

$$\bigwedge i \in T \;\; INT_i = \sum_{j \in E} (t_{i,j}^{14} - t_{i,j}^{03})(e_j^{14} - e_j^{96}), \qquad (7)$$

whereby:

- T is the set of five task content measures (as in Table 4), T_i^{1996} and T_i^{2014} are the average intensities of a given task content measure i per worker in 1996 and 2014, respectively,
- $t_{i,j}^{14}$ and $t_{i,j}^{03}$ are the average estimated values of task i for a worker j using O*NET 2014 and O*NET 2003, respectively,
- e_j^{14} and e_j^{96} are the weighted (LFS weights) shares of a worker j in total employment in 2014 and 1996 respectively, and E is the total set of individuals observed either in 1996 or 2014.[16]

For all five tasks contents considered, the between-occupation factor, i.e. the shifts in employment structure by occupations, was the most important driver of changes in task content intensity between 1996 and 2014 (see Figure 6). We find that the entire increase in the average intensity of non-routine cognitive analytical tasks can be attributed to an increase in employment in occupations with a relatively high intensity of these tasks. In the case of the (also growing) non-routine cognitive personal and routine cognitive tasks, it is 84% and 67% of the total change respectively. In the case of declining non-routine manual physical tasks – 82%. For routine manual tasks, the decline resulting from the changes in the employment structure is even greater than actually recorded. The within-occupation effect played a minor role, except for non-routine cognitive analytical tasks. We find that 6% of the total increase in average intensity of these tasks can be attributed to the increase in the non-routine cognitive analytical content of particular occupations. However, the interaction effect for these tasks was negative and also accounted for 6% of the total change. This means that employment growth, which drove the overall growth in these tasks, was encompassing jobs which had lower average non-routine cognitive analytical content than the jobs behind the non-routine cognitive analytical tasks in 1996. In the case of routine

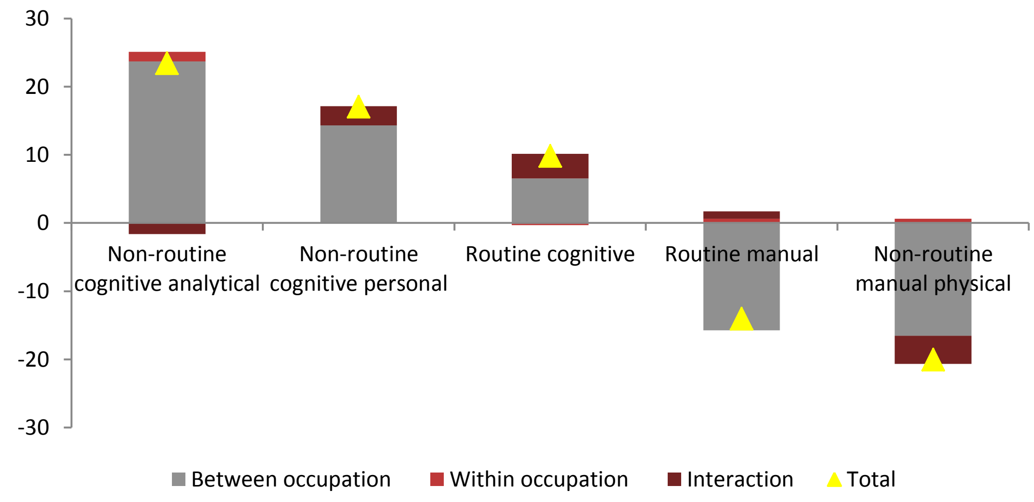
[14] Changes in the task content intensities of particular occupations can be interpreted as driven by technology (Levy and Murnane, 2013).

[15] For a given task, i is positive if the employment share of occupations with rising task i intensities also increases, and negative if it decreases (and vice versa).

[16] In the observations of different individuals in 1996 and 2014, each worker surveyed in 1996 was assigned a 0 weight in the 2014 sample, while each worker surveyed in 2014 has a 0 weight in the 1996 sample.

cognitive tasks, the interaction term was positive and contributed 36% of the total growth in these tasks. Consequently, employment increased in occupations which on the average had higher routine cognitive content than jobs behind the routine cognitive tasks in 1996 (which is consistent with an increase in the share of workers in low or medium-skilled non-manual occupations, see Figure 4). For manual tasks (both routine and non-routine) the opposite was true – employment in jobs encompassing these tasks was declining, and the jobs still performed in 2014 on average had a lower manual task content than those performed in 1996.

Figure 6. Decomposition of the task content intensity changes in Poland between 1996 and 2014 (multiplied by 100).



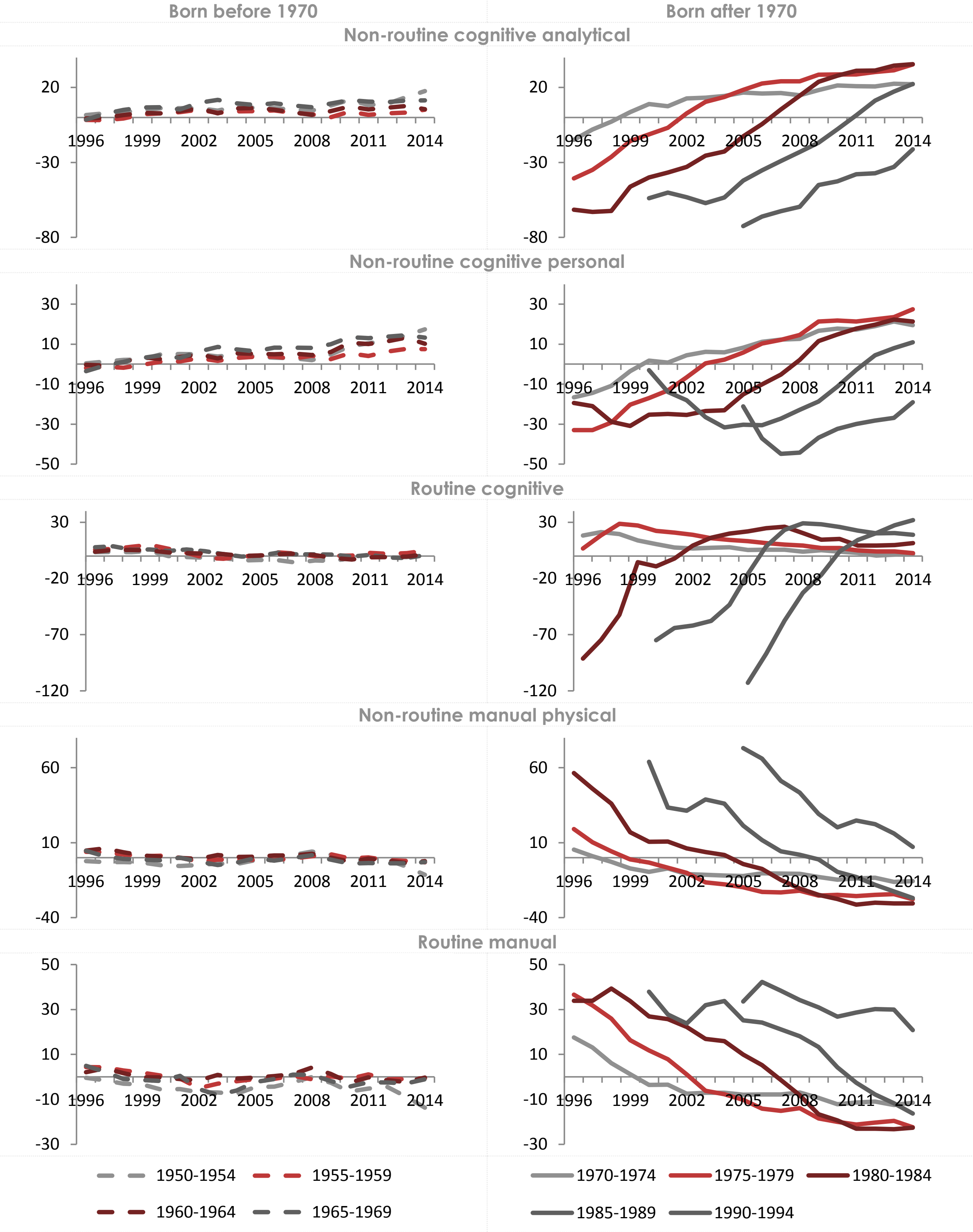
*Source: Own calculations based on LFS & O*NET data.*

3.2. The inter-generational dimension of task content changes

A striking difference emerges between the patterns observed for younger cohorts (born between 1970 and 1994) – who experienced task content evolution typical for most developed countries – and older cohorts (born between 1950 and 1969) – who did not. The latter were aged between 27 and 46 years in 1996 and were mostly active on the labour market, while the former were 26 and below in 1996 and mostly entered the labour market during the period studied. Figure 7 shows the evolution of task content between 1996 and 2014 by 5-year birth cohorts. For all tasks, the change in the average task intensity was lowest for the oldest cohorts in the study (i.e. people born in 1950-69) and was highest for the youngest cohorts. Among cohorts born between 1950 and 1969, all five task content intensities remained relatively stable over time,[17] especially those regarding the routine cognitive and non-routine manual tasks. The evolution of all five task content intensities was virtually identical for all 5-year cohorts born in the 1950s and 1960s.

[17] Across the 5-year cohorts born between 1950 and 1969, the average standard deviations of task content measures in 1996-2014 are between 2.4 (routine manual tasks) and 4.0 (non-routine cognitive personal).

Figure 7. The evolution of task content intensity in Poland by year of birth cohorts.



*Source: Own calculations based on LFS & O*NET data*

The picture is considerably different for younger cohorts,[18] who underwent rapid changes in task content intensities (see Figure 7).[19] Workers born between 1970 and 1974 constituted the first cohort entering the labour market after the transition shock. They turn out to be the first cohort experiencing substantial growth in non-routine cognitive tasks and a noticeable decline in non-routine manual as well as routine tasks (both cognitive and personal). The cohort born between 1975 and 1979 experienced these developments to an even greater extent. For each cohort studied, most of changes in the task content intensities occurred due to changes in the occupational structure – which were small among workers born before 1970 and substantial among workers born later.[20]

We find that for all 5-year cohorts born after 1970, the average intensity of non-routine cognitive (both analytical and personal) tasks had risen over time once a cohort turned 20. Moreover, each subsequent cohort had a greater average non-routine cognitive analytical task intensity at a given age than the previous cohort had at the same age (except for the 1980-84 cohort, which had a slightly higher non-routine cognitive task intensity at the age of 25-29 than the 1985-1989 cohort). Table 5 sheds more light on the processes experienced by people born after 1970. It compares the cognitive task intensities of various cohorts at the same stage of the life cycle. People born between 1975 and 1984 experienced the largest shifts in both non-routine cognitive and manual tasks intensity. Between the age of 20 and 39, workers in these cohorts underwent changes in the content of their jobs which were so strong that they leap-frogged the older cohorts regarding non-routine cognitive tasks, and ended up having less manual tasks than older workers (see Figure 7).[21]

Table 5. Average intensity of tasks for subsequent cohorts by age group (multiplied by 100)

Non-routine cognitive analytical				
Age / cohort	1970-74	1975-79	1980-84	1985-89
20-24	n/a	-15.7	-21.4	-13.5
25-29	3.6	14.1	25.6	23.2
30-34	14.6	28.0	33.0	n/a
35-39	17.0	33.1	n/a	n/a
Routine cognitive				
Age / cohort	1970-74	1975-79	1980-84	1985-89
20-24	n/a	27.0	20.1	27.9
25-29	13.8	14.2	11.8	13.6
30-34	7.7	3.9	3.5	n/a
35-39	5.6	-0.2	n/a	n/a

Note: Due to the availability of data, the mean values of task contents presented in the table have been calculated for the following years: 1999, 2004, 2009 and 2014.
*Source: Own calculations based on LFS & O*NET data.*

[18] This finding is consistent with the results of Arias et al. (2014) for several European and Central Asian countries in the period 2002-2010.

[19] Across 5-year cohorts born between 1970 and 1989, the average standard deviations of task content measures in 1996-2014 are between 16.1 (non-routine cognitive personal tasks) and 23.9 (non-routine cognitive analytical).

[20] Based on the cohort-specific decompositions of average task intensity calculated in accordance with equations (4)-(7). Detailed results available upon request.

[21] Due to a lack of data, we are unable to analyse people born before 1970 in their 20s (and 30s in the case of workers born before 1969). However, we think that they did not experience such pronounced growth in non-routine cognitive tasks at that age, because the intensity of their non-routine cognitive tasks in the 1990s turned out to be lower than intensity levels quickly achieved by workers born after 1970 (see Figure 7).

The situation concerning routine cognitive tasks was slightly different. For people aged between 30 and 39 there is a decreasing trend over subsequent cohorts, while for people aged between 20 and 29 no clear trend emerges (see Table 5). Nevertheless, workers in all 5-year cohorts born between 1970 and 1984 experienced a decreasing intensity of routine cognitive tasks as they grew older. This suggests that labour market entrants in Poland were employed in highly routine cognitive occupations, but over time the non-routine component of jobs and tasks they perform tends to rise. The manual task content of jobs (both routine and non-routine) also decreased with age, as well as over the subsequent cohorts.[22]

Workers born in 1975-1979 and 1980-1984 not only experienced the largest growth in non-routine cognitive tasks, but they also made the biggest contribution to the overall increase of these tasks. Table 6 presents the contributions of subsequent cohorts to the total change of task intensity between 1996 and 2014, divided into two sub-periods: 1996-2004 and 2004-2014. We focus on people born in the period 1950-1989, who constituted 73%, 90% and 92% of the working-age population in 1996, 2004 and 2014 respectively.[23] Regarding non-routine cognitive tasks, in the period 1996-2004 their growth was mainly driven by people born between 1970 and 1974, who entered the labour market in the 1990s. The 1975-1979 cohort, which was largely graduating in that period, contributed less, but still more than people born in 1960-64 and 1965-69, who mostly graduated before 1995. In the period 2004-2014, the increase in non-routine cognitive tasks was driven by workers born in 1975-1979 and 1980-1984, who contributed 3.3 and 6.8 respectively of the total growth in analytical task intensity of 13.9 in the population born in 1950-1994.[24] A similar pattern emerges in the case of non-routine cognitive personal tasks. Moreover, in the period 2004-2014, personal tasks grew less than analytical tasks among workers born between 1980 and 1989. Among workers born between 1950 and 1979 the opposite was true.

The findings are different for routine cognitive tasks. The total change in intensity of these tasks in the population born between 1950 and 1989 was relatively small – between 1996 and 2004 it amounted to -1.6, and between 2004 and 2014 to 1.8. In both sub-periods, the cohorts which made the biggest contribution to the total change in routine cognitive tasks were labour market entrants – the cohort born between 1975 and 1979 in the period 1996-2004, and the cohort born between 1985 and 1989 in the period 2004-2014. In the period 2004-2014, the 1975-1979 cohort, which by that time had established its position on the labour market, contributed most negatively to the change in the intensity of routine cognitive tasks.

The changes experienced by cohorts born between 1975 and 1989 were also of crucial importance for the evolution of manual tasks, both routine and non-routine. The decrease in the intensity of manual tasks accelerated in 2004-2014. Table 6 shows that this can be attributed to a persistent decline of these tasks among workers born in the 1970s, and a substantial decline among workers born in the 1980s in the period 2004-2014: out of the total change of -8.3 (-10.5) to the routine (non-routine) manual task content intensities in 2004-2014, -4.4 (-4.6) was due to the contribution of the 1980-1984 cohort.

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[22] Except for the non-routine manual tasks among 1975-1989 cohorts aged 20-24.

[23] People born before 1950 reached the statutory retirement age before 2014 and mostly left the labour market to retire. People born after 1989 only entered the labour market in the last few years of the period studied.

[24] The absolute change weighted by the shares of cohorts in total employment in the stated years.

Table 6. Contributions of subsequent cohorts to task content intensity changes in Poland, 1996-2004 and 2004-2014 (multiplied by 100)

1996-2004									
	1950-54	1955-59	1960-64	1965-69	1970-74	1975-79	1980-84	1985-89	Total
Non-routine cognitive analytical	0.6	0.9	0.9	1.4	3.6	3.6	-1.5	-0.5	9.0
Non-routine cognitive personal	0.5	0.8	0.8	1.4	2.6	1.7	-1.6	-0.3	5.8
Non-routine manual physical	-0.1	-0.9	-0.6	-1.0	-2.3	-3.3	0.0	0.4	-7.7
Routine cognitive	-1.0	-1.1	-0.5	-1.0	-0.8	1.7	1.6	-0.4	-1.6
Routine manual	-0.8	-1.1	-0.4	-1.4	-2.8	-2.6	1.1	0.3	-7.6
2004-2014									
	1950-54	1955-59	1960-64	1965-69	1970-74	1975-79	1980-84	1985-89	Total
Non-routine cognitive analytical	0.0	-0.1	-0.2	0.0	0.8	3.3	6.8	3.2	13.9
Non-routine cognitive personal	0.3	0.3	0.4	0.5	1.7	3.7	4.8	1.6	13.3
Non-routine manual physical	-0.1	-0.1	-0.3	0.1	-0.3	-1.6	-4.6	-3.6	-10.5
Routine cognitive	0.5	0.6	0.1	0.2	-0.9	-1.6	0.2	2.7	1.8
Routine manual	0.2	0.2	0.1	0.7	-0.5	-2.2	-4.4	-2.3	-8.3

*Source: Own calculations based on LFS & O*NET data.*

3.3. Education, task content and labour matching

In order to analyse to what extent the differences in task content developments experienced by various cohorts can be explained by the differences in the evolution of their educational structure, for each task i we decompose the change (between 1996 and 2014) in average task intensity in the cohort c, $T_{i,c}$, into contributions of three different factors: (i) changes in the educational structure of workers in the cohort, interpreted as the labour supply factor $LS_{i,c}$; (ii) changes in the task content intensities within a particular education group, interpreted as a task content factor $TC_{i,c}$; and (iii) the interaction between shifts in the employment structure of a given cohort and changes in the associated task intensity $LM_{i,c}$. The interaction term is positive (negative) if the task content i increases more (less) than would be implied by changes in the educational attainment of cohort c, and by changes in the task content of jobs held by cohort c in the initial year of the study. We therefore interpret it as a labour matching factor.

For each 5-year cohort c born in the period 1950-1984, the decomposition was calculated according to:

$$\bigwedge i \in T \ \ (T_{i,c}^{2014} - T_{i,c}^{1996}) = (\sum_{j \in H} t_{i,j,c}^{14} h_{j,c}^{14} - \sum_{j \in H} t_{i,j,c}^{03} h_{j,c}^{96}) = LS_{i,c} + TC_{i,c} + LM_{i,c}, \qquad (8)$$

$$\bigwedge i \in T \ \ LS_{i,c} = \sum_{j \in H} t_{i,j,c}^{03} \left(h_{j,c}^{14} - h_{j,c}^{96}\right), \qquad (9)$$

$$\bigwedge i \in T \ \ TC_{i,c} = \sum_{j \in H} h_{j,c}^{96} \left(t_{i,j,c}^{14} - t_{i,j,c}^{03}\right), \qquad (10)$$

$$\bigwedge i \in T \ \ LM_{i,c} = \sum_{j \in H} \left(t_{i,j,c}^{14} - t_{i,j,c}^{03}\right)\left(h_{j,c}^{14} - h_{j,c}^{96}\right), \qquad (11)$$

whereby:

- $t_{i,j,c}^{14}$ and $t_{i,j,c}^{03}$ are the average values of task content i for workers with education level j in cohort c, calculated using O*NET 2014 and O*NET 2003, respectively,
- $h_{j,c}^{14}$ and $h_{j,c}^{96}$ are the shares of workers with education level j among all workers in cohort c in 2014 and 1996 respectively, (except for the 1980-1984 cohort, where it is 2014 and 2004),
- T is the set of five task content measures (as per Table 4),
- H is a set of five different education levels: junior high, primary or no primary; basic vocational; general secondary; post-secondary and secondary vocational; tertiary education.

We find that the evolution of educational attainment, in particular the improvement in the educational structure of subsequent cohorts, was crucial for the evolution of task content of jobs held by workers of particular cohorts. It was a particularly dominant factor for non-routine cognitive analytical tasks (see Table 7).[25] Once again, the three youngest cohorts stand out here. The effect of the educational structure in the 1970-74 cohort was 2.2 times greater, and in the 1975-79 cohort approx. 2.8 times greater, than in the 1965-1969 cohort. In fact, people born in the 1970s were the first to participate in the educational boom in Poland and experienced the biggest increase in the share of people attaining tertiary education during the analysed period (25 pp. for the 1970-74 cohort between 1996 and 2014, and 37 pp. for the 1975-79 cohort between 1999 and 2014). However, the intensity of non-routine analytical tasks in the 1970-74 and 1975-79 cohorts increased much less between 1996 and 2014 than would be implied by the improvement in educational attainment. We interpret this as a negative labour matching effect – the demand for non-routine analytical tasks turned out noticeably lower than the supply of workers prepared to deliver these tasks (which rose due to the large shifts in the educational structure). In the case of the 1980-84 cohort, the labour matching effect was also noticeable (in 2004-2014), but contrary to the 1975-79 cohort it was positive. This again suggests that in the 2000s, workers born between 1980 and 1984 were moving up the occupational ladder to jobs which demanded more non-routine analytical tasks. The task content effect had a negative role (except for the 1980-84 cohort), especially for people born in the 1950-1979 period, which suggests that older workers were more affected by the routinisation occurring within occupations than younger workers. The labour matching effect was virtually irrelevant for older cohorts.

The decomposition of the non-routine cognitive personal task content changes provides similar results, but on average the contribution of educational structure factor was smaller. Also (contrary to analytical tasks) the task content effect played a positive role, showing that non-routine cognitive personal tasks were rising in jobs held by particular education groups within all cohorts. Once again, the 1975-79 cohort stands out with a relatively large and negative labour matching effect, therefore suggesting that in relation to demand, there may have been an over-schooling effect in that cohort.

[25] For workers born before 1960, the improvements in the educational structure were rather due to low-skilled people exiting the labour market, while for younger workers it was due to the increasing enrolment in tertiary education.

Table 6. The decomposition of cohort-specific task content intensity changes (multiplied by 100) in Poland into contributions of educational structure, task content and labour matching factors, 1996 vs. 2014

Cohort	Factors	Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Routine manual	Non-routine manual physical
1950-54	Educational structure	23.5	20.3	-6.7	-20.1	-19.9
	Task content	-7.6	1.4	0.5	6.7	12.4
	Labour matching	-0.2	-3.7	5.1	2.3	0.7
1955-59	Educational structure	14.0	11.3	-3.8	-11.7	-11.4
	Task content	-5.2	1.1	0.0	7.7	5.5
	Labour matching	-1.1	-1.1	2.5	0.8	0.0
1960-64	Educational structure	14.6	10.9	-4.5	-12.6	-12.1
	Task content	-4.6	2.9	0.7	12.4	7.1
	Labour matching	-1.3	0.4	1.0	0.6	-0.1
1965-69	Educational structure	20.7	14.7	-6.3	-17.5	-16.8
	Task content	-2.6	5.5	-5.1	11.3	11.1
	Labour matching	-3.8	-0.5	2.6	1.6	0.4
1970-74	Educational structure	45.1	29.5	-16.4	-41.0	-37.9
	Task content	-2.1	6.4	-12.0	5.8	19.6
	Labour matching	-7.4	0.0	8.6	4.7	-0.1
1975-79*	Educational structure	57.2	46.9	-16.9	-52.6	-50.4
	Task content	-2.6	7.8	-15.5	11.5	29.0
	Labour matching	-7.3	-8.8	6.7	1.9	-2.9
1980-84**	Educational structure	39.6	27.0	2.8	-32.4	-36.8
	Task content	11.8	13.6	0.7	12.0	21.3
	Labour matching	5.1	2.7	-11.6	-16.3	-14.9

Note: for the 1975-79 and 1980-84 cohorts decomposition is calculated for 1999-2014 and 2004-2014, respectively.
*Source: Own calculations based on LFS & O*NET.*

Routine cognitive tasks were in decline mainly due to the effect of the educational structure. For workers born in the 1970s, the task content effect was just as important, which suggests that workers at a given level of education were moving to jobs with less routine cognitive tasks. In the case of the 1980-1984 cohort (analysed here in 2004-2014) the intensity of these tasks also decreased, but the effect of the educational structure was slightly positive and was cancelled out by the matching effect.[26]

Contrary to cognitive tasks, manual tasks were depressed by the negative effect of the educational structure for all cohorts considered. Supposedly, the sources of this negative effect were different for younger and older workers. Among those born between 1950 and 1970, workers with a relatively low

[26] In 2004, tertiary graduates constituted 7% of workers in the 1980-1984 cohort and they performed rather routine cognitive jobs (the average relative intensity of these tasks amounted to 25.6). Over time the employment share of tertiary graduates in this cohort increased to 46.5%, causing the decomposition formula to predict an increase in routine cognitive intensity. However, the intensity of routine cognitive tasks in this group declined to -1.0 in 2014, hence the negative matching effect.

level of educational attainment were exiting the labour market earlier than better educated ones (IBS, 2010), therefore the impact of the educational structure on manual tasks in these cohorts was negative. In the case of individuals born after 1970, the observed pattern was driven by an educational boom. As the share of university graduates grew and the share of graduates with basic vocational education declined within cohorts,[27] significant shifts from highly manual jobs towards more cognitive ones appeared in the cohort-specific structures of employment, depressing the manual content of jobs.

Conclusions

In this paper we have applied the task-based approach of Autor, Levy & Murnane (2003) to analyse the interaction between the evolution of labour demand, the transformation of the labour supply, and the evolving nature of occupations in Poland between 1996 and 2014. We combined O*NET data from 2003 and 2014 with Polish LFS using a 4-digit occupation classification (approx. 400 occupations) to analyse the overall, between-occupation and within-occupation changes to task content of jobs. The economy-wide findings mostly fall in line with previous literature (e.g. Acemoglu and Autor, 2011; Autor et al., 2003; Spitz-Oener, 2006). We found an increase in the intensity of non-routine cognitive analytical and personal tasks, and a decrease in routine and non-routine manual tasks. The notable divergence from previous findings is the growth in routine cognitive tasks. We find that the between-occupation shifts contributed much more than within-occupation changes to the total change in all task content intensities examined. In general, Poland progressed in a similar direction to the US or Germany, but contrary to those economies increased the number of medium-skilled, non-manual jobs.

We have identified strong inter-generational differences with respect to the evolution of task content of jobs. Within the period 1996-2014, task content intensities underwent dynamic changes among people born after 1970, while hardly any changes occurred among those born before 1970. Every new cohort entering the labour market since the middle of the 1990s experienced a rise in the average intensity of non-routine cognitive (both analytical and personal) tasks after the age of 20. After the age of 25, every new cohort reached a higher intensity of non-routine cognitive analytical tasks than that achieved by the previous cohort at the same age. Consequently, younger generations may be increasingly likely to work in computerised jobs (in line with the interpretation of Levy and Murnane, 2013). On the other hand, after a dozen or so years of a decline in the intensity of manual tasks, in 2014 workers born between 1970 and 1989 exhibited a lower average intensity of manual tasks than workers born between 1950 and 1969, who have barely experienced any change since middle 1990s. As a result, the developments among the younger group accounted for the majority of the overall change in task contents recorded between 1996 and 2014. We attribute most of these inter-generational differences to the distinct educational paths followed by younger cohorts, starting with the path taken by those born in the 1970s and increasingly pursued by subsequent generations. We find that, from the viewpoint of task content, labour demand has largely accommodated the growing inflow of better-educated entrants without deteriorating their job prospects – in 2014 the intensities of non-routine analytical tasks in cohorts participating in the educational boom were over 80% of what could be predicted by the evolution of the educational attainment of these cohorts, and the task changes affecting the occupations per se.

[27] In the 1975-79 cohort the share of workers with basic vocational education was 51% in 1996, 24% in 2014.

Our findings have potentially important implications for countries at a comparable or lower level of development. Older workers may be left behind by technological progress and the emergence of new types of jobs, especially in countries with undeveloped systems of life-long learning. At the same time, younger and older workers may not compete for the same types of jobs, making the implementation of policies aimed at prolonging working lives easier. On the other hand, older workers in more routine and more manual jobs may face bigger obstacles to working longer than they would face if they had more non-routine and cognitive jobs. Finally, the fast changes in educational attainment are often accompanied by complaints about the decrease in quality and relative degradation of the graduates' labour market situation. However, the Polish experience shows that if the economy is able to take advantage of the new opportunities created by openness and technology, these risks might not be large and should not discourage the expansion of education.

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Appendix

Crosswalks used:

ISCO-08 to KZiS 2010: Wortal Publicznych Służb Zatrudnienia MPiPS

http://psz.praca.gov.pl/rynek-pracy/bazy-danych/klasyfikacja-zawodow-i-specjalnosci [2015-04-15]

ISCO-88 to SOC-00: National Crosswalk Service Center

http://www.xwalkcenter.org/index.php/downloads [2015-04-15]

ISCO-88 to KZiS-04: WageIndicator; Project *EurOccupations;* State-of-the-art report (First Reporting Period – D35)

http://www.wageindicator.org/main/Wageindicatorfoundation/projects/euroccp/euroccupations#euroccupations-deliverables [2015-04-15]; with own modifications to match the remaining occupations from the full occupational lists (available upon request).

KZiS-02 to KZiS-95 – Own work, based on minister's regulation (available upon request).

KZiS-04 to KZiS-02 – Own work, based on minister's regulation (available upon request).

O*NET SOC-10 to O*NET SOC-09 – O*NET cross walk

http://www.onetcenter.org/taxonomy.html [2015-04-15]

O*NET SOC-09 to O*NET SOC-06 – O*NET cross walk

http://www.onetcenter.org/taxonomy.html [2015-04-15]

O*NET SOC-06 to O*NET SOC-00 – O*NET cross walk

http://www.onetcenter.org/taxonomy.html [2015-04-15]

SOC-10 to SOC-00 – U.S. Bureau of Labor Statistics

http://www.bls.gov/soc/soccrosswalks.htm [2015-04-15]

SOC-10 to ISCO-08 – U.S. Bureau of Labor Statistics

http://www.bls.gov/soc/soccrosswalks.htm [2015-04-15]

INSTYTUT BADAŃ STRUKTURALNYCH

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