Impact of industrial change on skills during economic transition in Central and Eastern Europe

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Abstract

To what extent has the changing structure of economy during the transition in Central and Eastern Europe resulted in reskilling, deskilling, or upskilling of the labour force? Using unique data from the Life in Transition Survey (2006) we find that the scale of changes in the skill-sets has been surprisingly limited. Instead, transition has resulted in a generational change: workers from declining firms and sectors exited labour market, while the young cohorts took up the jobs in the emerging sectors. Furthermore, we find that pre-retirement exists can be explained by the type of inherited skills: workers with narrower and shallower skill-sets 'survived' in the labour market for a considerably shorter period of time.

1. Introduction

Transition from planned to market economies in Central and Eastern Europe (CEE) involved a large change to the structure of economy in a relatively short period. Large state owned enterprises (SOEs) gave way to small and medium sized private firms, and the relative size of agriculture and manufacturing declined, while previously neglected services expanded. As a result, labour moved (Campos and Coricelli 2002). However, the implications of these movements on the skills of the labour force are under researched in two respects.

First, to what extent has reskilling occurred? Earlier transition literature (e.g. Cazes and Nešporová, 2001) studying changes in the stocks of labour argues that there has been significant job-to-job mobility as labour moved from declining firms and sectors to the newly emerging ones. If this was the case, there should have been significant reskilling of the labour force. However, more recent literature (Tyrowicz and Velde, 2017) studying flows of workers argues that the scale of job-to-job mobility has been very limited. Instead, a generational change has occurred: as workers from declining sectors moved out of the labour market, new entrants have taken up jobs in emerging firms and growing sectors.

Second, what individual level factors can explain skill destruction (labour market exits) and reskilling / upskilling? Literature argues that narrow skills acquired as a part of vocational education and training (VET) have hindered successful adaptation to the changing structure of the economy (Rashid, Rutkowski and Fretwell 2005, Boeri 2000, Lamo, Messina, and Wasmer 2011). However, empirically and conceptually it is not clear, whether and why type of initial training should have a larger impact on adaptability of workers than depth and breadth of skills used at work.

Our analysis suggests that changes in economic structure have resulted in surprisingly low level of deskilling, reskilling, or upskilling in CEE transition countries. Instead, most of the workers who engaged in job-to-job mobility remained in the same occupational group. The largest flows, however, have been in and out of the labour force, which suggests that transition has resulted in destruction of "inherited" skills. Furthermore, we find that depth and breadth of skills that are linked with occupations rather than type of education and training had a significant impact on the survival of workers in the labour market. Empirical analysis is based on the Life in Transition Survey (LiTS) carried out by the EBRD and the World Bank in 2006. It provides comparable data on employment histories of respondents in all transition countries.

Although it has well known limitations (including recall bias), it is an only source that provides relevant data from 1989 onwards that is comparable across CEE (Bulgaria, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, and Slovakia).

The paper is structured as follows. First, we provide a brief overview of the transition, so as to scope further analysis in the light of the findings of previous studies. Section three outlines the proposed conceptual approach for study of how specificity of skills affect labour adaptation to the changes structure of the economy. Section four discusses data and methods. Section five discusses the directions and scale of changes in skills of the labour force in CEE, while section six explores what factors facilitated survival in the labour market during the transition. The last section concludes the paper, outlines the limitations of the analysis, and discusses directions for further research.

2. The story of economic transition: why and where has the labour moved?

Nearly 30 years since the start of the economic transition in CEE, the impacts of the changing economic structure on the labour movements appear to be well documented. The story, as is told in previous research, can be presented in terms of four stylised facts.

First, the planned economies of CEE inherited tightly integrated production chains. Large state owned firms that were designed to reap the benefits of specialisation in mass production of standardised outputs dominated the industrial landscape. This resulted in long chains of production, whereby each firm produces an intermediate output that is provided to few buyers and each of the inputs necessary for intermediate output are purchased from few providers (Blanchard, 1997).

Second, the logic of specialised mass production required a literate workforce with deep, but narrow, set of skills. Extensively developed education systems ensured that nearly everyone has acquired primary and secondary education. Large shares of students were enrolled in VET programmes (See Table 1), which provided narrowly defined skills. For example, VET schools in Poland taught around 300 occupational skills (World Bank, 1996, p. 124). Formal education was usually supplemented by in-enterprise training (Mertaugh and Hanushek, 2005, p. 209). Education and training systems focused on accumulation of facts (usually in a narrowly defined area of subjects) rather than application of knowledge in diverse contexts. International science and mathematics tests carried out in early transition strengthen this point. According to them transition countries tended to outperform peers from Western democracies in terms of awareness of facts, but they significantly underperformed in use of knowledge in unanticipated circumstances (World Bank, 1996 p. 125). The graduates were assigned to jobs where they were expected to work for most of their careers (i.e. job-to-job mobility was discouraged). Because of this, there was no need to acquire new or update existing skills. Lastly, work organisation within an enterprise mirrored the logic of specialised mass production, i.e. work was organised around routinisation and hierarchical specialisation of functions (Berryman, 2000 p. 8). This implies that the scope of work was typically very narrow and involved repetitive performance of limited set of tasks according to predefined procedures.

Table 1. Education systems

	Basic education enrolment rates in 1989 (% of 6/7 – 14/15 age group)*	**Vocational / technical upper secondary enrolment rates in 1989 (% of 15-18 age group)**	**Tertiary enrolment rates in 1989 (% of 18-22 age group)**
BG	98.4	47.7	16.4
CZ	97.6	73.6	12.7
EE	96.2	37.8 (refers to 1990)	14.2 (refers to 1990)
HU	99.0	62.7	13.9
LV	95.8	47.1	15.2
LT	94.0	59.9	17.7
PL	97.9	72.7	11.6
RO	93.6	79.2 (refers to 1990)	8.8
SI	96.1	61.5 (refers to 1993)	18.2
SK	96.8	70.7	13.2

Notes: * Source: Berryman, 2000, p. 111-116.

Third, economic transition involved restructuring of inherited enterprises as we well as reallocation of resources from public to private firms, and from dominant manufacturing to emerging services sectors (Blanchard 1997). The process of change in the structure of economies followed two phases (see Bruno (2006) among others). During the first phase, the initial shock of transition resulted in a collapse of output and wages, increasing unemployment, and declining activity rates. Blanchard and Kremer (1997) explain this by the disorganisation of the inherited long and tightly integrated chains of production. As central planners left the stage, each producer of intermediate input had to re-negotiate contracts with its suppliers. In many cases the negotiations failed (due to imperfect contracts, asymmetric information, or similar), which may have forced the other firms of the production chain into bankruptcy, since their intermediate inputs were of little value unless all of the critical inputs are supplied to produce the final output. This could explain why the decline in the Baltic countries (Estonia, Latvia and Lithuania), which were more tightly integrated into the production system of former USSR, was larger in comparison to other CEE countries. Assuming that GDP growth by at least 1% signals the end of transformational destruction, the first phase in most CEE countries ended around 1993 – 1995 (see Table 2).

The second phase is characterised by rebounding output as well as stabilisation and improvement in macro-economic conditions. The emerging private sector was the main driver of growth. However, it was only in the late 90s that job creation matched job destruction in most CEE countries (e.g. in Romania net employment losses continued throughout 90s;Rutkowski and Scarpetta, 2005, p. 8-9). The discrepancy between growing output and stagnating job creation through most of the 90s could be explained by the productivity catch-up (Rashid et. al. 2005, p. 61).

Table 2. Two phases of transition in CEE

Country	First phase	Second phase
BG	1989 – 1994	1995 – 2004
CZ	1989 – 1994	1995 – 2004
EE	1989 – 1995	1996 – 2004
HU	1989 – 1994	1995 – 2004
LV	1989 – 1996	1997 – 2004
LT	1989 – 1995	1996 – 2004
PL	1989 – 1992	1993 – 2004
RO	1989 – 1994	1995 – 2004
SK	1989 – 1993	1994 – 2004

Source: Berryman, 2000, p. 111-116

Fourth, because of the changing economic structure labour moved on an unprecedented scale in two directions. On the one hand, labour moved from employment to inactivity. To an extent this reflected adjustments from the inflated inherited participation rates. For example, participation rates in the Visegrad countries dropped from 95% in 1989 to 75% in 1996 (Bruno, 2006, p. 74). On the other hand, labour moved from public to private jobs and from agriculture / manufacturing to services (see Table 3). Cazes and Nešporová (2001) finds that during the first five years of transition average annual labour turnover fluctuated between 30% and 50%. Campos and Zlabkova (2001) estimate that around 30% of workers changed occupation during early transition in Hungary. The transitions were accompanied by persistently high levels of unemployment, particularly in Poland, Bulgaria, Slovak Republic, and Lithuania. The literature explained this by a sub-optimal speed of transition (Agion and Blanchard, 1994). During the first phase of transition, the scale of job destruction in SOEs and declining sectors significantly exceeded job creation in emerging sectors and private enterprises. The unemployment declined only at the end of the second phase, when job creation in the new sectors and firms was in full swing.

Table 3. Changes in employment structure (%)

	Agriculture		Industry		Services	
	1990	1998	1990	1998	1990	1998
CZ	11.6	5.5	46.4	41.0	42	53.6
EE	21.1	9.1	37.1	33.2	41.8	57.7
HU	18.3	7.5	37.0	34.2	44.7	58.3
LT	18.4	21.4	42.6	27.1	39.0	51.4
LV	17.1	17.6	38.4	24.4	44.4	57.9
PL	26.8	25.2	36.8	29.5	36.3	45.3
SI	9.4	6.7	46.7	41.6	44.0	51.7
SK	13.7	7.7	45.5	35.5	40.8	56.8

Source: UNECE, 2000.

The above story of transition has been recently challenged by Tyrowicz and Velde (2017), who find that between 1989 and 2006 the scale of labour flows from SOEs to private firms and from manufacturing to services has been very limited.

Instead, the shifts in the structure of employment can be explained by the intergenerational change: workers of declining sectors and SOEs (prematurely) left the labour market altogether, while the new jobs were taken up by the young cohort, who graduated after 1989. Furthermore, majority of job-to-job movements occurred with the same industry and sector of ownership. This stands in stark contrast to the above discussed story of transition, which holds that labour moved between firms and sectors. The divergence in findings can be explained by the different types of data. Most of the previous research covered a limited sample of countries and relatively short time series (typically from the second phase of transition). More importantly, due to data limitations the previous studies relied on data on changes in stocks of workers. Tyrowicz and Velde (2017) use Life in Transition Survey, which covered a representative sample of respondents from 27 countries in CEE and Central Asia. It contains question on all respondents' jobs held between 1989 and 2006 (including start and end dates), which provides unique information on worker flows during economic transition.

This has significant implications for changing skills of labour force. If workers moved between sectors and occupations, this should have resulted in significant upskilling, reskilling, or down-skilling. Conversely, if workers from declining sectors exited labour market, then change in the structure of economy brought about skill destruction. The next section explores individual level factors that could explain resilience in the face of structural changes.

3. Resilience of workers: the role of specificity of skills

Following the stylised facts discussed above, the transition literature has argued that high specificity of "inherited" skills proved to be an obstacle for smooth adaption of labour to the changing economic structure. The first strand of literature argues that the "inherited" skills were of little relevance and therefore lost value. Rutkowski (1996) studying Poland between 1987 and 1993, Chase (1998) analysing Czech and Slovak Republics between 1984 and 1993 as well as Kertesi and Kollo (2001) studying Hungary between 1986 and 1999 found that the returns to experience have declined during the transition. Furthermore, Kertesi and Kollo (2001) found that in Hungary during the second phase of transition young educated workers (post 1989 graduates) witnessed continued increase in returns to education, while older educated workers experienced stagnating relative wages. This suggests that the relative value of inherited skills has declined as economy rebounded from the initial shock of transition. While these findings can explain the magnitude of intergenerational change (see Tyrowicz and Velde (2017) above), they remain silent of the reasons, why some older workers adapted successfully, while others left the labour market.

The second strand of literature argues that vocational training provided specific skills, which therefore proved to be an obstacle for reallocation of labour (Rashid, Rutkowski and Fretwell (2005), Campos and Coricelli (2002), and Boeri (2000) among others). This is empirically supported by Lamo, Messina, and Wasmer (2011), who found that workers with vocational secondary qualifications were more likely to lose jobs and less likely to obtain new ones in comparison to the ones with academic education. However, this argument has several challenges. From an empirical point of view, the results could suffer from the selection bias. Prior to transition the education systems in CEE sorted less academically inclined students into vocational tract, which could result in poorer labour market outcomes during the transition. Malamud and Pop-Eleches (2006) studied labour market outcomes during the transition in Romania using a quasi-experimental design. They found that "the large cross sectional differences in labour market outcomes between graduates of vocational and general secondary schools are driven mainly by selection" (p. 4). Furthermore, it is not clear, whether VET certificates provide a good proxy for measuring specificity of skills. It is true that vocational education provided training for concrete occupations and, in most cases, particular jobs in nearby enterprises. However, the education systems of the planned economies more generally aimed to ensure a close match between the competences of all graduates and the requirements of jobs to which they were assigned.

From a conceptual point of view, the links between skill specificity and VET in the context of transition are problematic. Becker (1993) argued that specific skills are of value to one or few firms, while general skills are valuable to many firms. This implies that the level of specificity of "inherited" skills depends on the level and structure of labour market demand. Accordingly, "inherited" skills become specific, if labour market demand is subdued and/or the hiring firms rely on different combinations of knowledge and abilities than the ones used prior to transition. This, however, has little to do with the type of acquired education and training.

To address these issues we propose to use an alternative approach of conceptualising skill specificity. Following Lazear (2003) we assume that work encompasses a range of tasks. Productive performance of each task requires corresponding skills (combination of knowledge, psychomotor dexterity, etc.). Furthermore, each task may require different depth of skill that could range from basic knowledge to capacity to use advanced techniques. This implies that work at different firms, sectors and occupations rely on different combinations and depth of skills. For example, an engineer and a cashier both rely on arithmetic skill, although the former typically requires considerably deeper knowledge than the latter. In addition, to the extent that engineers perform larger number of tasks, their skill-set is wider than that of a cashier. Hence, the set of skill used at work can be expressed as a sum of depth λ of different skills, i.e. $\sum_{n=1}^{N} \lambda_n$.

This suggests that each skill *per se* is general, i.e. it can boost productivity in a large number of jobs that include the corresponding task. However, the differences in combinations and depth of skills make them specific (non-transferable) or transferable across firms, occupations, or industries. To use the same example, engineers have more transferable skills than cashiers, because the former has more and deeper skills than the latter. As a result, in the face of changing economic structure engineers can deskill and take-up the job of cashiers. However, cashiers cannot take up the job of an engineer due to lack of sufficient depth and breadth of skills.

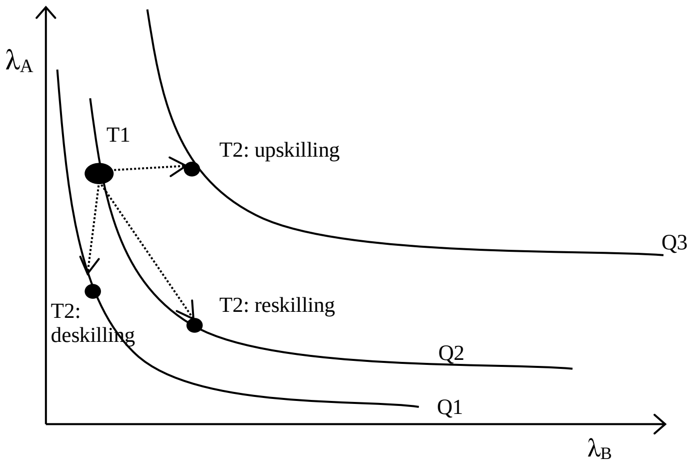
This approach to conceptualising skills has three important implications. First, it abandons the notion that some skills (e.g. the ones acquired in VET) are *per se* purely firm-specific or entirely transferable. Instead, it is the differences or similarities in the mix of skills that affect individuals' potential to productively transfer skills from one job to another. All else being equal, individuals with larger number and depth of skills have better chances of finding productive employment in different firms, sectors, and occupations. This suggests that skill formation systems of the planned economies, rather than skills *per se,* hindered adaptability of workers during transition. Focus on development of a limited number of skills directly linked to the future workplace and a very narrow definition of tasks in state enterprises resulted in a workforce with limited range of skills (although they might have been rather deep).

Second, this approach incorporates both transferability and levels of skills. Significant depth in one skill implies that individual is highly proficient in carrying out a corresponding task. However, it is the significant depth in a large number of skills that make that skill-set more transferable. Hence, depth (or higher level) of skills is a necessary, but not sufficient condition for transferability of skills.

Third, the proposed approach explicitly allows for re/de/upskilling. Reskilling involves loss of depth in one skill and acquisition of another one. Deskilling involves loss of depth of one or a set of skills. This may happen when previously used depth of skill is not utilised in a new workplace and therefore is lost over time. Upskilling involves larger depth of new or previously used skills. Deeper skills may be acquired through learning-by-doing or (in)formal education and training.

To illustrate change in the depth of skills, assume a simplified "island" economy that relies on two skills (A and B) that are not perfect substitutes. In period one, firms rely on depth of skill A and produce output along isoquant Q2 (see Figure 1). This is far from optimum production due to large distortions in market signals. In period two distortions are removed and three outcomes in terms of change in depth of skills emerge: a) upskilling, when higher depth of skill B allows moving to a higher isoquant; b) reskilling, when acquisition of skill B allows remaining on the same isoquant, but comes at a loss of skill A; c) deskilling that leads to decrease depth of skill A, but no corresponding increase in the depth of skill B. Thus, the output of labour critically depends on the trajectory of change in period two.

Figure 1. Changes in production and skills in period two.



Source: own elaboration.

Note: λ_A and λ_B refer to depth of skills A and B respectively. Isoquants Q1, Q2 and Q3 depict the amount of labour produced using two inputs: deeper skill A or deeper skill B.

The proposed approach to conceptualisation of skills suggests that workers with shallow set of skills should face the worse labour market outcomes during transition, i.e. we expect them to be forced out of the labour market. First, they are in poor position (as compared to individuals with deeper skills) to compete for new jobs requiring reskilling or upskilling. Second, their shallow skills do not allow for deskilling. These propositions are empirically tested in section five and six, while the next section discusses data and measurement strategies.

4. Data and empirical strategy

Similarly to Tyrowicz and Velde (2017) we use data from Life in Transition Survey (LiTS) that was carried out by the EBRD and the World Bank in 2006. The dataset contains responses from 29 thousand respondents aged 18 and over from 29 CEE countries. Our analysis focuses on nine countries that were part of the soviet bloc and currently are EU members – Bulgaria, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, and Slovakia (see Table 2 for basic descriptive statistics on these countries). The analysis covers period from the collapse of the Berlin wall in 1989 to the end of transition in 2004, when most of the countries joined the EU (Bulgaria and Romania joined the EU in 2007).

This database is used, because the survey contains a question asking respondents to provide start and end dates of all jobs held in 1989-2006. This provides a unique dataset on individual level employment histories throughout the transition in CEE countries. Alternative sources of data are significantly more restrictive. For example, Labour Force Survey (LFS) provides data for CEE countries only from 1998 (for some countries from 1995) and does not allow tracking of labour market flows over extended periods. In addition, prior to 1998, CEE countries used variants of national LFS and/or relied on establishment surveys. As a result, data from national sources is usually not comparable over time and between countries.

LiTS database, however, has several weaknesses. First, it may be subjective to recall bias. The respondents may not remember all jobs and/or remember job changes closer to the day they participated in the survey rather than at the beginning of transition. To test for this, Tyrowicz and Velde (2017) checked the structural characteristics of employment as contained in the LiTS database with the results reported by the LFSs as well as national longitudinal surveys. They find that there are no major differences, although LiTS data tends to overstate employment in services to a few percentage points for some countries.

Second, the LiTS contains only basic level data on occupations (one digit ISCO-88 codes) and economic sector (two digit NACE codes) of employment. Hence, only movement between major occupational groups (e.g. between professionals and clerks) could be accounted for. This restricts the granularity of analysis.

Third, the data does not distinguish between unemployed, inactive, and students. This is because data does not specify the reasons behind why a person was not employed during different time periods. Hence, it is difficult to interpret movement in to and out of employment.

Empirical measurements of depth and breadth of skills should ideally rely on data depicting skills profiles of workers prior to transition. However, such data was never collected. Hence, we use the O*NET database, which has been developed by the US Department of Labour[1]It is the most comprehensive source of information on the tasks performed, technological skills, abilities, knowledge, and work activities used in approximate 1000 occupations.

The analysis relies on 33 groups of knowledge domains to estimate the breadth and depth of skills. It was selected as the other variables (skills, abilities) used to describe occupations strongly correlate, which can lead to bias in the results. This is not the case for knowledge.

Accordingly, the indicator captures the sum of depth λ of knowledge domains, i.e. $\sum_{n=1}^{N} \lambda_n$. It is estimated in four steps. First, we extract information from the O*NET database on the extent to which extent each occupation relies on a particular group of knowledge and how frequently it is used (this information is provided by O*NET and is comprised from expert opinions and survey of individuals at each occupation). Second, we transform the two variables to a zero to one scale. This is necessary, because O*NET measures the two variables on different scales. Third, we multiply the values of two variables that reference the same occupation and knowledge group. This provides a numeric expression of the depth of all skills λ per each occupation. Lastly, we move from SOC-00[2] classification of occupations used in O*NET to ISCO-88 forth level of occupations. This is done with the help of crosswalk dataset[3]. This results in skills profiles for each ISCO-88 fourth level occupation. The profiles depict what skills are necessary for an occupation as well as the depth λ of each skill. Table 4 below provides illustrative examples on selected occupations. As one could expect, white collar high skilled occupations require larger number and deeper skills, whereas the skill-set in elementary occupations is narrow and shallow.

Table 4. Depth and breadth of skills in selected ISCO-88 level 3 occupations*

ISCO-88 level 3 occupations	Directors and chief executives	Secondary education teaching professionals	Secretaries and keyboard-operating clerks	Animal producers and related workers	Electrical and electronic equipment mechanics and fitters	Metal- and mineral-products machine operators	Building caretakers, window, and related cleaners
Administration and Management	0.88	0.16	0.03	0.22	0.01	0.00	0.01
Clerical	0.15	0.16	0.54	0.06	0.02	0.03	0.05
Economics and Accounting	0.62	0.02	0.06	0.14	0.01	0.00	0.00
Sales and Marketing	0.40	0.00	0.00	0.12	0.01	0.00	0.00
Personnel and Human Resources	0.54	0.01	0.00	0.17	0.01	0.00	0.01
Production and Processing	0.35	0.00	0.01	0.14	0.04	0.24	0.00
Food Production	0.01	0.00	0.00	0.46	0.00	0.00	0.00
Computers and Electronics	0.13	0.09	0.34	0.01	0.42	0.02	0.00
Mechanical	0.03	0.01	0.02	0.11	0.33	0.27	0.25
Mathematics	0.45	0.20	0.10	0.14	0.13	0.12	0.06
Psychology	0.35	0.24	0.01	0.01	0.00	0.00	0.01
Therapy and Counseling	0.06	0.30	0.00	0.00	0.00	0.00	0.00

[1] We used the 2002 version as it is the closest one to the transition period.
[2] 2000 version of the Standard Occupational Classification.
[3] For this task we used SOC-00 to ISCO-88 crosswalk created by the Institute for Structural Research (http://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-onet-soc-to-isco/)

Education and Training	0.51	0.72	0.01	0.07	0.02	0.00	0.00
English Language	0.53	0.44	0.23	0.09	0.07	0.03	0.04
Law and Government	0.49	0.03	0.03	0.03	0.02	0.00	0.00
Communications and Media	0.27	0.07	0.06	0.03	0.02	0.01	0.00
TOTAL SUM (includes all knowledge domains)	**6.85**	**3.03**	**1.64**	**2.42**	**2.11**	**1.03**	**0.92**

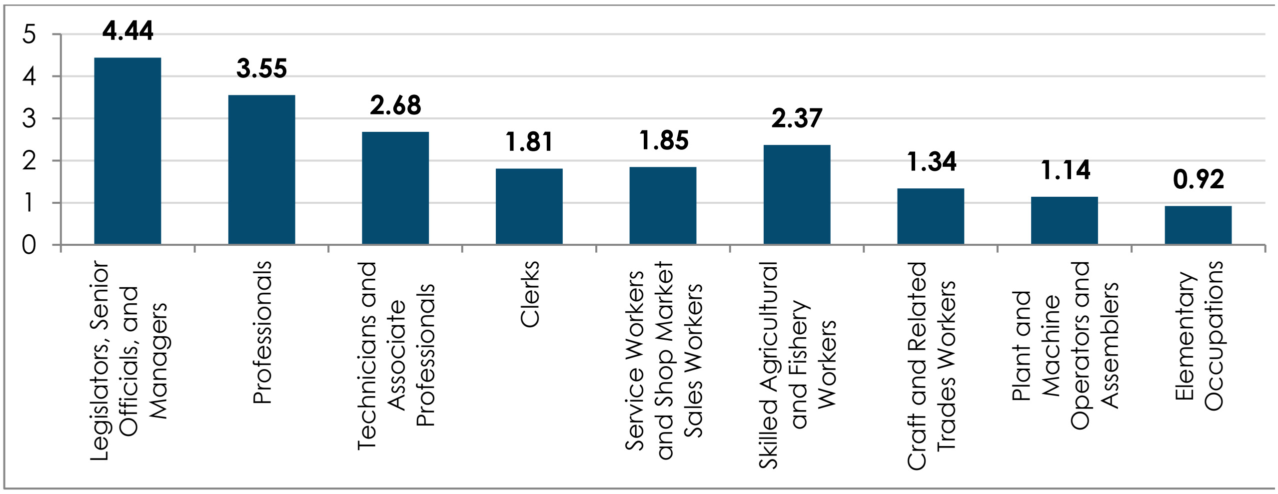
*Only knowledge domains that had a value of 0.25 or more for at least one occupation was included in the table. Excluded domains are: (i) Customer and Personal Service, (ii) Transportation, (iii) Engineering and Technology, (iv) Design, (v) Building and Construction, (vi) Physics, (vii) Chemistry, (viii) Biology, (ix) Sociology and Anthropology, (x) Geography, (xi) Medicine and Dentistry, (xii) Foreign Language, (xiii) Fine Arts, (xiv) History and Archeology, (xv) Philosophy and Theology, (xvi) Public Safety and Security, and (xvii) Telecommunications.
Sources: own compilation, based on the O*NET (2002) and LFS data.

However, the problem is that the estimates on depth and breadth of skills obtained on the basis of O*NET database are at ISCO-88 fourth level of occupations, while LiTS database contains information of the first level of occupations. This challenge is addressed in four steps. First, we move from the fourth to third level by averaging the knowledge profiles of all ISCO-88 level four occupations that correspond to the same ISCO-88 level three occupation. Second, we estimate the distribution of ISCO-88 level three occupations in each ISCO-88 level one occupation in percentage terms for each country. The distributions are obtained from the oldest available Labour Force Survey data for each country. This step is crucial as it ensures that none of the ISCO-88 level three occupations from the same ISCO-88 level one occupation is over or underrepresented in any country. In other words, by finding the distribution of occupations, we take in to account which ISCO-88 level three occupations comprise the majority of the ISCO-88 level one occupations. Third, we estimate the ISCO-88 level three to level ISCO-88 level one distribution for all CEE countries by averaging the estimated distributions for each individual country. This is necessary, as the available LFS data does not allow estimates of the distributions for each CEE country individually.[4] Forth, we estimate the depth of skills for each ISCO-88 level one occupation by using a weighted average of the knowledge profiles of the corresponding ISCO-88 level three occupations. The weights are the distribution (i.e. how ISCO level three occupations are distributed inside corresponding ISCO level one occupations), estimated during the previous step. Mathematically this step can be expressed as $K_{iy} = \sum_{n=1}^{N}(\lambda_{in}\ \omega_{in})$, where K_{iy} is one (i) out of the 33 knowledge groups corresponding to an ISCO-88 level one occupation (y), N is the number of ISCO-88 level three occupation corresponding to the y ISCO-88 level one occupation, λ is the depth estimated in step prior, and ω is the weight of a particular ISCO-88 level three occupation (n) to a corresponding ISCO-88 level one occupation (y).

This provides estimates of depth and breadth of skills for occupation. Figure 2 outlines the results. On the one hand, the results are rather intuitive: high skilled white collar occupations (e.g., managers, professionals) require more and deeper skills perform than others. On the other, it also shows that occupations that are lower, according to ISCO-88, such as skilled agricultural and fishery workers, require higher knowledge levels then some occupations that are higher, such as clerks. This result can be explained by the fact that clerks are considered as low skilled white-collar workers, while skilled agricultural and fishery workers are high skilled blue-collar (Eurofound, 2005).

Figure 2. Knowledge level of each ISCO-88 level 1 occupation

[4] Data is not available for Bulgaria, Poland, and Slovakia.



Sources: Authors own compilations, based on the O*NET (2002) and LFS data.

If a respondent held only one occupation, then the depth and breadth of her skills corresponds to the ones outlined in figure 2. However, if a respondent held multiple occupations, then her skills are estimated on the basis of weighted averages of each occupation that the person help. Weights reflect time spent in a particular occupation. For example, if an individual was employed as a professional for five years and a clerk for five more, unemployed for other periods of time, his or hers knowledge level would be equal to: $3.55 \times \left(\frac{5}{10}\right) + 1.81 \times \left(\frac{5}{10}\right)$.

5. Transition: change in skills or cohorts?

This section discusses whether changes in the structure of the economy were accommodated by changes in the skills of the labour force or changes in cohorts, or whereby workers with obsolete skills exit labour market and are over time replaced by the new entrants. Table 5 provides descriptive statistics of labour flows in 1989 – 2004 as well as in the two phases of transition: the initial phase from 1989 to mid-90s that was marked by economic disorganisation and output collapse and the economic stabilisation and recovery phase the start of which slightly differs in the CEE countries. Data on flows suggests that the average annual exit rate (including exits from employment and job-to-job movement) was over 10% throughout the transition. Exits from employment in 1989 – 1991 account for more than 70% of all exits. This can be explained by the job destructing economic disorganisation and the end to labour hording practices. As job creation picked-up, the share of exits from employment declined and from mid 90s and onwards on average approximately half of exit rates can be explained by job-to-job movement while the remaining half by exits from employment.

Table 5. Changes in labour market status and occupations in CEE countries during the transition

	Years	Moved to employment	Left employment		Reskilled*		Upskilled*	Deskilled*	No change	
			Older than 60	60 or younger	Same occupation	Different occupation			Same job	Remained outside employment
Bulgaria	1989-1994	7.93%	11.10%	8.32%	3.83%	0.79%	1.19%	1.06%	44.78%	21.00%
	1995-2004	13.87%	8.45%	11.36%	7.00%	1.85%	1.72%	1.59%	27.61%	26.55%
	1989-2004	20.34%	20.61%	17.17%	8.32%	1.85%	1.85%	1.85%	19.42%	8.59%
Czech republic	1989-1994	11.45%	6.65%	6.16%	7.39%	0.99%	1.48%	0.37%	41.63%	23.89%
	1995-2004	17.36%	9.11%	11.21%	10.10%	1.72%	2.59%	1.23%	29.06%	17.61%
	1989-2004	26.72%	16.75%	12.56%	9.48%	2.22%	2.46%	1.48%	19.70%	8.62
Estonia	1989-1995	10.55%	13.51%	6.82%	4.76%	1.42%	2.70%	3.60%	37.19%	19.43%
	1996-2004	13.64%	7.59%	6.05%	7.72%	1.67%	2.57%	3.99%	30.50%	26.25%
	1989-2004	23.04%	21.62%	11.33%	7.72%	1.93%	2.96%	6.44%	18.02%	6.95%
Hungary	1989-1994	9.77%	10.98%	9.10%	8.17%	0.80%	1.07%	0.94%	40.43%	18.74%
	1995-2004	15.66%	5.35%	14.32%	11.51%	2.14%	1.61%	1.07%	21.95%	26.37%

	1989-2004	20.21%	17.94%	19.81%	14.06%	2.54%	2.01%	1.07%	14.06%	8.30%
Latvia	1989-1996	10.20%	15.11%	8.82%	9.82%	1.89%	4.16%	3.02%	26.95%	20.03%
	1997-2004	22.26%	18.25%	15.94%	6.33%	1.09%	1.95%	0.85%	20.56%	12.77%
	1989-2004	21.66%	20.91%	9.95%	13.60%	1.64%	4.91%	6.55%	12.22%	8.56%
Lithuania	1989-1995	10.61%	14.83%	8.16%	4.35%	0.54%	0.95%	1.09%	36.73%	22.72%
	1996-2004	13.74%	9.39%	8.71%	4.35%	0.95%	0.95%	1.77%	25.99%	34.15%
	1989-2004	20.95%	25.71%	14.15%	5.58%	0.68%	2.31%	2.45%	15.78%	12.38%
Poland	1989-1992	4.58%	5.59%	5.01%	1.58%	0.14%	0.72%	0.14%	51.43%	30.80%
	1993-2004	20.34%	9.46%	18.48%	5.30%	0.72%	1.15%	0.57%	21.35%	22.64%
	1989-2004	22.64%	15.76%	22.06%	5.16%	0.86%	1.43%	0.43%	18.91%	12.75%
Romania	1989-1994	5.99%	11.39%	6.86%	3.80%	0.73%	1.31%	0.73%	45.26%	23.94%
	1995-2004	14.01%	5.84%	12.41%	8.32%	1.31%	1.31%	0.88	27.74%	28.18%
	1989-2004	20.44%	18.54%	18.39%	8.61%	1.75%	2.19%	1.17%	19.42%	9.49%
Slovakia	1989-1993	11.31%	7.18%	5.47%	1.95%	0.61%	0.49%	0.49%	48.78%	23.72%
	1994-2004	15.69%	9.61%	14.96%	6.33%	1.09%	1.82%	0.49%	27.62%	22.38%
	1989-2004	22.26%	18.25%	15.94%	6.33%	1.09%	1.95%	0.85%	20.56%	12.77%

Source: own estimates based on LiTS 2006 survey. Note * reskilling is measured when an individual moved from one occupation to another, but the difference in the values of the skill index is than 0.5; upskilling refers to change in occupations, when a new occupation has a value of skill index that is larger by at least 0.5 points, deskilling refers to change in occupation, when a new occupation has a value of skill index that is lower by at least 0.5.

Although these trends have been already well documented in the literature (including Tyrowicz and Velde 2017), deeper look into job-to-job mobility and employment exits provide important new insights. First, given the scale of economic restructuring, movement between occupations was very limited. The largest share of individuals who switched jobs remained within the same occupation (see Table 5). Similarly, the scale of upskilling (for example, movement from low skilled white collar occupation to high skilled ones) and deskilling has been very limited. This suggests persistence rather than dramatic change in skills. Second, working age individuals account for the majority of the exits from employment during the initial phase of transition (see Table 5). Furthermore, less than a third of pre-retirement age workers who were unemployed at the end of phase one of transition, have returned to employment during the phase two (see table 6). These two trends provide counter-evidence to the claims that transition has resulted in dramatic shifts in skills. Individuals with obsolete skills exited labour market rather than reskilled. Majority of the ones who remained in the labour market sought employment in similar occupations rather than engaged in radical skill shifts.

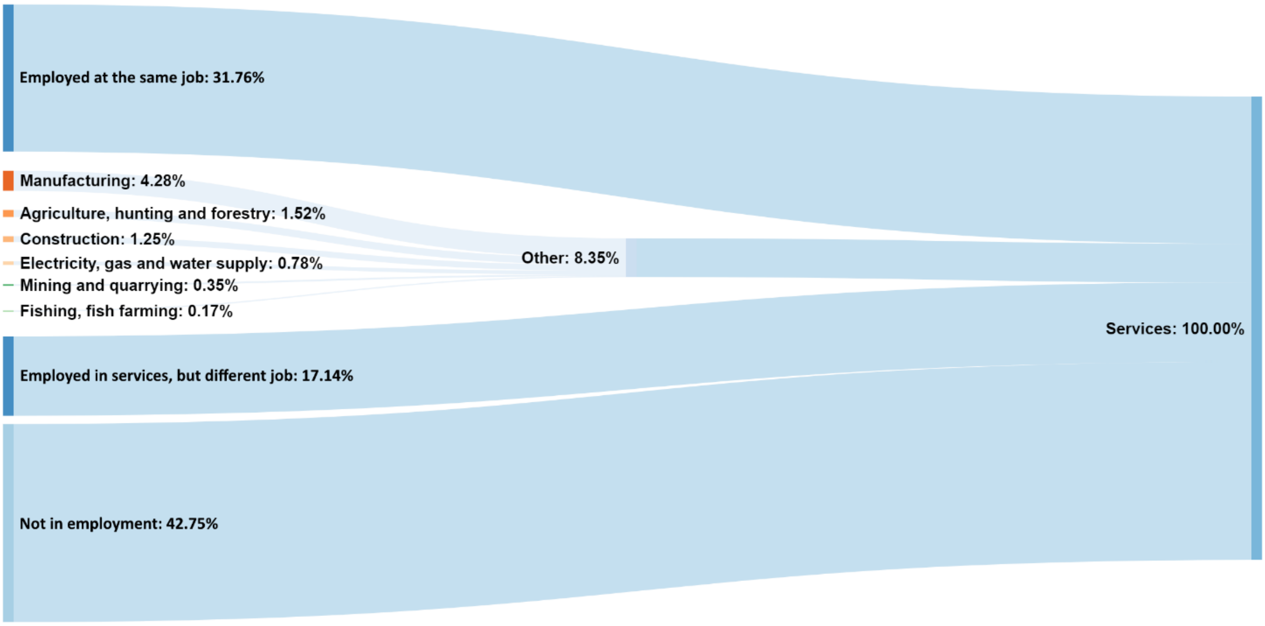
Table 6. Transitions from unemployment/inactivity in phase 2 (100%= persons, who left employment at the end of transition phase 1).

Country (end of transition phase 1)	**60 or above when left employment**		**Younger than 60 y.o. when left employment**	
	Did not enter employment in Phase 2	**Entered employment in Phase 2**	**Did not enter employment in Phase 2**	**Entered employment in Phase 2**
Bulgaria (1994)	9.9%	0%	75.5%	14.6%
Czech Republic (1994)	11.5%	0%	59.8%	28.7%
Estonia (1995)	20.8%	0%	61.3%	17.9%
Hungary (1994)	9.7%	0%	67.1%	23.2%
Latvia (1996)	20.4%	0%	58.3%	21.3%
Lithuania (1995)	20%	0%	64.4%	15.6%
Poland (1992)	12.5%	0%	63.8%	23.8%
Romania (1994)	17.7%	0%	72.3%	10%
Slovakia (1993)	10.2%	0%	60.2%	29.7%

Source: own computation based on LITS 2006 survey.

To illustrate the above trends, let us consider change in employment in manufacturing and services, which represents the one of the core sectoral shifts of transition. Figure 3 suggests that movement of labour from other sectors to services was rather limited. Entrants from other sectors constituted 8.35% of the workforce employed in services by the end of transition (in 2004) in our sample of CEE countries. Furthermore, majority of entrants to services were employed in the same occupation, which implies limited scale of reskilling. On the other hand, over 40% of those employed in services in 2004 represent the young generation that was still studying at the start of the transition. Hence, most of the growth of employment in services can be accounted for by entrants of new cohort of workers rather than workers moving from manufacturing to services. Interestingly, the story of change in manufacturing is very similar (see Figure 4). The main difference is that the proportion of young entrants was slightly lower and the share of entrants from other sectors higher.

Figure 3. Distribution of people employed in the service sector in 2004 compared to their labour market position in 1989



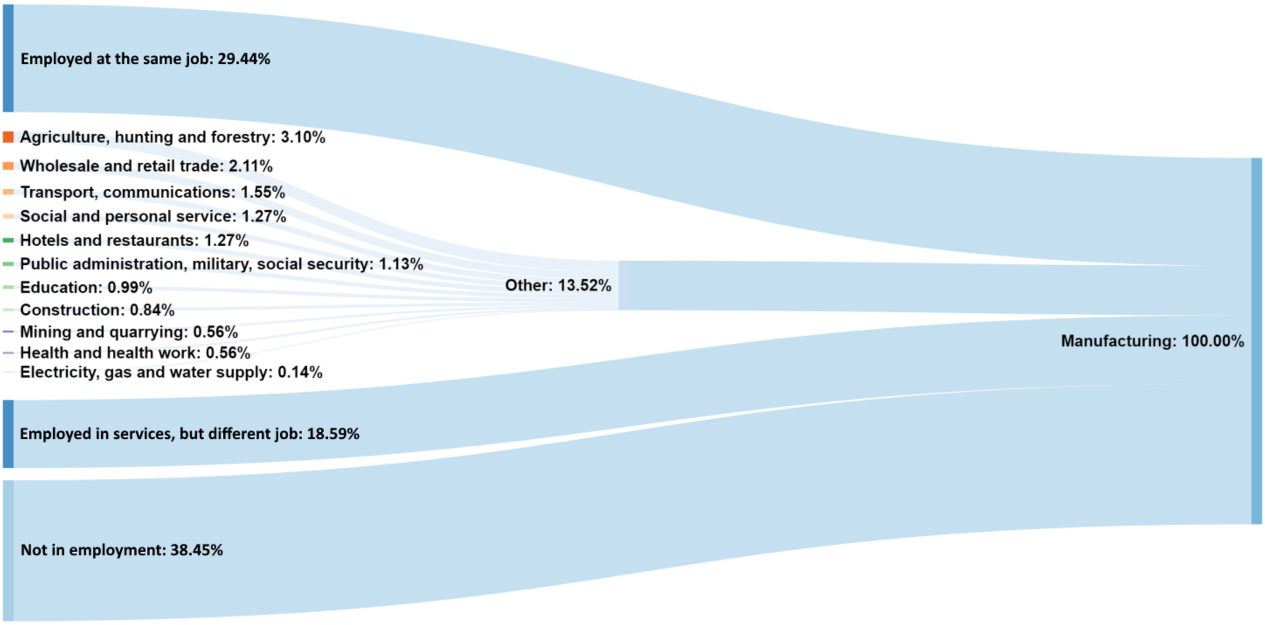
N = 2295

Note 1: Data set consists of respondents from: (i) Bulgaria, (ii) Czech Republic, (iii) Estonia, (iv) Hungary, (v) Latvia, (vi) Lithuania, (vii) Poland, (viii) Romania and (ix) Slovakia.

Note 2: People that were in the armed forces in 1989 or 2004 were omitted from the data set.

Note 3: Accordance with the NACE classification services were aggregated from nine NACE Rev. 1.1 groups: (i) wholesale and retail trade, repairs, (ii) hotels and restaurants, (iii) transport, storage and communications, (iv) financial intermediation; (v) real estate, renting and business, (vi) public administration, defence and social security, (vii) education, (viii) health and social work, and (ix) other community, social and personal services.

Figure 4. Distribution of people employed in the manufacturing sector in 2004 compared to their labour market position in 1989



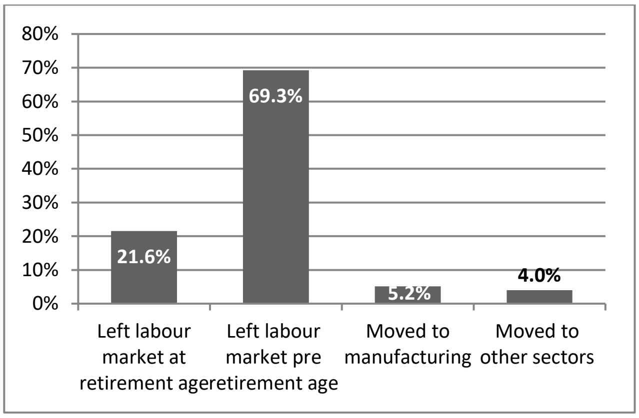
N = 707

Note 1: Data set consists of respondents from: (i) Bulgaria, (ii) Czech Republic, (iii) Estonia, (iv) Hungary, (v) Latvia, (vi) Lithuania, (vii) Poland, (viii) Romania and (ix) Slovakia.

Note 2: People who were in the armed forces in 1989 or 2004 were omitted from the data set.

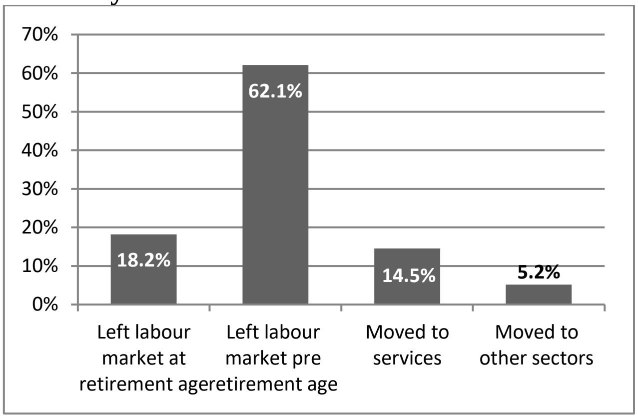
Another way to look at sectoral shifts is to ask: what happened to the workforce that was employed in respective sectors in 1989, but subsequently left them? As Figures 5 and 6 suggest, most of them left the labour market altogether at a pre-retirement age. Again, the scale of movement to other sectors was rather limited: less than 10% of those that left services and less than 20% of those that left manufacturing subsequently moved to other sectors. This again suggests that change in cohorts explain a significant share of change in the employment structure: workers with obsolete skills moved out of the labour market and were replaced with younger entrants. The scale of movement of labour, on the other hand, was limited.

Figure 5. Employment trajectory of people who worked in the service sector in 1989, but left it by 2004



N = 1181

Figure 6. Employment trajectory of people who worked in the manufacturing in 1989, but left this sector by 2004



N = 675

Note 1: Data set consists of respondents from: (i) Bulgaria, (ii) Czech Republic, (iii) Estonia, (iv) Hungary, (v) Latvia, (vi) Lithuania, (vii) Poland, (viii) Romania and (ix) Slovakia.

Note 2: People that were in the armed forces in 1989 or 2004 were omitted from the data set.

Note 3: Accordance with the NACE classification services were aggregated from nine NACE Rev. 1.1 groups: (i) wholesale and retail trade, repairs, (ii) hotels and restaurants, (iii) transport, storage and communications, (iv) financial intermediation; (v) real estate, renting and business, (vi) public administration, defence and social security, (vii) education, (viii) health and social work, and (ix) other community, social and personal services.

6. Factors behind premature exits from the labour market

This section explores what factors can explain pre-retirement exits from employment. To do so, we use an accelerated time failure survival analysis model.[5] In comparison to other similar models (e.g. Cox proportional-hazards regression model) it allows for an easier interpretation of the results. The dependent variable in the model measures how long a surveyed individual survived in the labour market, i.e. remained employed from the start of transition in 1989. Table 7 discusses measurement of independent variables. The analysis includes all respondents from CEE countries, who were working in 1989 and were younger than 55 in 2004.

Table 7. Independent variables

Variable	Operationalisation
Depth and breadth of skills	See section 4 for measurement strategy
Age	Age of a respondent in 2004
Education level Mothers education level	No of years spent in school: No education = 0; Compulsory school education = 5; Secondary education = 12; professional/vocational school/training = 12; higher professional degree (university, college) = 15; post graduate degree = 17
Real GDP per capita	Real GDP per capita in the year when an individual left employment (if an individual was employed in 2004, GDP per capita was estimated for 2004)
Services	Dummy variable that indicates if the job that an individual had in 1989 was in services
Gender	Dummy variable: 0 – female, 1 – male

The results of the survival analysis (see Table 8 below) suggest that depth and breadth of skills can be used to explain the survival of individuals in the labour market during transition. Change in one unit of the indicator increases survival by 13 % (or 1.95 years). This is a rather strong result, given that the model already controls for education levels.

As expected, education level and the real GDP per capita have a positive effect on survival. Age and mothers' education have a negative effect on employment. One additional year of age reduced length of stay in the labour market by 2% (or 0.3 years), while mother's higher education reduced survival by 1.7%. The effect of age, keeping in mind that the data only consists of individuals who were 54 years old or younger in 2004, suggests that older people found it more difficult to remain employed during the transition. The negative impact of mothers' education level is surprising and cannot be accounted for by standard explanations. Furthermore, the dummy variable of employment in service sectors in 1989 and the gender variable do not have a statistically significant impact on the survival rate. By removing these variables from the model, the results do not change much.

Table 8. Survival analysis on how long individuals remained employed during the transition

	Coefficients	Exponent of the coefficient	z-value	p-value
Intercept	0.0883	1.092	0.333	0.7664
Depth and breadth of skills	0.1207	1.1283	2.95	0.0032***
Age in 2004	-0.0197	0.9804	-3.96	<0.0001***
Education level	0.0434	1.0444	4.23	<0.0001***
Mothers education level	-0.0169	0.9832	-2.21	0.0271**
Real GDP per capita	0.0003	1.0003	19.17	<0.0001***
Services	-0.1329	0.8755	-1.6	0.1090
Gender (male)	0.0811	1.0844	1.25	0.2113

Note 1: Countries included in the regression model – (i) Bulgaria, (ii) Czech Republic, (iii) Estonia, (iv) Hungary, (v) Latvia, (vi) Lithuania, (vii) Poland, (viii) Romania and (ix) Slovakia.

[5] The survival model assumes a Weibull distribution of the dependent variable. This distribution was selected as it is one of the most often used distributions used in this type of analysis. However, as it does not mirror the real distribution, the results of the survival analysis serve as a compliment to previous results, even though the results are quite intuitive and do not seems to deny any existing research in this field.

Note 2: We did not include a dummy variable for each country, as real GDP per capita variable already takes in to account cross-country differences.
N = 2241

It is possible that the above results could be biased due to cross-national variation in generosity of social safety net (including early retirement schemes). Furthermore, it also could be the case that our indicator of depth and breadth of skills is a pseudo measure of vocational education, as the previous literature linked specificity of skills with those acquired in VET. Hence, to check these possibilities, we constructed a second survival model, which includes two new variables: social spending per capita[6] and a dummy variable for vocational education.

After introducing the two new variables, the significance of the depth and breadth of skills variable dropped from 0.0032 to 0.06. However, the variable remains significant after the changes at the alpha level of 0.1. Considering that the approach of estimating depth and breadth of skills rest on many assumptions the results imply that this variable still could be used to estimate length of survival in the rapidly changing labour market. In the new model (see Table 9) a one unit increase in depth and breadth of skill leads to an 8% increase in the length of survival. As expected, both social spending and vocational education have a negative impact on the length of survival.

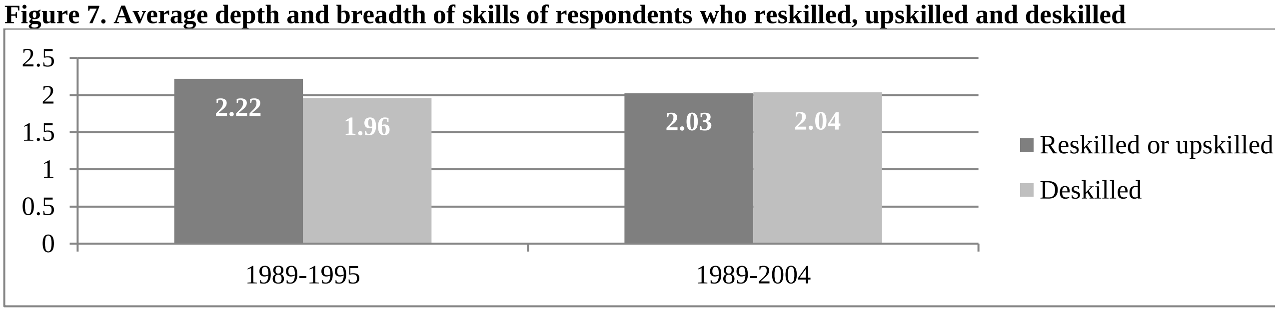
Table 9. Survival analysis on how long individuals remained employed during the transition

	Coefficients	**Exponent of the coefficient**	**z-value**	**p-value**
Intercept	-0.1124	0.8937	-0.40	0.6915
Depth and breadth of skills	0.0741	1.0769	1.87	0.06*
Age in 2004	-0.0176	0.9825	-3.77	0.0002**
Education level	0.0464	1.0476	4.42	<0.0001***
Mothers education level	-0.0171	0.9830	-2.43	0.015**
Real GDP per capita	0.0003	1.0003	20.98	<0.0001**
Services	-0.0098	0.9065	-1.25	0.2127
Gender (male)	-0.0083	1.0869	-1.36	0.1750
Social spending per capita	-0.00002	0.9999	-10.05	<0.0001***
Vocational education	-0.1861	0.8302	-3.00	0.002***

Note 1: Countries included in the regression model – (i) Bulgaria, (ii) Czech Republic, (iii) Estonia, (iv) Hungary, (v) Latvia, (vi) Lithuania, (vii) Poland, (viii) Romania and (ix) Slovakia.
Note 2: We did not include a dummy variable for each country, as real GDP and social spending per capita variables already takes in to account cross-country differences.
N = 2241

Lastly, to what extent does depth and breadth of skills have an effect on reskilling/upskilling or deskilling? As Figure 7 suggests, the individuals who reskilled or upskilled in 1989 – 1995, on average, had a larger depth and breadth of skills than the ones who deskilled (see Figure 3). However, this difference is not statistically significant according to the Mann–Whitney U test (p-value equals 0.119).[7] This difference disappears when looking at individuals from 1989 to 2004. This overall implies that depth and breadth of skills did not have a systemic impact on trajectories of skill change during the transition.

Figure 7. Average depth and breadth of skills of respondents who reskilled, upskilled and deskilled



[6] Social spending per capita in 2005 in all analysed countries. We selected 2005 as the year to use in the model as this is the only year which provides information about the spending on social benefits for all countries (i.e. Bulgaria only started to provide this statistic in 2005).
[7] Mann–Whitney U test was selected to compare the two groups - reskilled or upskilled and deskilled – as both of them have non-normally distributed knowledge profiles.

Source: own estimates based on LiTS 2006 survey.
1989-1995 N – 183, 1989 -2004 N – 130.

7. Conclusions

Overall, the paper argues that skills of labour force are “sticky”. In the face of large scale job destruction and creation the skills-sets of the labour force in CEE changed rather incrementally: the scale of flows of workers from declining sectors and occupations to the new ones has been limited in 1989-2004. Hence, we did not find evidence that transition in CEE (arguably the most significant change in national economic structure within a short period of time) has resulted in large scale radical reskilling, deskilling, or upskilling. Instead, the structural change in the economy has resulted in a change in cohorts of workers: as working age individuals with obsolete skills exited the labour market, young entrants met the demand for new types of skills sets.

In line with previous studies, we find that high skill specificity obstructed smooth adaptation of labour to the changing economic structure. However, while previous studies used VET as a proxy for skill specificity, we proposed an indicator measuring depth and breadth of skills used in occupations. More specifically, we found that change in one unit of breadth and depth of skills increases the length of survival of individuals in the labour markets by around 13% (or 1.95 years). However, this results drops to 8% and becomes only statistically significant at alpha 0.1 when a vocational training dummy variable is introduced in to the model. These results have significant policy implications. If we assume that VET is a source of skill specificity, this would imply that higher participation in academic tracks of education should improve adaptability of labour to continuously changing labour market. However, focus on depth and breadth of skills used at work allows distinguishing occupations that face the highest challenges and provision of tailored support.

How relevant are the lessons learned to other cases of economic restructuring? On the one hand, the scale and direction of restructuring as well as vastly different starting points diminish the relevance of experiences of transition. On the other hand, several general lessons stand out. First, skill formation systems should strive to balance static productivity (achieved by training for a particular job) and adaptive capacities (achieved by training for careers in dynamic labour markets). Very narrow focus of initial education and training on development of small set of skills that are directly relevant to specific jobs as well as absence of work-related lifelong learning has clearly diminished the capacities of workers of the planned economy to adapt to changing economic structure. Second, workers with narrow and shallow skill sets are the most vulnerable in the face of dramatic shifts. Third, “sticky skills” imply that there is significant path dependency in trajectories of economic development.