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From Socialism to Capitalism: Low-Skill-Biased Change in the Baltics during the Transition and Beyond

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Abstract: How did technological upgrading in the Baltics during the transition from planned to market economy affect labour? Existing academic literature would imply a skill-biased or polarising effect. However, we find that the opposite is likely true—technological upgrading predominantly benefited lower skilled workers. This is explained by an abundance of lower skilled labour, which fostered the usage of less advanced technologies that such workers could utilise. This article contributes to the discussion on the relationship between technology and labour by highlighting that technological upgrading may lead to low-skill-biased change.

Keywords: *labour market, (low-)skill-biased change, polarisation, technological upgrading, transition*

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1. Introduction

What is the impact of investments in technology on demand for skills? Skill-biased technological change (SBTC) hypothesis argues that technological upgrading creates demand for high-skilled employees (e.g., see Sevinc, 2017). They are needed to operate advanced machines, understand complex production systems, and comply with higher quality standards. However, SBTC has been contested from two perspectives. First, the polarisation hypothesis argues that technological upgrading leads to a comparative decline in wages and demand for medium-skilled individuals, while wages and demand for high- and low-skilled employees grows (Acemoglu, 1999; Goos, Manning & Salomons, 2014; Peugny, 2019). This is explained by the fact that medium-skilled occupations often have an abundance of routine tasks that can be automated by technology. Second, some (e.g., Acemoglu, 2002; Autor, 2013) argue that if the supply of low-skilled individuals is high, technological change can be low-skill-biased. In such cases, companies would focus on their abundant factors of production (i.e., low-skilled-labour) by introducing technologies that complement rather than replace it.

To contribute to the above discussion, we focus on three countries that witnessed huge investments in new technologies in a short period of time. The speed of change allows us to isolate the impacts of technological upgrading from other factors that take longer time to take hold, such as demographic change, different cycles of technologies, etc. In particular, we focus on the three Baltic States—Estonia, Latvia, and Lithuania. In a couple of decades, these countries transitioned from planned to market economy, integrated within the global value-added chains, and adopted new production processes and technologies that are close to the innovation frontier. All of these macro shifts implied rapid technological upgrading. In order to avoid potential noise caused by the disruptions of the early phase of transition, we focus on 1998–2018. The scale and speed of upgrading makes these cases highly valuable in studying the impacts of technological upgrading on the demand for skills, although the transformations in the Baltic States are also interesting *per se* and have been somewhat understudied. Finally, the research results provide useful insights on how the economy and labour reacts to rapid technological shifts, which is as relevant as ever due to rapid automatisation and developments in AI.

We found that technological upgrading predominantly benefited the lower-skilled employees from 1998 to 2018 in the Baltics, and these results are stable when different proxies of skills and technological upgrading are used. This implies that many companies in the Baltics, instead of focusing on highly skilled individuals, opted out to supplement the existing labour force by introducing less skill intensive technologies. However, we have also found that with a passage of time, the technological upgrading seems to become skill-biased, which mirrors many Central and Eastern European countries.

2. Three stories of how technology affects skills

2.1 Skill-biased technological change

The SBTC hypothesis argues that technological upgrading leads to higher demand for high-skilled individuals and higher income inequality between high- and low-skilled employees (Berman, Bound & Machin, 1998; Esposito & Stehrer, 2008; Sevinc, 2017; Mallick & Sousa, 2017). The main argument is that the adoption of new technologies requires specific skill sets, which low-skilled labour lacks. This leads to higher demand for higher-skilled workers (Goldin & Katz, 2008; Krusell *et al.*, 2000; Autor, Levy & Murnane, 2003). Although several technologies could be attributed to the growing demand for high skills, introduction of personal computer probably had the largest impact (Card & DiNardo, 2002).

Computers gave rise to wage and employment shifts primarily through two mechanisms. First, given that the elasticity of substitution between capital and unskilled labour is higher than between capital and skilled labour (Krusell *et al.*, 2000, p. 1030), many lower-skilled jobs have been, and are, replaced by machines (Hémous & Olsen, 2014). Second, unlike many other technologies, computers have changed almost all facets of life and business by enabling employers to automate many tasks, allowing for easy communication and share of information through the internet, and much more (Goldin & Katz, 2008).

Card and DiNardo (2002) and Goldin and Katz (2008) found evidence supporting the SBTC hypothesis in many developed countries during the 1970s–2000s. Berman, Bound and Machin (1998, p. 1273) found that skill-biased technological change (SBTC) can explain at least 70% of displacement of unskilled workers in the US. Moreover, Sevinc (2017) found that, by using different skill measures, a canonical SBTC model explains labour trends in the US during the 1980s and 1990s better than the polarisation hypothesis (i.e., rapid decline of the middle-skill occupations). More recent research by Taniguchi and Yamada (2020) also found support in several OECD countries. Similarly, Tarjáni (2004) found that SBTC had an impact on the input demand elasticity in Hungary, while Esposito and Stehrer (2008) explain the skill-premium through SBTC for the Czech Republic, Hungary, and Poland during the transition.

However, others argue that the growing demand for high-skilled employees and wage inequality cannot be solely attributed to technological change. Card and DiNardo (2002) argue that widespread adoption of computers coincided with the decreasing real value of minimum wage in the 1980s and slow-down in the growth of the number of college graduates in the US. This resulted in an increasing wage premium for high-skilled individuals, which coincided with technological change (Goldin & Katz, 2008, p. 96).

2.2 Job polarisation

The job polarisation hypothesis argues that technological upgrading created demand for more high- and low-skilled employees while employment in the medium-skill occupations remained stagnant or declined (see Autor, Levy & Murnane, 2003; Goos, Manning & Salomons, 2014; Acemoglu, 1999). Polarisation is driven by the automation of routine tasks. The latter cover activities that are well-defined, often manual, and that can be carried out following an explicit set of rules. Such tasks are typically carried out by medium-skilled workers. Accordingly, automation of routine tasks leads to the destruction of labour market demand for respective skills. On the other hand, non-routine tasks are those that require complex communication and/or problem solving. Such tasks are performed by high- and lower-skilled workers. Since it is challenging to automate non-routine tasks, the demand for high- and lower-skilled workers is expected to match overall economic growth.

Acemoglu (1999, p. 1275) argues that the polarisation hypothesis explains decline in employment in the medium-skilled occupations and growth in demand for higher- and lower-skilled occupations in the US in 1980s and the early 1990s. Antonczyk, DeLeire and Fitzenberger (2018), among others, found similar evidence for the US, as well as for Germany during a similar time period. Goos, Manning and Salomons (2014) also have found evidence of polarisation in selected OECD countries, while more recent research by Peugny (2019) presents evidence of polarisation in twelve developed EU countries (Austria, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Portugal, Spain, Sweden, and United Kingdom) during the 1990s, 2000s, and early 2010s. A similar study was conducted by Jerbashian

(2019), who investigated whether the decline in IT prices due to rapid technological upgrading had an impact on demand for high-, middle-, and low-wage employment in ten Western European countries from 1993 to 2007. It found that the decline in IT prices resulted in higher demand for high-wage occupations and decline in medium-wage occupations.

To date, the job polarisation hypothesis has been mostly tested in developed economies. However, it may not "travel" well to the developing countries due to relative differences in costs of capital and labour. Autor (2013, p. 187) illustrates this point: "When Nissan Motor Company builds cars in Japan, it makes extensive use of industrial robots to reduce labour costs. When it assembles cars in India, it uses robots far more sparingly." The key reason is that it was cheaper to use labour than technology in India. The same logic could be applied to many developing countries. For example, Lewandowski (2017) and Nchor and Rozmahel (2020) have found only tentative evidence for the polarisation hypotheses in CEE countries in the 2000s and 2010s. They stipulate that this is because in CEE countries it is often cheaper for companies to supplement labour with new technologies, in turn increasing productivity, rather than outright replacing mid-skilled labour.

2.3 Low-skill-biased technological change

Low-skill-biased technological change hypothesis argues that demand for high or low skills depends on their relative abundance. If a labour market is characterised by a large number of low-skilled workers, employers will adopt such technologies and work processes that can make the best use of available skills. Returning to the Nissan example, Autor (2013, p. 187) has stipulated that if there is an abundant number of low-skilled employees who would work for a relatively low wage, companies would adopt two inter-dependent strategies. First, work organisation process would rely more on relatively cheap labour than costly technologies. Second, the adopted technologies in such a setting would aim to make the best use of the available low skills (i.e., complement the employees) rather than replace them. Similarly, Acemoglu (2002) has found that when there is a large supply of unskilled labour, it is more profitable to introduce technologies that required lower skills. He has supported this claim with the example of England in the 19th century, where large cities received a great influx of migrants from rural areas, allowing for a wide utilisation of technologies that relied on low skills (Acemoglu, 2002, p. 9).

Standardisation of work processes and maturity of technologies can also lead to low-skill-biased technological change. For example, Eriksson *et al.*

(2019) stipulate that technological advancements first lead to an increase in the demand for highly skilled labour, but this demand dwindles as the use of technology becomes standardised. This is because completely new technology often comes with a lot of uncertainty that requires high-skilled labour to tackle it (Vernon, 1966; Eriksson *et al.*, 2019). However, as time passes and the technology becomes more commonplace, uncertainty is replaced with standardised procedures that can be performed by lower-skilled labour. In this respect, knowledge becomes embodied within machines and work organisation processes rather than workers themselves.

This logic can be also well applied to the case of the Baltic States. First, from the planned economy they "inherited" an abundant supply of workers with skills that were of little relevance in the market economy. This created incentives for companies to focus on technologies that would complement their abundant factors of production rather than introduce radically new technologies. Second, while most new technologies in the 1990s came to the Baltic States from the West, the majority of them were already well understood, and hence could have been utilised by lower-skilled individuals. This is further supported by the fact that, during this time, the level of innovation in the Baltics was relatively low. For example, in 1997, only 11 patent applications were filled to the European Patent Office from the three Baltic States combined (Eurostat, 2020a).

Keeping in mind the three stories of technology affecting labour, in the study we evaluate which of them best suits the case of the Baltic States. These three post-communist countries could be conceptualised as developing countries undergoing a rapid transition. More specifically, we test if technological upgrading in the Baltic States had a positive (i.e., SBTC), a negative (i.e., low-skilled-biased technological change), or polarising effect on the labour market. The next section discusses methods and data as well as explains the focus on the Baltic States in particular.

3. Methodology

The chapter explores, first of all, the logic behind focusing on the Baltics States in the analysis. Later it describes the variables that are used to evaluate the effects of technological upgrading on labour. It concludes with a short discussion on the empirical model.

3.1 Case selection

The research evaluates how technological upgrading affects the labour market in countries going through extreme transition by focusing on the Baltic States (i.e., Estonia, Latvia, and Lithuania). The Baltic States provide an interesting, and under-researched, case of countries that underwent a rapid transition from planned to a market economy which differs from many other Eastern European countries. First, the Baltic countries were part of the Soviet Union before its collapse, rather than members of the Council for Mutual Economic Assistance. As a result, Baltic economies were more interconnected with those of other Soviet Republics, had no private sector, and their knowledge-intensive sectors had a strong military orientation.

Second, Lithuania and Latvia received a relatively small influx of FDI during the early stages of the transition than many other Central and Eastern European countries. Hence, at the start of transition, the influx of higher-end technologies was limited. The exception is Estonia, which, comparatively, received more FDI.

Finally, the transition in the Baltic States, in a broad sense, was similar to other transitions in more developed countries (Rutkowski, 2001). However, one important difference is that in the Baltics, and in other CEE countries, this transition was comparatively faster. This, in turn, implies that by focusing on the Baltics, some insights might be also applicable to the developed world.

The research focuses on the period between 1998 and 2018, during which the Baltic States had gone through a period of rapid technological modernisation, fast economic growth, closer integration in global value chains, etc. (Staehr, 2015). While it would be interesting to extend the analysis to early transition (1990–1997), data for this period is scarce, often incomparable, and likely prone to biases.

3.2 Estimating (low-)skill-biased change

To estimate the effects of technological upgrading on labour, researchers generally use one of two proxies for changes in the latter. First, the wage ratio of high/low-skilled individuals is widely used (see Esposito & Stehre, 2008; Behar, 2016; Poschke, 2018). Second, others (see Berman *et al.*, 1998; Hutter & Weber, 2017; Sevinc, 2017), use the ratio of high- to low-skilled employees. In the article, we focus on the latter as there is a lack of robust data on the wages of high- and low-skilled individuals in the Baltic States.

We employ two proxies for the measurement of skills—education and occupation. Availability of data is the main reason for such a selection, although we recognise the limitations of such proxies (see Appendix A). Labour Force Survey (LFS) microdata is used to estimate the education level of the employed in the Baltic States during the reference period. Coding is as follows: persons with tertiary education are considered as high-skilled, while persons with education below tertiary are considered as low-skilled. The analysis does not distinguish between medium (secondary education) and low skills (below secondary), because LFS micro-data did not include a sufficient number of individuals with primary education only. In cases where there was missing data, it was imputed using the Multiple Imputation by Chained Equations (MICE) approach (see Appendix B for details).

The analysis of skills by occupation relied on the ISCO-88 classification. Individuals working in the first three ISCO-88 occupations (i.e., (i) legislators, senior officials, and managers; (ii) professionals; and (iii) technicians and associate professionals) are defined as high-skilled, while those from the bottom two (i.e., (i) plant and machine operators and assemblers and (ii) elementary occupations) are defined as low-skilled. The selection of these occupations was based on Eurofound's (2010) classification that defines the first three ISCO occupations as being high-skilled white collar, while the last two as low-skilled blue collar ones. In addition, in the analysis we will also use low-skilled white-collar and high-skilled blue-collar workers (ISCO 4-7) as a proxy for medium-skilled individuals.

3.3 Estimating technological upgrading

We use investments in machinery and equipment by companies as a proxy for technological upgrading. This includes investments in transport, ICT equipment, cultivated biological resources, intellectual property products, etc. A similar method was used by Hirvonen *et al.* (2022), who measured technological progress in Finland from 1994 to 2018 through financial firms' data. This approach was selected because, first, it provides a relatively direct measure of how much companies invest into new technologies, though it also includes some non-technological investments. Second, unlike with R&D expenditures, the available data does not have a lot of missing values and it contains information not only on countries, but also on the economic sector. Though it has one major weakness, as investments in machinery and equipment can capture technological upgrading and/or expansion of firms' capacities. To address this problem, the regression model used in this paper controls for investments in buildings (excluding dwellings).

3.4 Empirical model

The research predominantly uses the Labour Force Survey (LFS) micro-data, which was aggregated to fit the objectives of the study, and various national account statistics (see Table 1 below for more details). To add robustness to the research in cases where data was missing, it was imputed using the Multiple Imputation by Chain Equations approach (see Appendix B). Imputation was also necessary to check the stationarity of the data in order to ensure that the relationship observed in the study is not spurious.

In the research, we use panel data to estimate the impact of technological change on labour. The panel data set is separated into three dimensions: countries, economic sectors (expressed in NACE revision 1.1. classification), and time trends. However, the three-dimensional nature of the data complicates the analysis, as existing methods for three-dimensional panel data set analysis are still in their infancy (e.g., Balazsi, Matyas & Wansbeek, 2015). Hence, in order to carry out the research with more conventional and more tested approaches, the two cross-sectional dimensions (i.e., country and sector) were combined into one.

The effect of technological upgrading on (low-)skill-biased change is estimated through a panel regression analysis. The following form of the regression equation was used for the analysis:

$$\frac{H_{it}}{L/M_{it}} = \beta_0 + \beta_1 IM_{it} + \beta_2 IB_{it} + \sum_{k=3}^{K} \beta_k C_{kit} + \omega_{it},$$

where H_{it} and L/M_{it} are the numbers of high- and low-skilled individuals in a subsector and country i in year t, IM_{it} is the investments in machinery and equipment by firms, IB_{it} is investments in buildings, which serves as one of the main controls. C_{kit} is an additional list of controls. It includes, first, employment in a country and sector i, which helps to control economic growth. Second, the percentage of individuals with tertiary education in a country to control the growing population of highly educated individuals in the Baltic States (see Fig. 1 in the next section). This percentage, as well as the *Year* variable, which is another control, are also used as time-trend controls. To control sectors that might be "younger" and hence might have more higher-skilled individuals, *Average age* of employees is also included as a control variable. Finally, the regression equation includes a control variable for when the Baltic States joined the EU, and for the 2008 financial crisis. A concise summary of all the variables, their roles, as well as sources is provided in Table 1 below. To control inflation, all variables expressed in monetary terms are represented through chain linked volume (2005).

Table 1. Data and its sources.

Roles	Variables	Measure	Source
Dependent variables	Ratio of high- to low- skilled individuals	Two ratios were calculated, one using occupation level and another using education level Hence, in the analysis two different models were also built and analysed.	Eurostat Labour Force Survey micro-data / Eurostat Labour Force Survey micro-data cross-tabulations
Independent variables	Investments in machinery	Gross fixed capital formation expressed in chain linked volume (2005) million euros	Eurostat National Account statistics [nama_10_a64_p5]
Controls	Investments in buildings (excludes dwellings)		
	Number of employed	Number of employees in a select country and sector	Eurostat National Account statistics [nama_10_a64_e]
	Education level	Percentage of individuals with tertiary education in the select country	Eurostat Labour Force Survey micro-data / Eurostat Labour Force Survey micro-data cross-tabulations
	Average age	The average age of employees in the select country and sector	
	Years	Indication of the time period an observation represents	–
	Joined the EU	Dummy variable indicating before ascension [2004-2018 (1)], and after [1998-2003 (0)]	
	The 2008 financial crisis	Dummy variable indicating the period during the crisis [2008-2011 (1)] and after it [other years (0)]	

The regression equation is evaluated using the random effects regression model. With this in mind, ω_{it} represents the random effects residuals comprised from a random effect of subject i and the general residuals of the model. Random effects panel regression model was selected, first, because it is, together with fixed effects models, often used in similar studies exploring effects of technological change on labour (e.g., see Haapanala, Marx & Parolin, 2022; Badran, 2019). Second, it was selected instead of a fixed effects model because, according to the Hausman (1978) test, we could not reject the null hypothesis (i.e., the *p*-values were above all standard thresholds) implying that the random effects model is more appropriate for our data. Finally, there is a growing movement amongst academics to avoid fixed effects models generally (Bell, Fairbrother & Jones, 2019). Because of this, we predominantly relied on the results of the random effects model. However, in Appendix C we also provide results from a Fixed and Pooled OLS panel regression to ensure transparency.

In the analysis we also explored a possibility of adding lags to the model to account for delayed relationships between variables. However, lags did not produce many improvements and hence original data, without them, was used.

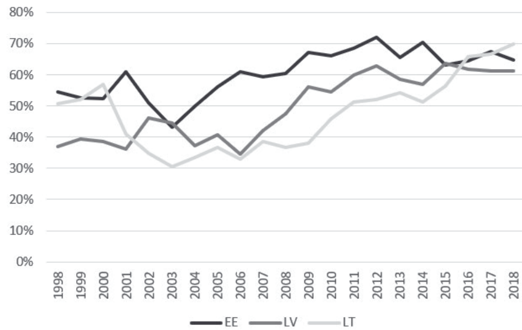
4. Empirical analysis

4.1 Descriptive analysis

The early stages of transition in the Baltic States could be described in three stylised facts. As the Baltic States left the USSR, the stated-owned manufacturing sector collapsed, leading to de-industrialisation and large declines in the outputs. That led to employment in the manufacturing sector to rapidly decline during the early stages of transition in the Baltic States (wiiw, 2010). This, in turn, led to a reallocation of resources from the manufacturing companies to the newly emerging services sector (Blanchard, 1997).

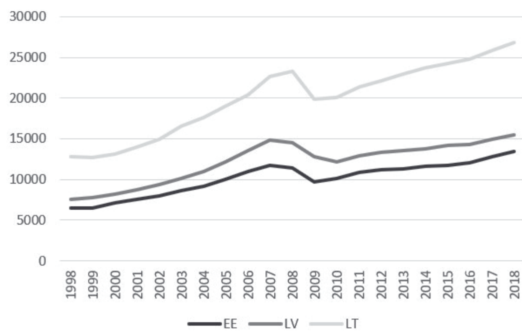
However, from around 2002, the situation started to improve. The percentage of individuals with tertiary education was on a steady upward trend, though with a lot of volatility. Similarly, value added by companies was also growing from around 2002, ignoring the sharp decline during the 2008 financial crisis (see Figs. 1 and 2 below). Similarly, the ratio of high- to low-skilled individuals was steadily growing as well (see figures in Appendix D). However, at the sectoral level, in the majority of cases, the ratio of high- to low-skilled individuals remained relatively constant, with some exceptions. Sectors with a clear upward trend in the ratio of high- to low-skilled employees were: (i) electricity, gas, and water supply; (ii) transport, storage, and communication; (iii) financial intermediaries; and (iv) education. This implies that the composition of workers in the majority of sectors did not change drastically. However, as expected with the growing education level, a weak positive trend could be observed at the aggregated level (see Fig. D9 in Appendix D).

Figure 1. Percentage of individuals with tertiary education (15–74 years old).



Source: Own estimations based on Eurostat Labour Force Survey aggregated data [lfsa_e2ged]

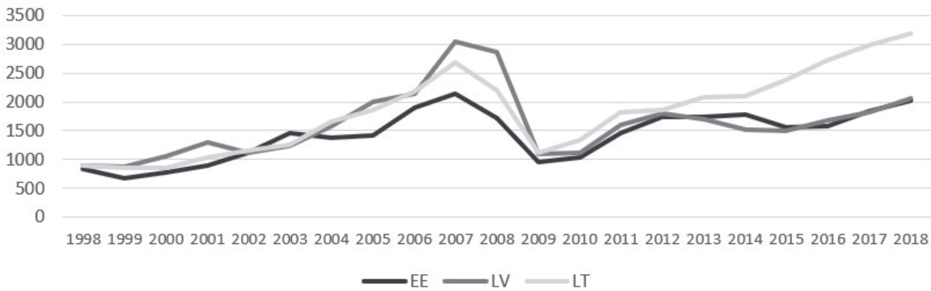
Figure 2. Value added expressed in chain linked volume (2005), mln euros.



Source: Own estimations based on Eurostat National Account statistics [nama_10_a64]

Finally, investments in machinery and equipment, which we used as a proxy for technological upgrading, also had a positive trend, ignoring the large drop during the 2008 financial crisis (see Fig. 3).

Figure 3. Investments in machinery and equipment expressed in chain linked volume (2005) million euros.*



Source: Own estimations based on Eurostat National Account statistics [nama_10_a64_p5] (Eurostat, 2020b)

* The figure was created using imputed data.

4.2 Regression analysis

The random effects panel regression analysis indicates that there is a negative relationship between technological upgrading and skills (see Table 2). Specifically, an increased investment in machinery and equipment by 100 million euros (130 million is the average in all sectors and countries) would lead to a decrease of around 0.08 in the ratio of high- to low-skilled individuals estimated by education level. Similarly, an increase by 100 million also leads to a decrease by 0.3 in the ratio of high- to low-skilled individuals, calculated by occupations. This implies that in the Baltic States, technological upgrading predominantly helped lower-skilled individuals, as with more investments into technology, the number of lower-skilled employees grew, compared to higher-skilled ones.

In addition to investments in machinery, the other independent variables that are statistically significant include investments in the construction sector, education level for the model based on education, and years for the model based on occupations. These results are not surprising, but they provide some interesting additional insights. The positive coefficient in the investments in buildings implies that, as companies expand, they hire more higher-skilled individuals than lower-skilled ones. The positive trend in the education variable also implies that as the number of educated individuals grows, companies shift to more educated workforce.

Table 2. Random effects regression results on the ratio of high- to medium/low-skilled employees by education and occupation (N=756; includes imputed values).

	By education level (high/low)	By occupation (high/low)
Constant	0.8472 (0.8917)	-106.070** (51.3557)
Investments in machinery	-0.0008** (0.0003)	-0.0030** (0.00146)
Investments in buildings (excludes dwellings)	0.0006** (0.0003)	0.0046** (0.00205)
Number of employed	0.0006 (0.0010)	0.0008 (0.00411)
Average age	-0.0307 (0.0226)	0.0653 (0.07515)
Education level	0.0500*** (0.0079)	–
Years	–	0.0526** (0.02622)
Joined the EU	0.0160 (0.0692)	-0.0347 (0.18724)
The 2008 financial crisis	0.0689 (0.0900)	0.0963 (0.20868)

Notes:
* indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.
1. The main two variables (i.e., the ratio of high- to medium-skilled individuals and investments in machinery) were stationary according to the Levine-Lin-Chu (2002) unit root test.
2. No collinearity issues were present in the model.
3. Arellano (1987) heteroskedasticity- and autocorrelation-consistent robust standard error was used in the model to account for heteroskedasticity and autocorrelation present in the model.
4. Due to severe lack of data and/or the sectors being too small in the Baltic States, the following economic sectors were excluded from the analysis: (i) mining and quarrying; (ii) activities of private households; (iii) extraterritorial organisation and bodies; and (iv) other community, social and personal services activities.

These results are consistent with other regression models (see Table 3) and with different regression modifications (see Appendix C: Sensitivity analysis). Although, one interesting difference can be observed. By adding time dummies to the model using education level as a proxy for skills, and removing education level, years, EU, and crisis variables, which strongly correlate with time, we saw that time dummies that indicated early stages of transition had a negative effect on the ratio, while later this effect became positive. And although the same trend cannot be observed when using occupations as proxies for skills (see Appendix C), this implies that, with time, companies in the Baltics focused on lower-skilled individuals at first, while later the focus shifted to higher skills.

Finally, to further add robustness to the results, other proxies of technological upgrading were also used in the regression. These include R&D

expenditures, investments into ICT equipment, and consumption of fixed capital by the company. According to the results, which are summarised in Table 4 below, we also found a negative effect on the ratio of high- to low-skilled individuals. This provides additional support to the statement that technological upgrading in the Baltic States had a negative effect on the ratio of high- to lower-skilled individuals.

Table 3. Impact of technological upgrading on the ratio of high- to medium/low-skilled individuals according to different regression models (N=756; includes imputed values).

	By education level (high/low)			By occupation (high/low)		
	Pooled OLS	Fixed effects	Weighted least squares	Pooled OLS	Fixed effects	Weighted least squares
Constant	-0.7076	0.9746	-1.0346***	−169.890	-103.5090*	-115.012
Investments in machinery	-0.0027***	-0.0007**	-0.0017***	−0.0102231	-0.0026*	-0.008
Investments in buildings (excludes dwellings)	0.0012*	0.0006**	0.0013***	0.00694357	0.0045**	0.005
Number of employed	-0.0004	0.0011	-0.0007***	0.00246727	0.0018	0.003
Average age	0.0161****	-0.0352***	0.0242***	0.110352	0.0600	0.100
Education level (for education) / Years (for occupations)	0.0424	0.0502	0.0371***	0.0837236	0.0514*	0.056
Joined the EU	0.0801	0.0127	0.0055	0.157969	-0.0489	0.197
The 2008 financial crisis	0.0012	0.0817	-0.0996**	−0.291728	0.1272	-0.287
Adjusted R-squared / Weighted least squares	0.2663	0.3333	0.4665	0.2470	0.1788	0.3764

Notes:

* indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.

1. The main two variables (i.e., the ratio of high/ to medium/low/skilled individuals and investments in machinery) were stationary according to the Levine-Lin-Chu (2002) unit root test.
2. No collinearity issues were present in the model.
3. Arellano (1987) heteroskedasticity- and autocorrelation-consistent robust standard error was used in the model to account for heteroskedasticity and autocorrelation present in the model.
4. Due to severe lack of data and/or the sectors being too small in the Baltic States, the following economic sectors were excluded from the analysis: (i) mining and quarrying; (ii) activities of private households; (iii) extraterritorial organisation and bodies; and (iv) other community, social and personal services activities.

Table 4. Random effects regression results on the ratio of high- to medium/low-skilled employees using different proxies for skills and technological upgrading (N=756; includes imputed values).

	By education level (high/low)			By occupation (high/low)		
	R&D expenditures	Investments into ICT equipment	Value added	R&D expenditures	Investments into ICT equipment	Value added
Constant	1.1291	0.9242	0.7779	-90.9467*	-89.3514*	-117.7330**
Variable from the column	-0.0054**	-0.0021*	-0.0002***	-0.0229**	-0.0056	-0.0008***
Investments in buildings (excludes dwellings)	0.0005*	0.0005	0.0005*	0.0042**	0.0041**	0.0042**
Number of employed	0.0004	0.0008	0.0015	-0.0001	0.0008	0.0049
Average age	-0.0381	-0.0334	-0.0280	0.0456	0.0589	0.0783
Education level (for education)	0.0497***	0.0493***	0.0492***		-	
Years		-		0.0454*	0.0443*	0.0582**
Joined the EU	-0.0165	-0.0047	0.0183	-0.1225	-0.1049	-0.0055
The 2008 financial crisis	0.1161	0.1082	0.1106	0.3104	0.2552	0.2078

Notes:
* indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.
1. The main two variables (i.e., ratio and investments in machinery) were stationary according to the Levine-Lin-Chu (2002) unit root test.
2. No collinearity issues were present in the model.
3. Arellano (1987) heteroskedasticity- and autocorrelation-consistent robust standard error was used in the model to account for heteroskedasticity and autocorrelation present in the model.
4. Due to severe lack of data and/or the sectors being too small in the Baltic States, the following economic sectors were excluded from the analysis: (i) mining and quarrying; (ii) activities of private households; (iii) extraterritorial organisation and bodies; and (iv) other community, social and personal services activities.

Hence, to summarise, the results of the regression analysis imply that there was a low-skilled-biased technological change during the transition and beyond it in the Baltic States. Why was there a low-skilled-biased change in the Baltic States, in contrast to many other CEE countries? We will explore this in the next section.

5. Discussion and conclusion

Conventional wisdom in academic and policy circles tends to relate technological upgrading with increased demand for higher skill levels. However, our research shows that this is not necessarily true in all cases. In the article, we find that technological advancement in the Baltics led to a decline in the ratio of high- to low-skilled individuals. This, in turn, implies that companies in the Baltics were upgrading their technological capacities by investing more into lower-skilled individuals, which led to an increase in their demand compared to the demand for higher-skilled employees. These results were stable when different metrics of skills and technological upgrading were used, as well as different statistical models.

We believe that an abundance of lower-skilled individuals can explain this. During the early stages of transition, employees in the Baltic States had very specific skill sets necessary only during the Soviet times, but not as relevant for the capitalist world. Namely, due to the Soviet legacy, many individuals in the Baltic States were quite knowledgeable about solving specific problems, but underperformed in using knowledge in unforeseen circumstances (World Bank, 1996, p. 125), which hampered them from using new and complex technologies. Hence, the relative competitive advantage of the Baltics at the start of transition was closely linked with cheap, but low-skilled labour force. As a result, companies chose not to replace but rather supplement their skills with new, easy-to-use technologies. However, from 2007 onwards, as the Baltic economies climbed up the value-added chain and acquired the knowhow, investments in technologies became increasingly high-skill-biased (see Appendix C).

These findings make several contributions to the academic discussion. First, it provides insights into the relationship between technology and labour in the Baltic States, which is a somewhat under-researched region in the academic literature. Second, it expands on the literature on the relationship between technology and labour by demonstrating that it might not have only a polarising or skill-biased effect on it, but also a low-skilled biased effect, which is much less explored than the two others. Finally, the findings show how technological upgrading might affect the labour market during large-scale economic transitions and restructuring, which might be relevant for other countries that are, or will be, undergoing a similar rapid change.

The results also provide several implications for policy makers. First, industrial policies, which aim to coordinate investments in specific sectors, should prioritise making the best use of regionally existing resources (including skills) rather than copying policies adopted elsewhere. This article shows that private investments in technology utilised the abundance of low skills, which produced positive social and economic outcomes in terms of economic growth and low unemployment. A hypothetically alternative pathway—investments in high skill-intensive technologies—in the 1990s and early 2000s probably would have faced a shortage of high skills and under-utilised the existing skill sets, thus leading to unemployment. Second, the results also point towards the emergence of learning effects in the economy: as the Baltic economies climbed the value-added chains, technological upgrading became increasingly high-skill-biased. This suggests that countries starting with low skill-intensive technologies do not necessarily get stuck in low productivity, wages, and skills equilibrium.

However, we also acknowledge that the research has several important limitations, the majority of which are related to lack of data. First, given the gaps in the data, some of it had to be imputed, which might have introduced some bias. However, based on the sensitivity analysis of imputation explored in the Appendices, it is unlikely that this bias is severe. Second, technological upgrading was measured through proxies. To mitigate biases that this might have introduced, an array of different controls was used in the analysis. Finally, the regression analysis does not cover the effects of FDI on the labour market or on technological upgrading due to lack of data. However, given that the influx of FDI during the transition in the Baltics (except for Estonia) was much lower than in Central European countries, we do not consider this as a major omission.

Nevertheless, even with these limitations, this article provides interesting insights and introduces ample questions for future research in this area. This includes questioning whether other countries undergoing a large-scale transformation of economies and also relying predominantly on their own capabilities exhibit similar trends? How would the results change if a wage dimension was introduced to the analysis? How much does the amount of FDI and the initial number of lower-skilled individuals affect the relationship? Answers to these questions would expand the discussion on (low-)skill-biased change even further, while the theory, methodology, and empirical results discussed in this article may serve as a stepping stone for this future research.

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Appendices

Appendix A: Measurements of skills

The table below provides a short overview of different approaches to estimating skills, as well as their strengths and weaknesses. To summarise, we decided to use education level and occupation as a proxy for skills, as there is large data availability issues with other approaches. In addition, using both education and occupation as measures for skills allows mitigating, to some extent, the issues present in the two measures.

Table A1. A shortlist of possible skill measures.

Skill estimation approach	Short explanation	Strengths	Weaknesses
Education level / years of schooling	More education leads to more skills	Easy to use. Large data availability. Provides a relatively straight-forward cross-country comparison.	Assumes that skills are static (e.g., not improved on the job). Can be considered as a measure of potential of carrying out a task than a measure of skill. Has relatively low variation (i.e., majority of people have a similar education level).
Occupational	Individuals with high-level occupations (e.g., managers, professionals) are more skilled than those in lower level occupations	Easy to use. Provides a relatively straight-forward cross-country comparison. A more precise measure of skills that individuals use in their jobs, if compared to education.	Assumes that individuals from the same occupation have the same skill set. Higher-level occupations do not necessarily have a higher skill level.

Wage	Individuals with higher wage have a higher skill level	Can be used to differentiate between individuals with the same occupation, education level, etc. Provides a measure of skill that heavily varies between individuals, which might mean this measure is more precise.	Can provide misleading results if the labour market situation in the country is ignored (i.e., higher wage might be due to large demand and small supply for an occupation rather than higher skills). Cannot be used to assess the impact of skills on wage. Often only very aggregated data is available.
Task-based approach	Use tasks that individuals perform in their jobs as a proxy for skills	Might provide one of the most exact measures of skills. Can provide information on both skill differences between and within occupations.	Available data spans through a relatively short timeframe. Available data provides only very basic information on tasks. Difficult to implement in practice due to lack of data and lack of agreed upon making of tasks to skills.
Survey based appro-aches	Directly measure skills individuals possesses through surveys (e.g., via the Programme for the International Assessment of Adult Competencies survey)	Could provide very exact information on the micro-level Can provide information on both skill differences between and within occupations, as well as between and within countries.	Would provide only quantitative information, as it is unlikely that individuals would be able to accurately measure their own skill level. Available data encompasses only a very small number of skills and covers a short timeframe.
Dictionary of Occu-pations (DoT) and O*NET	Data sets containing information on skills, knowledge, abilities, etc. necessary for over 1,000 occupations	Provides one of the most comprehensive lists of skills, knowledge, and abilities for individuals for a large number of occupations. Information expressed in quantitative terms, allowing for a very precise comparison between occupations.	The skills necessary for occupation in the US are not necessary the same in the Baltic States. Has many redundancies that have to be removed before usage. The representativeness of the data set could be questioned.

Source: Authors based on Mincer, 1958; Becekr, 1964; Hanushek & Kimko, 2000; Autor, 2013; Autor & Handel, 2013; Martinaitis, 2014; Goos, Manning & Salomons, 2014; Hanushek *et al*., 2015; Mane & Miravet, 2016.

Appendix B: Imputation of missing data

Imputation was performed through a three-step process: estimating the reason why the data is and imputing missing data. The first step refers to checking the reasoning behind the missing data. This is a crucial step, for if the data is not missing completely at random, or at least at random, any imputation, or even the use of the data without it, might produce biased results (Pampaka *et al*., 2014). This is because if there is some underlying reasoning behind the missing data, research could arrive at biased results. Estimation of the nature of the missing data was carried out using Little's MCAR test (Little, 1988). According to its results, the data is missing completely at random, which allows us to use imputation.

For this task we employed the Multiple Imputation by Chained Equations (MICE) method, which is considered one of the best imputation approaches (Azur *et al*., 2011). Selection of parameters[1] for this approach was carried out by evaluating the quality of inputted data for each variable. This was done by, first, removing some values from the variable at random; second, imputing the missing data with each method; and, third, comparing the imputed results with the removed values to estimate the parameters' accuracy. More specifically, the comparison was done by calculating the percentage error between real and imputed data, which is expressed as follows:

$$Percentage\ error = 100 \times \frac{Imputed\ value - Real\ value}{Real\ value}$$

The raw percentage difference, as can be seen in the equation, rather than the percentage difference expressed in absolute values was used to account for both over- and underestimation. This is necessary as the MICE algorithm provides an iterative approach, where imputation of too large values could be mitigated by imputation of smaller values. In addition, to further add robustness to the imputation check, this process was repeated 100 times, each time removing and imputing a random sample of values ranging anywhere from ten to fifty.

The table below provides a summary of this imputation check. As can be seen from the table, the average error of the imputation was relatively low for the majority of variables. However, in the case of R&D expenditures, the

1 The following types of MICE imputation were tested: (i) Pmm—predictive mean matching; (ii) Midas touch—weighted predictive mean matching; (iii) Sample—random sample from observed values; (iv) CART—Classification and regression trees; (v) RF—random forest imputation; (vi) Norm—Linear regression ignoring model error; (vii) Norm boot—Linear regression using bootstrap.

imputations were very inaccurate. This can be explained by the relatively large number of missing observations in this variable. Hence, this variable was excluded from the majority of the empirical analysis as it might introduce bias.

Table B1. Results of imputation methods' diagnostics (N=756).

Variable	Number of missing values	Selected method	Average error (standard error)
Low education level	287	Norm boot	-2.71% (16.7)
Medium education level	21	Norm	3.57% (8.6)
High education level	36	Norm	3.45% (10.1)
Ratio between high- and low-skilled individuals (ISCO)	111	Norm.boot	-2.21% (32.6)
Ratio between high- and medium-skilled individuals (ISCO)	52	Norm	-3.95% (41.0)
Ratio between medium- and low-skilled individuals (ISCO)	110	Norm.boot	-0.05% (7.5)
Investments in machinery	8	Norm boot	2.55% (14.5)
Other buildings and structures gross	8	Rand forest	14.42% (47.4)
Total employment	63	Norm boot	3.05% (2.2)
R&D expenditures	400	-	Over 500% (over 1000)

Appendix C: Sensitivity analysis

Table C1. Impact of technological upgrading on different rations of high/medium/low -skilled individuals based on random effects regression model (N=756; includes imputed values).

	By education level			By occupation		
	High/low	High/medium	Medium/low	High/low	High/medium	Medium/low
Constant	-29.9732**	0.8472	-10.3026*	-106.07**	-13.099	-38.9939
Investments in machinery	-0.0082**	-0.0008**	-0.0008	-0.0030**	0.0002	-0.0019**
Investments in buildings (excludes dwellings)	0.0027	0.0006**	-0.0053**	0.0046**	0.001**	0.0002
Number of employed	0.0027	0.0006	-0.0064	0.0008	0.001	0.0108**
Average age	0.7611**	-0.0307	0.5030***	0.0653	-0.008	0.0219
Education level (for education) / Years (for occupations)	0.1721***	0.0500***	-0.1354***	0.0526**	0.007	0.0197
Joined the EU	0.5739	0.0160	1.0946**	-0.0347	0.104	0.0748
The 2008 financial crisis	-0.8439	0.0689	-0.3195	0.0963	0.083	-0.0947

Notes:

* indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.

1. The main two variables (i.e., the ratio of high- to medium-skilled individuals and investments in machinery) were stationary according to the Levine-Lin-Chu (2002) unit root test.
2. No collinearity issues were present in the model.
3. Arellano (1987) heteroskedasticity- and autocorrelation-consistent robust standard error was used in the model to account for heteroskedasticity and autocorrelation present in the model.
4. Due to severe lack of data and/or the sectors being too small in the Baltic States, the following economic sectors were excluded from the analysis: (i) mining and quarrying; (ii) activities of private households; (iii) extraterritorial organisation and bodies; and (iv) other community, social and personal services activities.

Table C2. Random effects regression results on the ratio of high- to medium-skilled employees calculated by education without imputed values (N=686).

	Coefficients (standard error)
Constant	0.7825 (0.8931)
Investments in machinery	-0.0008** (0.0003)
Investments in buildings (excludes dwellings)	0.0006** (0.0003)
Number of employed	0.0005 (0.0010)
Average age	-0.0295 (0.0217)
Education level	0.0514*** (0.0078)
Joined the EU	0.0520 (0.0800)
The 2008 financial crisis	0.0140 (0.0581)

Notes:

* indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.

1. No collinearity issues were present in the model.
2. Arellano (1987) heteroskedasticity- and autocorrelation-consistent robust standard error was used in the model to account for heteroskedasticity and autocorrelation present in the model.
3. Due to severe lack of data and/or the sectors being too small in the Baltic States, the following economic sectors were excluded from the analysis: (i) mining and quarrying; (ii) activities of private households; and (iii) extraterritorial organisation and bodies; and (iv) other community, social and personal services activities.

Table C3. Random effects regression results on the ratio of high- to medium-skilled employees calculated by occupations without imputed values (N=583).

	Coefficients (standard error)
Constant	-113.5520* (64.5362)
Investments in machinery	-0.0030* (0.0017)
Investments in buildings (excludes dwellings)	0.0050** (0.0021)
Number of employed	0.0017 (0.0049)
Average age	0.0725 (0.1059)
Years	0.0560* (0.0330)
Joined the EU	-0.2084 (0.2055)
The 2008 financial crisis	0.0866 (0.2170)

Notes:

* indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.

1. No collinearity issues were present in the model.
2. Arellano (1987) heteroskedasticity- and autocorrelation-consistent robust standard error was used in the model to account for heteroskedasticity and autocorrelation present in the model.
3. Due to severe lack of data and/or the sectors being too small in the Baltic States, the following economic sectors were excluded from the analysis: (i) mining and quarrying; (ii) activities of private households; and (iii) extraterritorial organisation and bodies; and (iv) other community, social and personal services activities.

Table C4. Random effects regression results on the ratio of high- to medium-skilled employees by education level with time dummies (N=756; includes imputed values).

	Coefficients (standard error)
Constant	2.3006* (1.292)
Investments in machinery	-0.0010** (0.0005)
Investments in buildings (excludes dwellings)	0.0007** (0.0003)
Number of employed	0.0010 (0.001)
Average age	-0.0372 (0.030)
1999	-0.0201 (0.037)
2000	-0.0766 (0.067)
2001	-0.2162*** (0.079)
2002	-0.2307** (0.092)
2003	-0.2435*** (0.088)
2004	-0.1467 (0.094)
2005	-0.0975 (0.116)
2006	-0.0665 (0.112)
2007	0.0086 (0.157)
2008	0.0364 (0.144)
2009	0.1458 (0.148)
2010	0.2035 (0.145)
2011	0.2968 (0.187)
2012	0.3372 (0.206)
2013	0.4652* (0.257)
2014	0.5035** (0.251)
2015	0.4494** (0.222)
2016	0.4985** (0.231)
2017	0.5692** (0.2724)
2018	0.5668** (0.2657)

Notes:
* indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.
1. The main two variables (i.e., ratio of high- to medium-skilled individuals and investments in machinery) were stationary according to the Levine-Lin-Chu (2002) unit root test.
2. No collinearity issues were present in the model.
3. Arellano (1987) heteroskedasticity- and autocorrelation-consistent robust standard error was used in the model to account for heteroskedasticity and autocorrelation present in the model.
4. Due to severe lack of data and/or the sectors being too small in the Baltic States, the following economic sectors were excluded from the analysis: (i) mining and quarrying; (ii) activities of private households; and (iii) extraterritorial organisation and bodies; and (iv) other community, social and personal services activities.

Table C5. Random effects regression results on the ratio of high- to low-skilled employees by occupations with time dummies (N=756; includes imputed values).

	Coefficients (standard error)
Constant	-1.3074 (3.4279)
Investments in machinery	-0.0030** (0.0014)
Investments in buildings (excludes dwellings)	0.0048** (0.0022)
Number of employed	0.0015 (0.0044)
Average age	0.0740 (0.0790)
1999	0.0253 (0.0935)
2000	0.0438 (0.1406)
2001	0.0673 (0.1426)
2002	0.1427 (0.1767)
2003	0.0437 (0.1742)
2004	0.0721 (0.2291)
2005	0.2942 (0.2571)
2006	0.2397 (0.2804)
2007	0.4190 (0.3031)
2008	0.1689 (0.2980)
2009	0.3247 (0.2509)
2010	0.6514*** (0.2367)
2011	0.9704** (0.4424)
2012	0.9259** (0.3829)
2013	0.7908*** (0.3031)
2014	0.8028*** (0.2806)
2015	0.7152** (0.3316)
2016	1.1575*** (0.4307)
2017	0.8989** (0.3755)
2018	0.6945 (0.4522)

Notes:

* indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.

1. The main two variables (i.e., ratio of high- to medium-skilled individuals and investments in machinery) were stationary according to the Levine-Lin-Chu (2002) unit root test.
2. No collinearity issues were present in the model.
3. Arellano (1987) heteroskedasticity- and autocorrelation-consistent robust standard error was used in the model to account for heteroskedasticity and autocorrelation present in the model.
4. Due to severe lack of data and/or the sectors being too small in the Baltic States, the following economic sectors were excluded from the analysis: (i) mining and quarrying; (ii) activities of private households; and (iii) extraterritorial organisation and bodies; and (iv) other community, social and personal services activities.

Table C6. Impact of technological upgrading on the ratio of high- to medium/low-skilled individuals before and after the 2008 financial crisis [N=393 (before 2009, with imputed data); N=360 (during and after 2009, with imputed data)].

	By education level (high/medium)		By occupation (high/low)	
	Year < 2009	Year > 2008	Year < 2009	Year > 2008
Constant	0.3198	-0.0057	-100.34	-137.76
Investments in machinery	-0.0003*	~0	-0.0015**	-0.0017*
Investments in buildings (excludes dwellings)	~0	-0.0001	0.0025**	0.0005
Number of employed	0.0010	-0.0034*	-0.0010	-0.0050
Average age	-0.0165	0.0093	0.0313	-0.0644
Education level	0.5372***	0.0327**	-	
Years	-		0.0505*	0.0716

Notes:

* indicates a statistical significance of 0.1; ** indicates a statistical significance of 0.05; *** indicates a statistical significance of 0.01.

1. The main two variables (i.e., ratio of high- to medium-skilled individuals and investments in machinery) were stationary according to the Levine-Lin-Chu (2002) unit root test.
2. No collinearity issues were present in the model.
3. Arellano (1987) heteroskedasticity- and autocorrelation-consistent robust standard error was used in the model to account for heteroskedasticity and autocorrelation present in the model.
4. Due to severe lack of data and/or the sectors being too small in the Baltic States, the following economic sectors were excluded from the analysis: (i) mining and quarrying; (ii) activities of private households; and (iii) extraterritorial organisation and bodies; and (iv) other community, social and personal services activities.

Appendix D: Additional figures

Figure D1. Average ratio of high- to low-skilled individuals (by education) in different industries.*

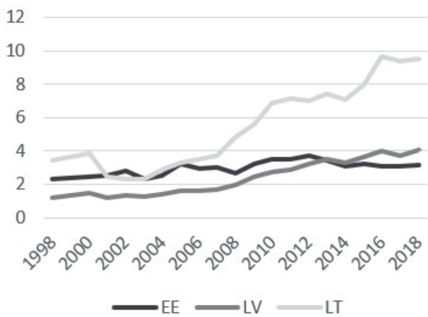
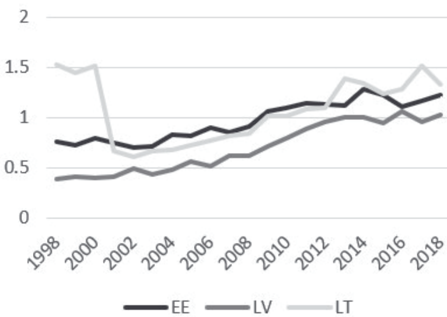


Figure D2. Average ratio of high- to medium-skilled individuals (by education) in different industries.*



Source: Own estimations based on Labour Force Survey 2020 micro-data.

* The figures were created using the imputed data.

Note: The steep decline for Lithuania in the second figure is due to the fact that according to LFS micro-data in 2001 there was a steep decline in the number of highly educated individuals and an increase in the number of more educated individuals. This could imply a change in the estimation strategy in Lithuania, which is not accounted for in the micro-data. However, a similar steep decline can also be observed in the aggregated data (e.g., see Fig. 1).However, this is not a major issue as by only focusing on 2002–2018 data (after the major decline) results only marginally shift as well as the regression analysis already takes into account the shift by using LFS micro-data to estimate education.

Figure D3. Average ratio of high- to low-skilled individuals (by occupation) in different industries.*

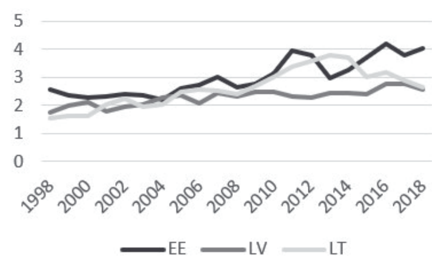
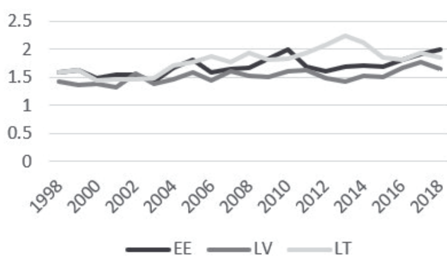


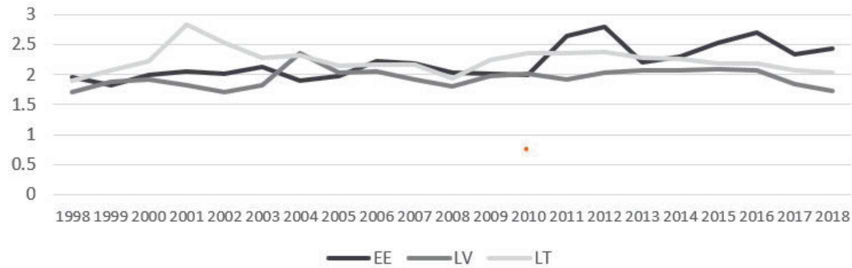
Figure D4. Average ratio of high- to medium-skilled individuals (by occupation) in different industries.*



Source: Own estimations based on the Labour Force Survey 2020 micro-data

* The figures were created using the imputed data.

Figure D5. Average ratio of medium- to low-skilled individuals (by occupation) in different industries.*



Source: Own estimations based on the Labour Force Survey 2020 micro-data
* The figures were created using the imputed data.

Figure D6. Composition of employees by education level in Estonia.*

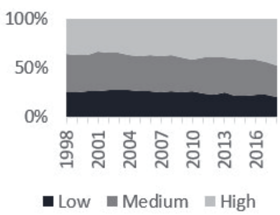


Figure D7. Composition of employees by education level in Latvia.*

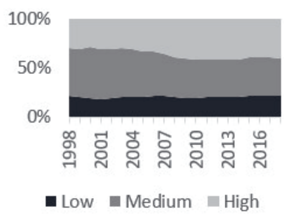


Figure D8. Composition of employees by education level in Lithuania.*

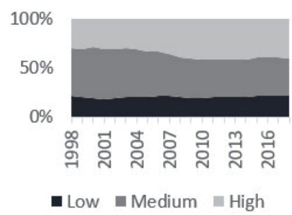


Figure D9. Composition of employees by occupation in Estonia.*

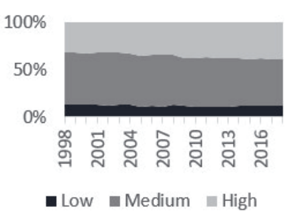


Figure D10. Composition of employees by occupation in Latvia.*

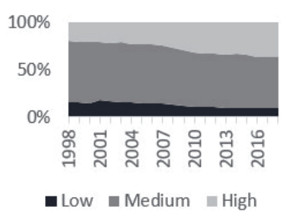
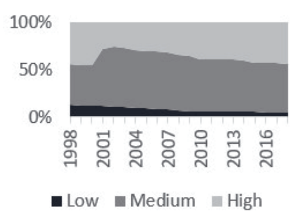


Figure D11. Composition of employees by occupation in Lithuania.*



Source: Own estimations based on the Labour Force Survey 2020 micro-data.
* The figures were created using the imputed data.