From socialism to capitalism: (un)skill-biased change in Lithuania manufacturing subsectors during the transition

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Abstract

The authors examine how trade liberalisation and technological advancement affected the skills in the Lithuania's manufacturing subsectors during the transition from socialism to capitalism. Using the Labour Force Survey, Comtrade, OECD structural analysis database, and wiiw Industrial Database authors found that these factors led to unskill-biased change. Though surprising, as the prevailing literature primarily finds a positive relationship between trade liberalisation, technological advancement, and skills, the results could be explained through a relatively low amount of FDI that Lithuania attracted during this period. Hence, the paper introduces some doubt to the prevailing idea that trade liberalisation and technological advancement indivertibly leads to skill upgrading in our day and age. It also opens several interesting questions, including if the heavily research positive relationship between the aforementioned factors fails in situations when there is an abundance of low skilled individuals and lack of new know-how.

Keywords

(un)skill-biased change; post-socialist; Lithuania; technological advancement; trade liberalization; manufacturing sector

JEL codes

J24, P33, O33

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Introduction

The transition period in Central and Eastern European (CEE) countries from planned to market economy after the collapse of the Soviet Union was characterised by a substantial shift in the structure of employment from low-sklled to high-skilled workers (Havlik, 2001) as well as a rise in wage inequality, quickly reaching Western European levels (Rutkowski, 1996). Though a large body of academic literature already covered these trends, some questions relating to their cause are still left unanswered. A variety of explanations were proposed for the aforementioned shifts in transition countries, as well as developed ones, which had similar trends in the 70s-00s (Berman et. al. 1998). For transition countries these factors include: the decentralisation of wage setting (Rutkowski 2001), destruction of over-manned positions (Loecker and Konings, 2006), which predominantly employed unskilled workers, and a diminishing number of graduates from universities in the early years of transition (Esposito and Stehrer, 2008). For the developed countries the shifts include: a shift to final goods that were mostly created by high-skilled workers (Schimmelpfennig, 1998) and a shift to high-skill products as developed countries could not compete with the cheap labour of developing ones (Wood, 1998). However, the two factors that most likely lead to the shifts in employment and wage premiums were technological upgrading (Tarjáni, 2004; Esposito and Stehrer, 2008) and trade liberalisation (Vivarelli, 2012).

On the one hand, several researchers found a strong positive relationship between technological upgrading and skills, which they named as skill-biased technological change (SBTC). For example, Berman *et al*. (1998, pp. 1273) found that at least 70% of displacement of unskilled workers in the US is accounted by skill-biased technological change. Sevinc (2017) found that, by using different skill measures, canonical SBTC model explains labour trends in the US during the 80s and 90s better than a similar yet more widely used polarisation hypothesis (i.e.

rapid decline of the mid-skill occupations). Similarly, Tarjáni (2004) found that SBTC had an impact on the input demand elasticity in Hungary, while Esposito and Stehrer (2008) explained the skill-premium through SBTC for Czech Republic, Hungary, and Poland during the transition.

On the other hand, Vivarelli (2012) found that the shift to high-skilled labour in some developing countries could be explained through trade liberalisation. He stipulated that trade liberalisation, as well as FDI, fostered an exchange of know-how and technologies between developed and developing countries. This, in turn, increased the demand for skilled labour to utilise this new know-how and technologies in the developing world. Conte and Vivarelli (2010) found some support for this idea with cases of 28 developing countries across the world, which, after opening their markets, saw an increase in the demand for skills. Similarly, Feenstra and Hanson (1997) and Fajnzylber and Fernand (2009) found similar evidence for Mexico and Brazil respectively during the 90s.

However, the discussion does not end here as some stipulate that trade liberalisation and technological change does not always have a positive effect on skills. For example, Acemoglu (2002) indicated that if the supply of low-skilled individuals is high, technological change can be unskill-biased predominately focusing on lower skills. Similarly, Vivarelli (2012) also indicated that trade liberalisation might force developing countries to lean stronger on unskilled labour as they face difficulties competing with developed countries that enjoy a large skilled labour pool. Alternatively, Eriksson *et al*. (2019) also noted that as new technologies and products go through their lifecycle, the demand for skilled labour drastically shifts. In the beginning of a product's lifecycle, uncertainty is high and requires advance skills, while, at the tail end, this uncertainty is replaced with standardisation that allows lower skilled individuals to produce the product.

Hence, it is not a given that technology and/or trade liberalisation indivertibly lead to skill-upgrading. Hence, to add to the discussion, we evaluate the effects of trade liberalisation and technological improvement on skills in Lithuania's manufacturing subsectors. Lithuania was chosen for the analysis as, unlike many other CEE countries, it attracted less FDI and, forcing many local businesses mainly to rely on their own abilities to survive during these turbulent times. This, combined with the fact that CEE countries that did not attract a lot of FDI during the transition are not as well researched as those that did, makes Lithuania and interesting case to explore. In addition, the case of Lithuania provides with methodology and results that could be used by other researchers who wish to explore the rapid transformation of a country where companies predominately rely on their internal resources to survive and prosper.

According to the research both trade liberalisation and technological change had a negative impact on skills during the transition period from 1998 to 2008. Such results are somewhat surprising because the majority of research on skill-biased change found a positive relationship between technology and skills. However, given that Lithuanian companies had to rely on their own capabilities to survive and there was an abundance of low-skilled individuals, it stands to reason that many businesses relied on low-skilled labour and therefore predominately introduced low-skill intensive technologies.

The remainder of the paper is structured as follows. Section two describes the three trajectories skill-biased change could take due to changes in technology and/or trade liberalisation. Section three elaborates in more detail why Lithuania was selected for the analysis and describes the research methodology. Section four provides empirical evidence for skill-biased change in Lithuania using descriptive and panel regression analysis. The last section (section five) discusses the study results and concludes the paper with final remarks.

Three stories of skill- and unskill-biased change

Skill-biased change

Many researchers (e.g. Berman et. al., 1998; Esposito and Stehrer, 2008; Sevinc, 2017; Mallick and Sousa, 2017) found that technological upgrading often leads to changes in the labour market that favour highly skilled individuals. This trend was named as skill-biased technological change (SBTC). SBTC includes an increase in the proportion of highly skilled individuals and a widening wage gap between the high- and the low-skilled employees. This trend was especially prominent during the 70s-00s in developed countries (Card and DiNardo, 2002; Goldin and Katz, 2008).

An often-cited factor that gave rise to the SBTC is the inherit skill-bias of technological change (Krusell *et al*., 2000; Autor *et al*. 2003; Vivareli, 2012; Aghion *et al*., 2018). The inherit bias is due to the fact that new technologies often require specific skill-sets that lower skilled individuals often lack (Goldin and Katz, 2008). However, it could be argued that similar technological shifts happened throughout history (e.g. the industrial revolutions), which did not produce the SBTC. Academics rebut this claim by adding that technological improvements during the 70s-00s were skill-biased due to the introduction of computers to the workspace (Card and DiNardo 2002; Goldin and Katz, 2008). Computers gave rise to wage and employment shifts primarily through two mechanisms. First of all, given that the elasticity of substitution between capital and unskilled labour is higher than between capital and skilled labour (Krusell *et al*., 2000, pp. 1030), many lower-skilled jobs were and continue to be replaced by machines (Hémous and Olsen, 2014). And second, unlike many other technologies, computers 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 and Katz, 2008).

However, although many agree that technological shifts are biased, some criticise this view as telling only part of the story. Card and DiNardo (2002) found that even though the rise of computer usage at the workplace coincided with rising wage inequality in the US, during the 90s, the change in wage inequality slowed down while at the same time the computer usage was still rapidly growing. Hence, they stipulated that another driver of SBC in US during the 80s was the fall of the real value of minimum wage, which widened the gap. Goldin and Katz (2008) adds that just as important as technological change is the supply of highly-skilled individuals. They tested this assumption on the US case to explain why, during the 50s-70s, there was very little to no SBTC specifically linked to the rising wage premium for skilled individuals, while during the 80s-00s STBC became strongly prevalent. They found that even though during both periods there were quite a lot of technological changes, only during the second period was there a decrease of college graduates that normally explains the rising premiums (Goldin and Katz, 2008, pp. 96). Card and DiNardo (2002, p. 774) also highlighted the decline in the number of college graduates as a possible factor behind this change. Other scholars (e.g. Aghion, Caroli, and García Peñalosa (1999); Dunne *et al*. (2000)) claimed that technology is not inherently biased, but the flatter organisational structure it created is. It is biased towards high-skilled individuals because it entails more autonomy with vertical communication lines being replaced by horizontal ones, higher homogeneity of skills in firms, and such (Sanders and Weel, 2000). This also leads to more skill-homogeneous firms than before, where the bulk of the employees were either high or low-skilled (Dunne *et al*., 2000).

In addition, Vivarelli (2012) also stipulates that the main factor behind skill-biased changes for developing countries might be trade liberalisation. According to him, trade liberalisation creates opportunities for developing countries to learn from the developed ones. This, in turn, leads

to an increase in the demand for skilled-labour in order to use and/or implement the new know-how and technologies (Meschi and Vivarelli, 2007). The type of trade that creates an inflow of technologies and know-how was names skill-enhancing trade (Robbins and Gindling, 1999).

Though not as widely researched as SBTC, there is also some empirical support for skill-enhancing trade view. Conte and Vivarelli (2010) found that trade openness and technological transfer were strong determinants to increased demand for skilled labour in 28 developing countries across the world (including some European countries such as Cyprus, Greece, Malta) during the 90s. Feenstra and Hanson (1997) and Fajnzylber and Fernand (2009) found similar evidence for Mexico and Brazil respectively during the similar time period.

Unskill biased change

Acemoglu (2002), though strongly agreeing with the SBTC hypothesis, also asks why in the early nineteenth century technological change was predominantly unskilled-biased? He found that due to a large supply of unskilled labour during this period, it was more profitable to introduce technologies that required a low amount of skills. More specifically, during the early nineteenth century large cities in England received a great influx of migrants from rural areas, allowing for a wide utilisation of low-skill technologies (Acemoglu 2002, p. 9). On the contrary, during the second part of the nineteenth century, it became more profitable to use technologies favouring the highly skilled due to an expanding number of college graduates (Acemoglu, 1998, 2002). Hence, it is possible to maintain that the effect of technologies on the labour market is heavily rooted in the supply of low and high-skilled labour.

Similarly, Vivarelli (2012) stipulates that trade liberalisation might create unskilled-biased change. The reasoning behind such claim holds that even with new technologies and know-how

brought through trade liberalisation, developing countries still do not possess a large pool of highly skilled individuals. As a result, they face difficulties competing with countries that are already endowed with more highly skilled labour. Hence, following the Stolper-Samuelson theorem (1941), which states that "trade openness will benefit a country's relatively abundant factor" (Meschi and Vivarelli, 2007, pp. 2), developing countries should start specialising in unskilled labour-intensive goods to thrive in the open market. This logic is also closely linked to Acemoglu's (2002) view, whereby the supply of labour affects the trajectory of technological change, and vice versa. However, while this line of reasoning is sound, there is not a lot of empirical support for the negative impact of trade liberalisation on skills. Vivarelli (2012), who performed an extensive overview of many papers in this field, only found that Menezes-Filho (2006) had noted this kind of a relationship in Brazil in the years of 1990-1998.

Nevertheless, as Lithuania, the case study of this research, exhibited many trends that might have created unskilled-biased change, this hypothesis will also be evaluated. More specifically, during the transition Lithuania was heavily lagging behind and did not received a lot of FDI (see next section for details), which implies that it did not receive a lot of know-how and technology from abroad. Also, after the collapse of the Soviet Union Lithuania inherited a lot of archaic technologies and a large pool of unskilled labour. Hence, it is likely that during the transition a lot of companies leaned towards the large unskilled pool for survival.

Production cycle approach

Finally, there is a third view by Eriksson *et al*. (2019) which holds that technological advancements first lead to an increase in the demand for skilled labour, but this demand dwindles as the technology becomes standardised. More specifically, according to Vernon (1966), highly skilled labour is necessary to develop a product from the beginning as there is quite a lot of uncertainty.

However, as product lifecycle slowly comes to an end, the complexity and uncertainty is replaced with standardised procedures that can be performed by lower skilled labour.

Recent academic literature provides some empirical support for this idea. Eriksson *et al*. (2019) investigated the reasons why Japan failed to surpass the USA as a manufacturing powerhouse in the years of 1975-1985, as many thought it would, and why China succeeded several decades later. According to these scholars, Japan's failure is explained by the fact that at the time both Japan and USA were relying on high-skilled labour to create products that were, in that period, in their early stages of development (e.g. computers, video and audio equipment, circuit boards). This meant that Japan did not have a strong competitive advantage over USA. However, China succeeded where Japan failed because even though the products did not change much, they had already moved to the tail end of their lifecycle. This allowed China to employ cheap lower skilled labour, which was available in multitudes, to take away production jobs from USA and become the worlds' leading manufacturing hub.

Applying this logic to Lithuania, it can be stipulated that during the transition from planned to market economy some new products were introduced through trade liberalisation and influx of know-how. In addition, companies had to adapt to new markets, given that after the collapse of the Soviet Union, the majority of their cliental disappeared (i.e. they lost the planned nature of their production). It is likely that many companies started to produce goods that were completely new to them because of this, and, consequently had to employ more high-skilled individuals. However, as the transition continued, the processes became standardised and the necessity for high-skilled individuals was replaced by lower skilled ones. Support is added to this possibility as some researchers (e.g. Rutkowski (2001)) found that many changes happening in CEE countries during this time mirror those in developed countries, and are only accelerated in nature.

In the article we evaluate all three possibilities in the Lithuania's manufacturing subsectors case during the transition. To do this, we propose to test three hypotheses: (i) technological advancement and trade liberalisation led to an increase in the demand for highly skilled labour; (ii) technological advancement and trade liberalisation led to an increase in the demand for low-skilled labour; (iii) technological advancement and trade liberalisation first led to an increase in the demand for high-skilled labour while later this demand shifted to lower skilled individuals. The next section provides a comprehensive reasoning why Lithuania was selected for this analysis and discusses the exact methodology that is used to test these hypotheses.

Methodology

Case selection

The research focuses on the case of Lithuania. It was selected, because it provides an interesting case of a country that underwent a rapid transition from planned to market economy. It also differs from many other CEE countries that went through a similar transition (e.g. Czech Republic, Hungary, Slovakia) given that it attracted much less FDI (see Table 1 below). Because of this, many Lithuania companies did not receive know-how and new technologies from the developed world and were forced to rely on their own capabilities during the transition. This is in contract to many other CEE countries that attracted more FDI and managed to build on their existing assets by, for example, building a strong automobile industry (Haiss, Mahlberg, and Molling 2009).

Furthermore, Lithuania provides quite a unique, and rather under analysed, example that could serve as a stepping stone for other countries that underwent a rapid transition from planned to market economy. For example, the case of Lithuania could be compared to cases of Latvia and Estonia, both of which attracted more FDI (see Table 1), to estimate the effects of FDI on changes in the labour force. The case can also be used as a stepping stone for other research to evaluate

SBC in other transition countries that did not receive a lot of FDI, such as Bulgaria, Makedonia, Romania.

Finally, the transformation in Lithuania, just like in many other CEE countries, was very similar to many developed countries (Rutkowski, 2001). The only difference is that in CEE these transformations were accelerated in nature. Research on Lithuania during the transition period may shed some light on many different large-scale transformations in the developed world, and especially regarding questions linking technological change and/or trade liberalisation to the labour market.

Table 1. Cumulative FDI inflows in 1989-2003 per capita (USD)

CZ	HU	EE	SK	HR	SI	LV	PL	LT	BG	MK	RO	AL
3710	3364	2402	1894	1857	1647	1454	1355	1067	795	501	486	352

Source: European Bank for Reconstruction and Development annual report (2004)

The research focuses on the period between 1995 and 2008. This period was selected based on the availability of data. In some cases, we include older data to add to the discussion, but it is not used to arrive at any conclusions due to uncertainty of its representativeness. This time period does not cover the earliest stages of transition. Hence, we will not be able to robustly test the third hypothesis linking first an increase in demand for skilled labour, then followed by a drop. However, the data still allows us to shed some light on the possibility of the third hypothesis being true. Finally, the research also focuses on manufacturing subsectors, because these sectors underwent changes of the largest scale during the transition.

Estimating (un)skill-biased changed

To estimate the extent of skill-biased change, generally researchers use one of two proxies as dependent variables: wage ratio of high/low-skilled individuals (e.g. see Nickell and Bell (1996), Greenan *et al*. (1998), Esposito and Stehre (2008)) or the ratio of high/low-skilled employees (e.g. Katz and Murphy (1992), Beaudry and Green (1998), Berman *et al*. (1998)). In the paper we focus on the latter as there is a lack of data on the wages of high and low-skilled individuals in Lithuania during the transition period. Furthermore, given the relatively large inflation, there is a risk that the wage approach could produce biased results.

The skill level of individuals used to estimate the ratio is defined according to their occupations. Individuals from 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.

Occupation is used as a proxy for skill rather than more frequently used education level. The latter is problematic, because it assumes that skills are static (Hanushek & Kimko, 2000), does not take in to account which skills are used on the job (Autor and Handel 2013), apart many other issues (Martinaitis, 2014). We also recognise that the approach we use does not allow us to accurately estimate the extent of SBC in Lithuania. However, this paper only aims to determine whether there was (un)skill-biased change rather than examine its extent, and therefore this issue is omitted from the discussion. Data on the number of high and low-skilled individuals was collected from the Labour Force Survey 1998-2008 micro data.

Estimating trade liberalisation and technological changes

As we have previously discussed, trade liberalisation might impact the ratio of high- to low-skilled individuals. However, there is no conventional way of estimating it. Hence, in this research we do not examine trade liberalisation *per se*, but its positive effects. More specifically, we explore how a change in the quality of exports impacted the ratio of high- to low-skilled individuals in the manufacturing subsectors during the transition period.

We define change in the quality of exports following Dulleck *et al*. (2004), who stipulated that an increase in quality of goods for CEE countries can be approximated by an increase in their unit price (i.e. price per kilogram) of their exports to EU-15 countries. Trade with EU-15 is analysed specifically because of high-quality standards – a unit price increase of export to the area provides a better proxy of production quality than trade to any country in general (Dulleck *et al*., 2004). Although it could also be argued that the unit price may also stem from companies exercising their power of monopoly. However, during this time Lithuanian companies were lagging behind Western European enterprises. Hence this possibility may be omitted. For the sake of simplicity, terms "export upgrading" and "change in the quality of exports" are used interchangeably.

The data on Lithuanian manufacturing subsectors' exports to the EU-15 was gathered from Comtrade. It must be noted that Comtrade had some missing information about exports in 2005 and 2006. Hence, the missing values were inferred using Multiple Imputation by Chained Equations, which imputes missing data by observing how a collection of variables without missing observations correlate with variables that have missing parts (Azur *et al*., 2012).

The second factor that may influence the ratio of high to low-skilled individuals is technological change. The technological change in Lithuania is estimated through two variables: gross fixed capital formation (GFCF) and gross investment in machinery and equipment. The data for GFCF was collected from OECD structural analysis database (STAN). The data for investments in machinery was collected from Eurostat structural business statistics.

Empirical analysis

Skill-biased change is predominantly estimated through regression analysis. The paper also includes a contextual overview of Lithuania and how it evolved during the transition period to add context and provide initial insights whether there was skill- or unskilled-biased change. The following form of the regression equation is used for the analysis:

$$\frac{H_{it}}{L_{it}} = \Delta ID_{it} + C_{it},$$

where H_i and L_i are number of high and low-skilled individuals' in a subsector i at year t, ΔID_{it} is the change of one of the independent variables, either export upgrading or technological changes, while C is a list of controls, including the GDP level of a subsector, the number of employees, average age of employees of the subsector, etc. A concise summary of all the variables, their roles, as well as sources is provided in the table below.

Table 2. Data and its sources

Roles	**Variables**	**Source**
Dependent variable	Ratio of high- to low-skilled individuals	Labour Force Survey micro data (1998-2008)
Independent variables	Export upgrading (a.k.a. ΔExport price)	Comtrade (1995-2008)

	ΔCapital formation	OECD structural analysis data (1995-2008)
	ΔInvestments in machinery	Eurostat structural business statistics (1995-2008)
Controls	ΔNumber of employees	wiiw Industrial Database 1995-2008
	ΔGDP	
	Average age	
	Joined the EU (2004)	-
	Year	

It is important to note that in the regression equation instead of raw data, we use the percentage difference of the independent variables, GDP per sector, and the number of employees. The variables are not stationary in raw form and could make the regression spurious (i.e. provide misleading information about the relationship between variables). The stationarity of the variables was checked using the Levin, Lin, and Chu (2002) unit root test for panel regressions.

The regression equation is evaluated using the random effects regression model. This model is the best for capturing variation that was noticed between economic sectors (see next section). In addition, the regression equation is built using the 1998-2008 data due to a lack of data for the early stages of the transition period (e.g. Labour Force Survey data that is used to estimate the ratio of high to low-skilled individuals is only available from 1998). The overview of Lithuania includes earlier data. Finally, some manufacturing subsectors are excluded from regression analysis due to a small sample size as well as to having large outliers that add bias to the model. The list of excluded subsectors and the reasoning is included in the notes for each regression.

As the number of observations analysed is relatively small, and there is doubt regarding the quality of data collection during the transition period, the results of the regression are validated

through sensitivity analysis. This includes, first of all, supplementing the random effects model with results from fixed effects and pooled OLS models. Second, evaluating whether results change if only high technologically intensive or low technologically intensive subsectors are analysed[4]. Finally, evaluating whether results change if only data for years 1998-2004 is used, given that it is a period before Lithuania joined the EU.

Lithuania during the transition period and skill-based technological change

Descriptive analysis

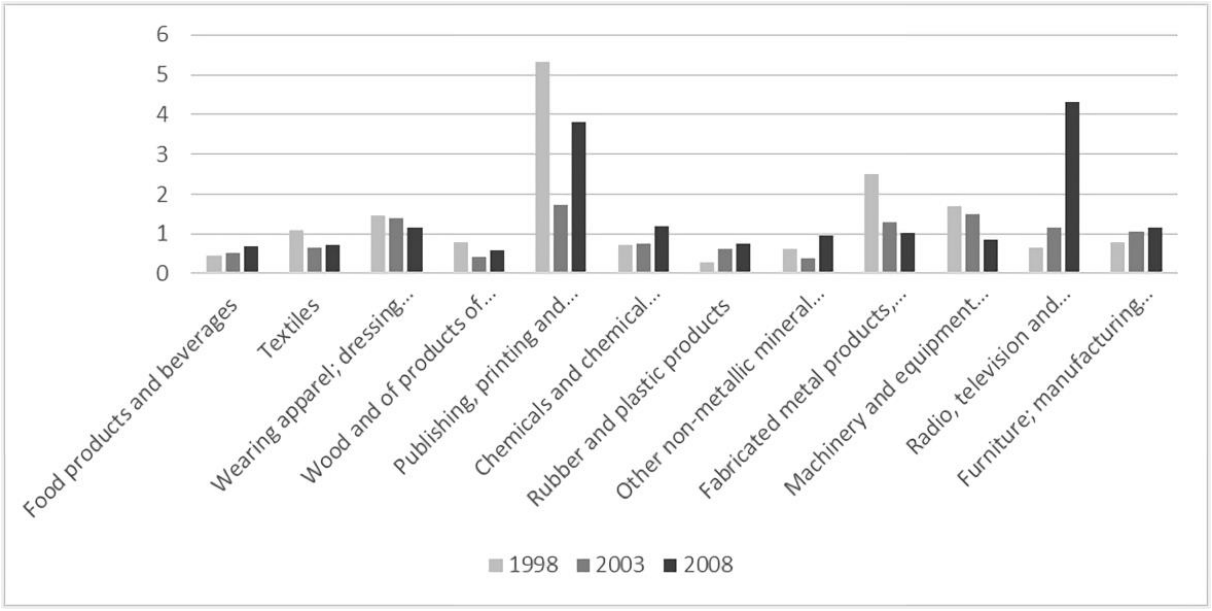
During the transition period Lithuania went through changes typical to CEE countries. From 1989 to 2001, according to the Lithuanian census data, the ratio of people employed with higher or special secondary education increased by 8.16%. In addition, from 1995 to 2004 the average number of employees was steadily dropping at around 2.4% annually, while the average wage of the subsectors was growing at a round 11.7% (see Table 6 in the Appendix A). However, as inflation in Lithuania during the early years of the transition period was quite high, a better indicator of wage change are the years between 1998 and 2004, during which wages were growing by an average of 4.5%. Similarly, between 1998 and 2008, the average wage growth was 9.2%.

We did not observe a clear trend when evaluating how the ratio of high to low-skilled individuals changed in each manufacturing subsector between 1998 and 2008 (see Figure 1). On the one hand, manufacturing of textile, wearing apparel, publishing, fabricated metal, and machinery and equipment subsectors experienced a downward trend (see Figure 1 below). On the other hand, for subsectors such as manufacturing of food production, chemicals, rubber, other non-metallic mineral production, radio and television, and furniture the trend was upward. To some

[4] For this task we used Eurostat's (2016) classification of manufacturing subsectors according to their technological intensity.

extent, these divergences can be explained by differences in technological intensity – higher-tech had a growing trend, while lower tech sectors witnessed a decline – but this is not sufficient to fully account for these trends.

Figure 1. Ratio of high to low-skilled individuals (according to ISCO-88) in different sectors for different years



Note: Due to missing data the regression excluded manufacturing of (i) tobacco products, (ii) luggage, handbags, etc., (iii) pulp, paper, and paper products, (iv) office machinery, (v) coke, refined petroleum, nuclear flue, and (vi) motor vehicles, trailers, and semi-trailers.

Looking at the changing share of low- and high-skilled employees in the manufacturing sectors further reinforces this trend. If we consider that ISCO-88 level one occupations are listed in a descending order in terms of skill level (i.e. managers (1) are the most skilled, while elementary occupations (9) are the least), then we do not observe any clear trends in the manufacturing sector

(see Figure 2). Similarly, no trends are observed if we rank occupations according to the average wage of individuals[5], assuming higher wage indicates higher skill level (see Figure 3).

Figure 2. Change in the share of employees in ISCO-88 level one occupations 1998-2008

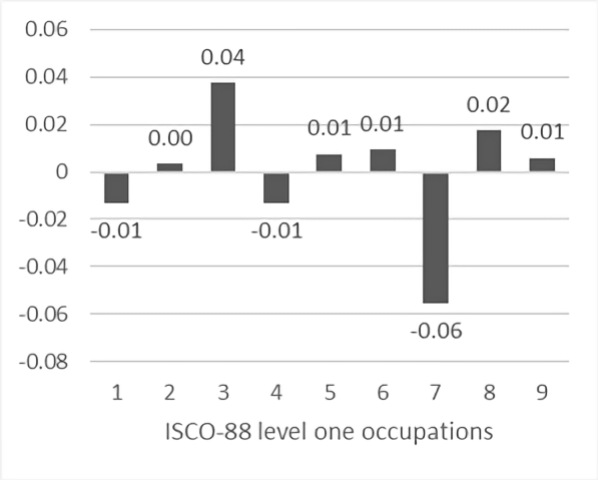
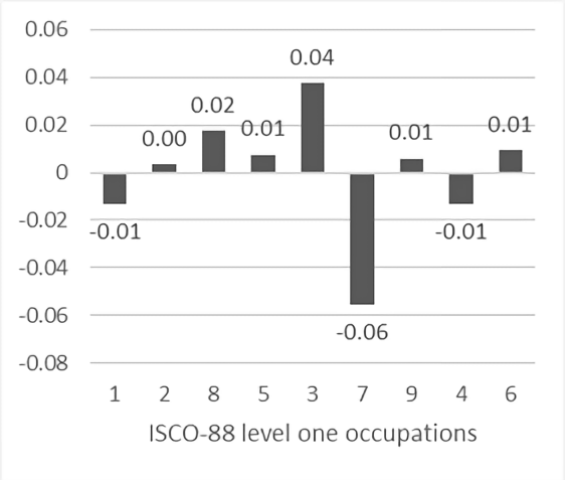


Figure 3. Change in the share of employees in ISCO-88 level one occupations ranked by the average wage 1998-2008



Source: Own compilations based on the Lithuania Labour Force Survey 1998-2008 microdata

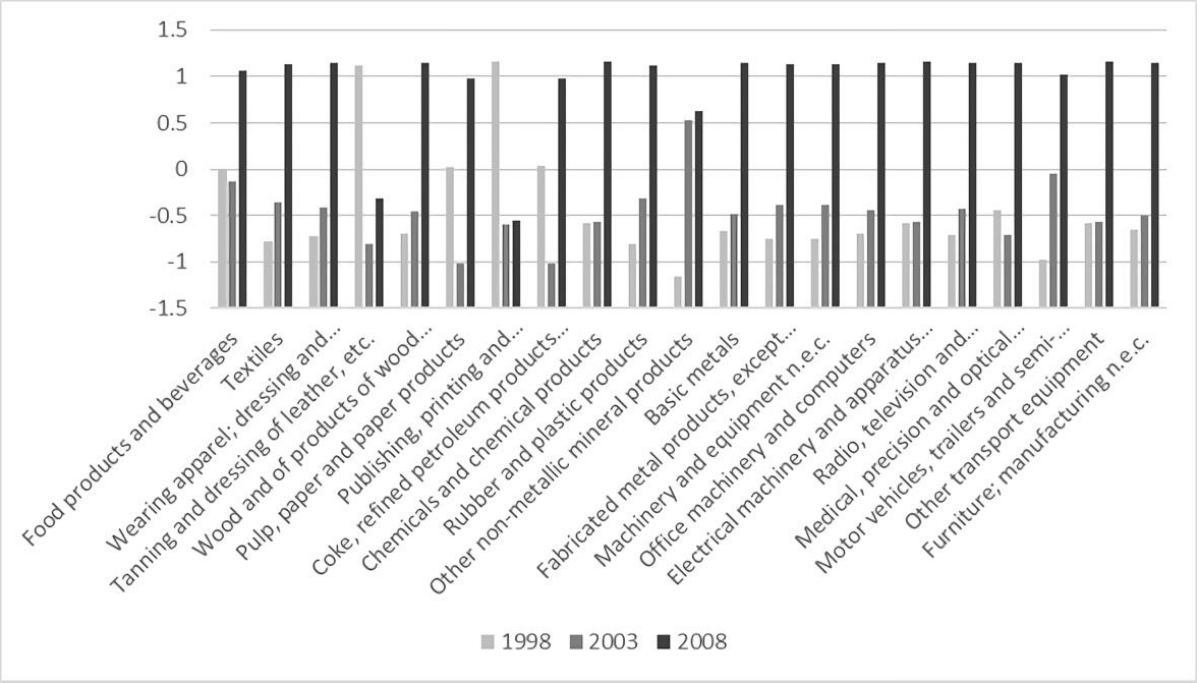
We observe several clear trends in evaluating the independent variables. Looking at export upgrading, we see an average annual growth rate of 15.3% from 1998[6] to 2008. The three subsectors with the largest average growth rate were manufacturing of (i) office machinery and computers (48.42%), (ii) other non-metallic mineral products (47.19%), and (iii) basic metals (32.32%). Although other subsectors also observed a rapid growth during this period (see Figure

[5] Ranking was performed using information to which wage group individuals working in different occupations belong. Wage groups rather than raw data was used due to availability of data.
[6] 1998 was selected as the starting point for export upgrading because there are wild variations before this period as shown in Table 6 in the appendix A.

4). The only two subsectors that declined were manufacturing of (i) wearing apparel and (ii) publishing, both of which saw a sharp decline and later – a rise.

Similar growth rate is observed in industrial manufacturing, which saw an average annual growth of 13.1% between 1995 and 2008 (see Table 6 in the Appendix A). Manufacturing subsectors with fastest average growth were manufacturing of (i) office machinery and computers (50.1%), (ii) motor vehicles, trailers and semi-trailers (41.01%), (iii) rubber and plastic products (21.34%), (iv) basic metals (17.93%), and (v) furniture (17.29%).

Figure 4. Normalised export price in different sectors for different years

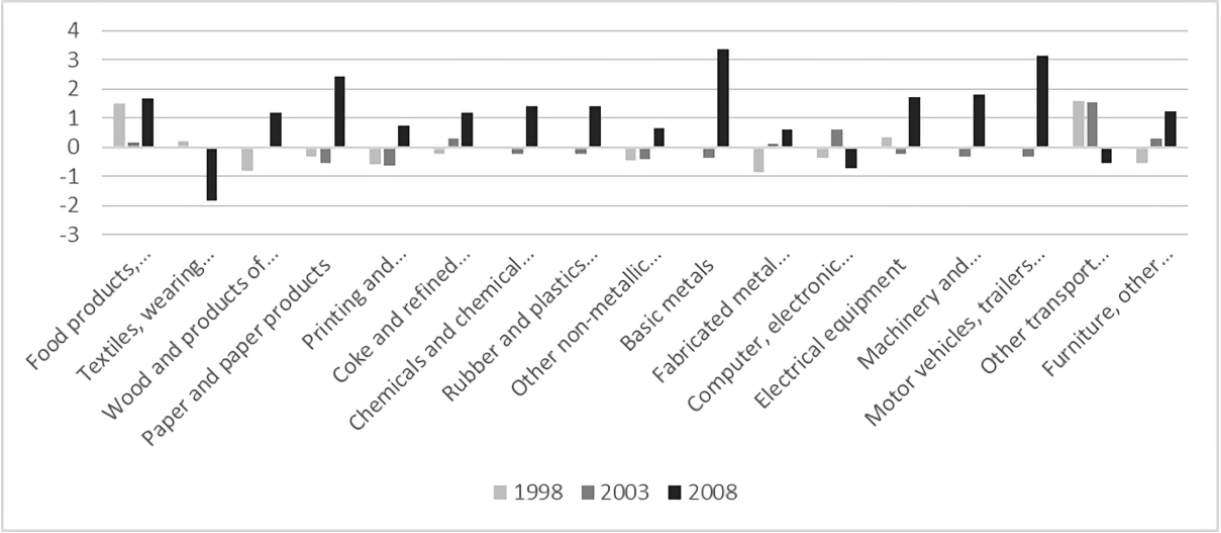


Note: Data was normalised for each sector individual to improve comparability

Similarly to export upgrading and industrial production, in majority of cases gross fixed capital formation was growing throughout the years in question (see Figure 5). The only two

notable exceptions are manufacturing of (i) textiles and wearing apparel, (ii) computer electronics, and (iii) other transport sectors, both of which saw a decline.

Figure 5. Normalised gross fixed capital formation in different sectors for different years



Note: Data was normalised for each sector individual to improve comparability

These results provide some support for the first skill-biased technological change hypothesis, because they demonstrate a large decline in the number of employees as the average education level, export upgrading, and industrial production rapidly grew. However, we did not observe similar trends in the ratio of high to low-skilled individuals, hence it is unclear which of the hypotheses is more plausible and a more robust analysis is necessary.

Regression analysis

Results indicate that there is a negative relationship between export upgrading and the ratio of high to low-skilled individuals. According to these results (see Table 3), a 100% increase in the export price leads to around 0.14 point decrease in the ratio of high to low-skilled individuals. These results are consistent when using data only for years 1998-2004, although in that case, the coefficient decreases to -0.0048 (i.e. 100% increase in export price leads to 0.48 decrease in ratio)

and remains statistically significant, implying a stronger negative effect before Lithuania's accession to the EU. The relationship is also consistent when using different panel regression models (see Appendix B). We did not find statistically significant results when separately looking at low and high technologically intensive manufacturing subsectors, but this could be due to the small sample sizes.

Results indicate that it is likely that there was an opposite to skill-enhancing trade in Lithuania's manufacturing subsectors during the transition. This provides support for the second hypothesis. However, results need to be treated with caution, because almost no variables except for export upgrading and the number of employees, are statistically significant, while the sample size is relatively small (N=119).

Table 3. Regression results of the effect of export upgrading on the ratio of high to low-skill individuals in manufacturing subsectors

	Coefficients	Standard error	z	p-value
Constant	-36.7254	41.5308	-0.8843	0.3765
Export upgrading	-0.00139	0.00045	-3.108	0.0019***
ΔNumber of employees	0.00445	0.00250	1.786	0.0742*
ΔGDP	0.00073	0.00182	0.3992	0.6898
Average age	0.02169	0.02185	0.9926	0.3209
Joined the EU (2004)	-0.14800	0.09413	-1.572	0.1159
Year	0.01835	0.02093	0.8770	0.3805

N = 119

*** indicates a statistical significance of 0.01; ** indicates a statistical significance of 0.05; * indicates a statistical significance of 0.10.

Note 1: No collinearity issues were present in the model

Note 2: Robust HAC standard error was applied to control for heteroskedasticity and autocorrelation, which was presented in the data

Note 3: Due to a small number of employees surveyed some sectors were excluded from the analysis, including manufacturing of (i) tobacco products, (ii) textile, (iii) tanning and dressing of leather, (iv) manufacture of pulp, paper, and paper products, (v) Coke, refined petroleum products, and nuclear fuel, (v) basic metals, (vi) office machinery and computers, (vii) electrical machinery and apparatus n.e.c., (viii) motor vehicles, trailers and semi-trailers, (ix) transport equipment, and (x) medical, precision and optical instruments

Note 4: The publishing subsector was removed from the analysis as it underwent a huge transformation from 1998 to 1999 in terms of export upgrading (see Table 6 in the Appendix)

Regarding the impact of technological changes, we did not find a statistically significant relationship between investments into machinery and the ratio of high to low skilled individuals. However, we did find that gross fixed capital formation has a statistically significant negative effect on the ratio (see Table 4). More specifically, a 100% increase in the gross fixed capital formation leads to 0.06 point decrease in the ratio of high to low skilled individuals. However, these results are not as consistent as export upgrading, because in using pooled OLS, the relationship was not-statistically significant (see Appendix B). In addition, the relationship lost its significance in cases when data only for the years of 1998-2004 was used or only low- or high-tech sectors were analysed. Hence, even though these results also provide support for the second hypothesis, the evidence is much weaker here due to inconsistencies in the sensitivity analysis.

Table 4. Regression results of the effect of gross fixed capital formation on the ratio of high to low skill individuals in the manufacturing subsectors

	Coefficients	Standard error	z	p-value

Constant	-47.2883	34.7946	-1.359	0.1741
ΔCapital formation	-0.00067	0.00020	-3.341	0.0008***
ΔNumber of employees	0.00195	0.00268	0.726	0.4681
ΔGDP	0.00023	0.00213	0.106	0.9159
Average age	0.00472	0.02371	0.199	0.8420
Joined the EU (2004)	-0.15569	0.10224	-1.523	0.1278
Year	0.02397	0.01749	1.370	0.1705

N = 98

*** indicates a statistical significance of 0.01

Note 1: No collinearity issues were present in the model

Note 2: Robust HAC standard error was applied to control for heteroskedasticity and autocorrelation, which was presented in the data

Note 3: Due to a small number of employees surveyed some sectors were excluded from the analysis, including manufacturing of (i) tobacco products, (ii) textile, (iii) tanning and dressing of leather, (iv) manufacture of pulp, paper, and paper products, (v) Coke, refined petroleum products, and nuclear fuel, (v) basic metals, (vi) office machinery and computers, (vii) electrical machinery and apparatus n.e.c., (viii) motor vehicles, trailers and semi-trailers, (ix) transport equipment, and (x) medical, precision and optical instruments

Note 4: The publishing subsector was removed from the analysis as it underwent a huge transformation from 1998 to 1999 in terms of export upgrading (see Appendix A)

Note 5: Some of the sectors were grouped together (e.g. textiles, wearing apparel, and leather and related products) as data used to estimate gross fixed capital formation only provides information on these groups and not on separate subsectors.

Finally, when export upgrading and capital formation are included in the regression equation, both variables are statistically significant, without drastically changing the direction of their relationship nor their coefficient. In addition, control variables are more statistically significant. These results

further support the second hypothesis, which implies that trade liberalisation and technological advancement had a negative impact on the ratio of high to low skilled individuals.

Table 5. Regression results of the effect of gross fixed capital formation and export upgrading on the ratio of high to low skill individuals in the manufacturing subsectors

	Coefficients	Standard error	z	p-value
Constant	-60.2366	32.9204	-1.830	0.0673*
ΔCapital formation	-0.00066	0.00018	-3.617	0.003***
Export upgrading	-0.00155	0.00047	-3.283	0.001***
ΔNumber of employees	0.00119	0.00240	0.4952	0.6204
ΔGDP	0.00095	0.00207	0.4564	0.6481
Average age	0.01260	0.02307	1.832	0.0670*
Joined the EU (2004)	-0.18683	0.08871	-2.106	0.0352**
Year	0.03029	0.01654	1.832	0.0670*

N = 98

*** indicates a statistical significance of 0.01

Note 1: No collinearity issues were present in the model

Note 2: Robust HAC standard error was applied to control for heteroskedasticity and autocorrelation, which was presented in the data

Note 3: Due to a small number of employees surveyed some sectors were excluded from the analysis, including manufacturing of (i) tobacco products, (ii) textile, (iii) tanning and dressing of leather, (iv) manufacture of pulp, paper, and paper products, (v) Coke, refined petroleum products, and nuclear fuel, (v) basic metals, (vi) office machinery and computers, (vii) electrical machinery and apparatus n.e.c., (viii) motor vehicles, trailers and semi-trailers, (ix) transport equipment, and (x) medical, precision and optical instruments

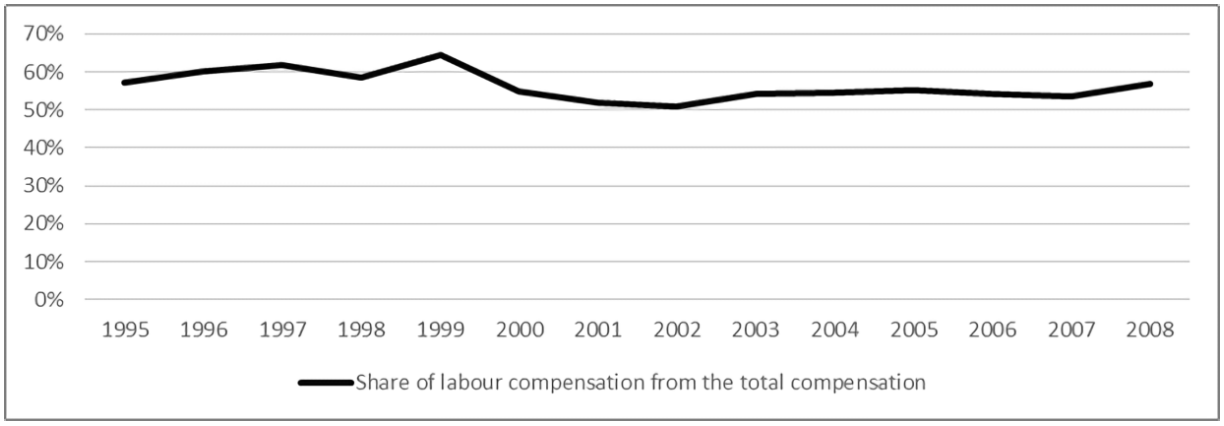
Note 4: The publishing subsector was removed from the analysis as it underwent a huge transformation from 1998 to 1999 in terms of export upgrading (see Appendix A)

Note 5: Some of the sectors were grouped together (e.g. textiles, wearing apparel, and leather and related products) as data used to estimate gross fixed capital formation only provides information on these groups and not on separate subsectors.

It must be noted that even though results provide a strong support for the second hypothesis, they are insufficient to rule out the third, which stipulates that trade liberalisation and technological advancement first had a positive effect on the ratio, but then contributed to its decline. Due to lack of data on the early stages of the transition period, we cannot robustly check this hypothesis. However, in assuming that the third hypothesis is correct, we should observe a relatively large increase in compensation for labour when compared to capital compensation during the early years of the transition period and a decline during the later years of the transition period. That is because, if the third hypothesis holds, during the early years' companies should have relied on highly skilled labour while later it would have been replaced, to some extent, by capital and lower skilled labour.

However, when looking at the share of labour compensation from total compensation (i.e. labour plus capital compensation), we did not observe any clear trends for each subsector between 1995 and 2008. Similarly, there were no visible trends when the sectors were grouped (see Figure 6). Nonetheless, it must be noted that only the data from 1995 was available. A flat trend implies that the likelihood for observing a similar trend during the early stages of transition is high.

Figure 6. Share of labour compensation from the total compensation in all subsectors for years 1995-2008



Source: own compilations based on the World Input-Output Databases Socio Economics Accounts

Discussion and conclusion

The article finds that both trade liberalisation and technological advancement led to a decline in the ratio of high to low individuals in Lithuania's manufacturing subsectors during 1998-2008. Even though such results go against a large body of academic literature, which finds a positive relationship between the two factors on skill upgrading, they are not without merit. According to Accemoglu (2002), a large supply of low-skilled workers leads to technological change that is unskilled-biased, because relying on the abundant factor of production is more profitable. Similarly, according to Vivarelli (2012) and the Stolper-Samuelson theorem, countries should exercise their abundant factors of production to compete in an open market. In the case of Lithuania, as it was mentioned prior, relatively cheap and unskilled labour was the abundant factor.

However, although this explains the negative trend in Lithuania, it goes against most academic literature on other CEE countries (e.g. Czech Republic, Hungary, and Poland), which found a positive relationship between technology and trade liberalisation with skills. We stipulate that the difference is due to the fact that many other CEE countries attracted significantly more

FDI than Lithuania during the transition period. As a result, Lithuania could not rely on the know-how that often accompanies FDI and which would have probably utilised high-skilled individuals. This led Lithuanian companies to rely on their own knowledge and experience as well as the archaic machinery from the Soviet period. Combined with an abundant number of low-skilled workers during the early stages of the transition period, this likely led to technological change that can utilise the abundant factors (i.e. low-skilled labour).

Hence, the article introduces some doubt on the prevailing notion that technological advancement and trade liberalisation inevitably lead to skill upgrading. The article also introduces ample open questions for further research. This includes questioning whether other countries, undergoing a large-scale transition and also relying predominantly on their own capabilities, exhibit similar trends. Are these results consistent with different proxies of technological advancement and/or trade liberalisation? How would the results change if a wage dimension was introduced to the analysis? Answers to these questions would expand the discussion on skill-biased change even further, while the theory, methodology, and empirical results discussed in this article may serve as a stepping stone for further research.

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Appendix

Appendix A

Table 6. Average change in employment, wage, industrial production, and quality in Lithuania's manufacturing subsectors

Manufacturing subsectors		1995-1996	1996-1997	1997-1998	1998-1999	1999-2000	2000-2001	2001-2002	2002-2003	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008
Food products and beverages	Change in the monthly wages (raw)	32.3%	18.1%	8.9%	0.5%	-4.4%	1.7%	2.3%	3.7%	2.4%	8.7%	16.5%	24.2%	17.5%
	Change in number of employees	-9.1%	-3.4%	2.5%	-0.9%	-3.0%	-8.1%	-2.0%	-4.0%	-1.8%	5.6%	-3.0%	-1.4%	-1.6%
	Change in industrial production (GDP)	-0.7%	2.2%	4.8%	-9.7%	7.2%	2.1%	-1.6%	10.1%	3.9%	8.1%	11.6%	14.6%	-3.4%
	Export upgrading	-7.6%	8.2%	-31.6%	-17.8%	20.0%	-2.7%	22.3%	31.7%	19.1%	-19.5%*	27.7%*	36.0%*	-8.4%
Textiles	Change in the monthly wages (raw)	35.0%	24.4%	13.0%	4.7%	3.3%	3.9%	-2.0%	1.0%	7.5%	2.8%	15.2%	20.2%	13.3%
	Change in number of employees	-12.6%	-9.5%	-6.1%	-12.2%	-9.4%	-3.7%	-7.4%	-2.2%	-6.0%	-5.4%	-2.6%	-11.9%	-27.6%
	Change in industrial production (GDP)	2.1%	-2.0%	2.0%	-7.3%	8.7%	13.7%	1.5%	-9.5%	7.5%	-3.0%	10.5%	3.9%	-17.0%
	Export upgrading	26.9%	-7.4%	21.5%	16.6%	-19.7%	1.7%	5.9%	16.5%	12.1%	-2.2%*	13.4%*	12.3%*	8.4%
Wearing apparel; dressing and dyeing of fur	Change in the monthly wages (raw)	55.7%	21.7%	11.8%	0.6%	-1.1%	-2.2%	5.4%	0.8%	5.0%	9.1%	14.4%	19.2%	15.0%
	Change in number of employees	2.8%	10.8%	8.0%	0.5%	7.9%	4.0%	8.6%	-2.0%	-8.1%	-9.3%	-8.0%	-11.9%	2.8%
	Change in industrial production (GDP)	23.1%	9.9%	17.6%	14.6%	6.0%	8.0%	-1.8%	11.7%	-9.8%	-7.4%	1.6%	-5.5%	-20.1%
	Export upgrading	-31.7%	-90.7%	-6.6%	5.7%	-7.8%	-4.1%	9.1%	18.1%	12.4%	-16.8%*	8.9%*	52.5%*	20.6%
Tanning and dressing of leather; luggage, handbags, saddlery, harness and footwear	Change in the monthly wages (raw)	24.9%	29.8%	6.5%	2.0%	2.5%	5.7%	-1.5%	3.4%	8.6%	4.0%	9.9%	19.6%	14.8%
	Change in number of employees	-15.6%	-15.0%	-2.7%	-20.8%	-30.4%	-16.2%	2.9%	-13.5%	-15.0%	-11.7%	-14.2%	-6.2%	-9.8%
	Change in industrial production (GDP)	-4.4%	5.4%	-10.6%	-3.1%	22.0%	-16.4%	-14.0%	-17.9%	-41.4%	8.5%	7.5%	5.1%	-20.2%
	Export upgrading	32.8%	-1.1%	12.7%	15.5%	-13.7%	14.3%	-11.1%	-59.9%	148.7%	-19.4%*	-2.5%*	4.0%*	-32.6%
Wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	Change in the monthly wages (raw)	21.2%	39.3%	13.8%	10.6%	-3.9%	-1.2%	4.6%	3.8%	7.6%	16.8%	19.1%	28.3%	18.6%
	Change in number of employees	15.9%	1.7%	-2.9%	-10.3%	5.2%	12.0%	14.0%	7.1%	-5.8%	2.6%	2.3%	-0.1%	-16.5%
	Change in industrial production (GDP)	13.1%	13.5%	15.3%	18.0%	33.2%	14.0%	23.6%	23.9%	7.0%	10.3%	6.5%	7.6%	-12.0%
	Export upgrading	-1.2%	-9.1%	11.1%	7.0%	-11.1%	-3.0%	1.7%	26.3%	29.0%	-15.4%*	13.9%*	55.2%*	4.8%
Pulp, paper and paper products	Change in the monthly wages (raw)	20.1%	19.8%	10.3%	0.0%	3.0%	4.0%	5.3%	5.8%	8.5%	0.9%	16.5%	20.3%	17.5%
	Change in number of employees	-9.7%	-7.5%	-7.2%	-12.0%	10.8%	-5.4%	-41.6%	-15.0%	2.2%	1.7%	8.7%	10.2%	-3.8%

	Change in industrial production (GDP)	-6.3%	5.0%	-2.9%	-18.9%	22.8%	23.5%	6.8%	10.3%	8.3%	11.4%	14.8%	1.9%	11.8%
	Export upgrading	-15.3%	53.9%	21.1%	-16.1%	-17.1%	-10.9%	-12.3%	32.6%	20.2%	-12.8%*	15.5%*	27.3%*	13.0%
Publishing, printing and reproduction of recorded media	Change in the monthly wages (raw)	16.0%	20.7%	11.2%	11.5%	-5.4%	9.2%	2.6%	-3.1%	9.0%	0.5%	2.3%	20.3%	17.5%
	Change in number of employees	1.9%	15.7%	-0.3%	-0.8%	-5.2%	-5.9%	0.6%	2.5%	-4.7%	2.4%	-0.6%	10.2%	-3.6%
	Change in industrial production (GDP)	5.2%	39.5%	29.1%	9.7%	-8.2%	3.4%	-12.2%	32.3%	6.2%	-2.4%	9.2%	15.8%	0.4%
	Export upgrading	12.5%	112.1%	549.1%	-49.8%	-81.8%	-3.1%	24.1%	14.8%	-44.3%	46.0%*	11.9%*	23.7%*	1.9%
Coke, refined petroleum products and nuclear fuel	Change in the monthly wages (raw)	-	-	-	-	-	-	-	-	-	-	-	-	-
	Change in number of employees	-0.8%	2.9%	8.1%	-0.2%	1.8%	-7.4%	3.6%	-0.7%	-1.3%	-3.6%	-1.9%	3.5%	-5.5%
	Change in industrial production (GDP)	12.9%	23.7%	15.1%	-34.5%	-8.1%	49.1%	-6.4%	7.0%	23.7%	4.4%*	-8.8%*	-27.1%*	55.3%
	Export upgrading	-9.7%	-83.1%	497.5%	-6.6%	-45.8%	60.8%	-32.1%	-47.2%	10.2%	182.0%	30.8%	82.2%	-23.9%
Chemicals and chemical products	Change in the monthly wages (raw)	37.2%	13.1%	9.4%	12.0%	3.8%	-2.3%	3.4%	6.3%	7.2%	11.9%	23.9%	24.7%	17.9%
	Change in number of employees	1.0%	-3.6%	-9.8%	-12.5%	-9.1%	-9.3%	-8.5%	1.5%	-7.3%	3.3%	7.0%	3.9%	10.3%
	Change in industrial production (GDP)	10.8%	4.2%	14.7%	5.6%	7.4%	-10.7%	24.1%	1.8%	0.0%	14.2%	33.9%	53.2%	-5.0%
	Export upgrading	-13.5%	-16.6%	-10.4%	-15.4%	1.5%	-6.7%	-6.1%	36.0%	30.5%	-37.4%*	98.3%*	97.5%*	39.8%
Rubber and plastic products	Change in the monthly wages (raw)	23.7%	46.0%	20.2%	-11.4%	5.3%	2.3%	-1.5%	12.0%	9.9%	16.6%	19.0%	26.7%	15.6%
	Change in number of employees	3.3%	3.0%	4.9%	3.3%	5.9%	8.8%	13.1%	4.9%	2.3%	10.2%	7.9%	4.7%	-0.9%
	Change in industrial production (GDP)	19.8%	7.8%	76.6%	3.5%	21.4%	30.2%	16.0%	55.4%	12.5%	23.4%	18.0%	-0.5%	-6.7%
	Export upgrading	7.3%	0.8%	1.3%	-2.5%	19.7%	-5.3%	6.0%	23.6%	18.3%	9.1%*	-0.6%*	37.1%*	9.0%
Other non-metallic mineral products	Change in the monthly wages (raw)	24.0%	33.7%	17.5%	9.8%	-5.7%	3.4%	4.1%	6.0%	9.2%	11.4%	25.0%	24.9%	11.5%
	Change in number of employees	-18.5%	-12.2%	-6.4%	-14.7%	-9.1%	-2.8%	-5.5%	-0.9%	-0.3%	6.3%	5.1%	4.0%	-7.8%
	Change in industrial production (GDP)	-2.5%	-5.8%	21.4%	-7.1%	-4.1%	2.5%	3.8%	32.6%	14.1%	34.3%	33.4%	3.0%	-18.1%
	Export upgrading	0.4%	-9.7%	0.9%	77.2%	106.9%	103.0%	65.2%	88.0%	-4.8%	-37.0%*	-1.9%*	67.9%*	7.3%
Basic metals	Change in the monthly wages (raw)	46.0%	25.5%	2.9%	5.9%	18.3%	9.7%	-18.8%	8.8%	34.6%	2.1%	9.4%	32.1%	9.1%
	Change in number of employees	16.3%	-5.5%	-20.5%	6.0%	-13.8%	-0.2%	0.8%	-30.1%	-7.9%	2.8%	-3.0%	5.4%	-10.0%
	Change in industrial production (GDP)	-24.6%	-8.4%	32.4%	116.9%	48.8%	3.7%	-20.5%	-26.3%	-22.3%	24.6%	-15.0%	25.1%	98.8%
	Export upgrading	-13.5%	-23.4%	-16.4%	21.5%	27.1%	0.6%	21.0%	5.8%	35.1%	96.5%*	96.5%*	99.6%*	42.0%
Fabricated metal products, except machinery and equipment	Change in the monthly wages (raw)	27.7%	29.9%	13.6%	4.6%	0.4%	-0.5%	0.6%	14.3%	25.6%	-2.5%	22.7%	32.1%	9.1%
	Change in number of employees	-23.2%	21.5%	4.5%	-2.8%	1.2%	6.3%	10.7%	13.4%	12.1%	9.5%	9.7%	5.3%	-10.6%
	Change in industrial production (GDP)	9.7%	6.3%	13.6%	-41.1%	13.6%	22.6%	7.4%	57.4%	29.8%	23.8%	28.0%	31.5%	-24.7%
	Export upgrading	16.3%	-1.0%	10.0%	2.6%	-1.6%	1.8%	17.4%	20.1%	27.1%	-4.5%*	23.2%*	38.2%*	11.7%
Machinery and equipment n.e.c.	Change in the monthly wages (raw)	31.9%	16.7%	13.9%	13.6%	5.4%	-2.3%	13.7%	5.8%	8.1%	9.4%	23.3%	22.1%	11.8%
	Change in number of employees	-20.2%	-10.5%	-13.2%	-19.8%	-13.2%	-5.6%	0.1%	-6.5%	2.3%	-9.2%	6.6%	2.8%	-7.9%
	Change in industrial production (GDP)	-22.0%	-4.5%	-1.2%	7.4%	-6.1%	21.5%	30.5%	3.0%	11.7%	11.9%	7.9%	18.6%	6.5%
	Export upgrading	27.7%	-86.4%	11.3%	8.2%	2.2%	1.3%	11.9%	13.7%	29.2%	-1.1%*	8.3%*	52.8%*	6.4%

Office machinery and computers	Change in the monthly wages (raw)	66.9%	14.0%	20.8%	6.2%	-6.2%	32.1%	-1.2%	-1.4%	10.8%	15.2%	18.7%	17.7%	19.6%
	Change in number of employees	-19.1%	-17.0%	-30.2%	-69.0%	-8.7%	20.8%	2.8%	-33.4%	78.9%	-28.4%	-0.4%	-9.5%	-4.4%
	Change in industrial production (GDP)	-2.7%	-9.9%	108.6%	214.6%	-62.6%	10.8%	-20.4%	9.4%	10.9%	-10.4%	39.2%	39.4%	333.4%
	Export upgrading	98.6%	-73.4%	133.8%	304.3%	-55.8%	-44.1%	50.9%	41.2%	68.7%	16.6%*	-6.1%*	35.0%*	73.5%
Electrical machinery and apparatus n.e.c.	Change in the monthly wages (raw)	57.0%	14.4%	16.4%	4.6%	12.3%	4.4%	-4.3%	0.0%	10.3%	4.1%	24.1%	17.7%	19.6%
	Change in number of employees	-27.5%	-16.7%	-13.5%	-23.1%	10.9%	19.1%	-1.3%	32.5%	5.6%	-6.3%	-8.4%	-9.5%	-4.8%
	Change in industrial production (GDP)	22.0%	46.4%	38.4%	8.4%	8.5%	4.3%	11.9%	57.9%	20.4%	-7.3%*	-8.2%*	-3.4%*	-19.0%
	Export upgrading	94.0%	38.0%	-26.6%	-53.4%	-14.5%	-8.2%	31.4%	108.5%	6.7%	-14.6%	5.7%	26.3%	-9.2%
Radio, television and communication equipment and apparatus	Change in the monthly wages (raw)	59.7%	35.5%	10.5%	8.2%	9.7%	6.2%	3.8%	-10.3%	7.2%	2.0%	17.4%	17.7%	19.6%
	Change in number of employees	-16.7%	-13.0%	-15.2%	-15.2%	10.5%	-5.9%	2.1%	0.5%	11.2%	-12.1%	-45.6%	-9.5%	-4.6%
	Change in industrial production (GDP)	15.0%	3.4%	16.9%	18.6%	29.3%	12.1%	25.6%	35.5%	14.4%	4.5%	-10.5%	-23.6%	-10.1%
	Export upgrading	-13.1%	-96.4%	-3.1%	6.3%	0.5%	5.2%	16.7%	5.6%	-4.5%	-6.9%	56.5%	43.6%	25.8%
Medical, precision and optical instruments, watches and clocks	Change in the monthly wages (raw)	61.4%	35.2%	31.9%	4.9%	2.2%	3.3%	8.3%	1.6%	11.8%	2.2%	15.3%	17.7%	19.6%
	Change in number of employees	-39.8%	-4.0%	-24.7%	0.8%	35.8%	-1.6%	8.4%	-3.2%	-9.6%	14.1%	-3.5%	-9.5%	-4.9%
	Change in industrial production (GDP)	-50.3%	2.1%	62.6%	-6.8%	-9.3%	9.1%	-3.7%	17.4%	21.6%	5.0%	20.1%	33.7%	-1.0%
	Export upgrading	51.0%	-44.6%	-25.0%	10.3%	-10.7%	-27.7%	-0.6%	33.1%	17.6%	-22.7%	7.4%	20.4%	20.7%
Motor vehicles, trailers and semi-trailers	Change in the monthly wages (raw)	6.3%	54.9%	57.0%	-5.4%	-31.8%	-2.2%	21.9%	23.9%	7.8%	14.4%	33.7%	22.3%	23.1%
	Change in number of employees	22.6%	-26.4%	23.5%	-30.0%	-76.3%	-25.7%	27.3%	3.5%	2.1%	147.6%	3.8%	7.8%	7.6%
	Change in industrial production (GDP)	-19.1%	20.9%	40.6%	-49.7%	64.9%	101.9%	64.5%	24.7%	90.0%	31.7%	98.4%	49.6%	14.6%
	Export upgrading	87.3%	-79.9%	28.6%	110.6%	32.8%	-22.5%	-21.5%	24.1%	21.9%	-15.4%	10.3%	21.3%	16.9%
Other transport equipment	Change in the monthly wages (raw)	30.7%	30.2%	15.3%	14.6%	1.7%	9.4%	-3.2%	2.8%	4.9%	16.9%	12.1%	22.3%	25.8%
	Change in number of employees	-6.1%	-3.9%	-1.5%	2.4%	-5.7%	-5.9%	5.0%	2.3%	-7.7%	5.6%	2.2%	7.8%	3.4%
	Change in industrial production (GDP)	27.9%	-7.3%	42.5%	-6.1%	20.3%	12.8%	-3.0%	3.8%	17.2%	43.1%	14.9%	0.8%	19.0%
	Export upgrading	-57.6%	-94.9%	-31.3%	8.9%	-12.9%	-6.9%	-37.5%	84.5%	27.9%	-33.7%	35.7%	76.6%	49.7%
Furniture; manufacturing n.e.c.	Change in the monthly wages (raw)	32.2%	26.0%	13.7%	12.8%	-5.6%	-2.3%	5.6%	10.7%	8.3%	9.7%	16.1%	26.2%	13.5%
	Change in number of employees	-8.0%	2.4%	-2.6%	-7.5%	8.8%	8.7%	21.4%	14.0%	9.2%	10.5%	10.5%	1.7%	-0.8%
	Change in industrial production (GDP)	-8.3%	-8.3%	-8.3%	-8.3%	-8.3%	-8.3%	-8.3%	-8.3%	-8.3%	-8.3%	-8.3%	-8.3%	-8.3%
	Export upgrading	68.5%	-99.4%	7.2%	-1.3%	-7.7%	0.4%	6.3%	6.7%	7.2%	-14.7	20.7%	20.9%	6.9%

Note 1: Values were estimated using the MICE algorithm and 1998-2008 data. This data range was used as there are quite a lot of outliers in the export upgrading variable before this range

Note 2: Tobacco consumption and recycling were excluded from the analysis due to lack of data

Source: Authors own compilations based on wiiw Industrial Database (2010) and Comtrade data.

Appendix B

Table 7. Effects of export price change on the ratio of high to low-skilled individuals using different panel regression

	Pooled OLS	Fixed Effects	Random Effects
Constant	-31.4255	-39.1453	-36.7254
ΔExport price	-0.00207*	-0.00135**	-0.00139***
ΔNumber of employees	0.00604*	0.00414	0.00445*
ΔGDP	-0.00474	0.00082	0.00073
Average age	0.05194*	0.01511	0.02169
Joined the EU (2004)	-0.17081*	-0.14610	-0.14800
Year	0.01511	0.01970	0.01835

N= 119

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

Note: All regressions used robust HAC standard error to control for heteroscedasticity and autocorrelation, which was presented in the data

Table 8. Effects of gross fixed capital formation on the ratio of high to low-skilled individuals using different panel regression

	Pooled OLS	Fixed Effects	Random Effects
Constant	-23.5196	-51.9918	-47.2883
ΔCapital formation	-0.00455	-0.00070**	-0.00067***
ΔNumber of employees	0.00379	0.00154	0.00195
ΔGDP	-0.00175	0.00283	0.00023
Average age	0.05701*	-0.00469	0.00472
Joined the EU (2004)	-0.1452	-0.15848	-0.15569
Year	0.0110	0.026513	0.02397

N= 98

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

Note: All regressions used robust HAC standard error to control for heteroscedasticity and autocorrelation, which was presented in the data