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Technological change and labour demand

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1. Cörvers, F., **Meriküll, J** (2007). Occupational structures across 25 EU countries: the importance of industry structure and technology in old and new EU countries. *Economic Change and Restructuring*, 40(4), 327–359.

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2. **Meriküll, J** (2008). The Impact of Innovation on Employment: Firm- and Industry-level Evidence from Estonia. Bank of Estonia, Working Paper Series, No 1/2008.
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1. **Meriküll, J**. "The Impact of Innovation on Employment: Firm- and Industry-Level Evidence from Estonia," School of Slavonic and East European Studies, University College London, workshop "Innovation and Organisations: Economic, Social and Institutional Aspects from Estonia", UK, London, 17.04.2008.
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INTRODUCTION

Structure

This thesis consists of four chapters based on a "general to specific approach". The first chapter provides a theoretical discussion of the relationship between technological change and employment. Chapters 2–4 provide empirical analyses of the impact of technological change on employment structure and total employment. The empirical chapters start with a cross country comparison of labour demand of the EU countries and country level analysis; and go further to firm-level analysis on Estonia. The thesis is organised as follows:
Chapter 1: Theoretical background for the research
Chapter 2: Skills structure of EU countries: result of developments in industry structure or technological change
Chapter 3: The impact of innovation on employment: firm- and industry-level evidence from Estonia
Chapter 4: The impact of innovation on skill upgrading: interaction with FDI and the export destination

The importance of the topic

Market of production factors is one of the basic components of economic system besides the goods production and consumption. Traditional production factors like labour, land and capital have entered the discussion of economic theory since its very first formulations. Capital is internationally more mobile and correspondence of its supply and demand is more easily achievable compared to labour. Labour is no doubt the most complex factor of production, holding limited international mobility and comprising of different and un-substitutable components of skills. Hence the achievement of a targeted balance of labour demand and supply is a difficult objective to meet. Acemoglu (2002b) argues that the vast technological changes over the past 150 years have mostly been labour augmenting. He backs up his argument by the stylised fact that in the US and Western Europe the prices of capital have been relatively constant, while wages have steadily increased.

The supply side of labour market is rigid in terms of investments output to desired outcome. Investment in education or health affects to increased human capital with a time-lag up to decades. Moreover, demand side shocks can make a difference in the labour market within a very quick time. This property of rigid demand and sensitive supply has never shaken the labour market as much as it did in the Post-Soviet countries after their turn to market reforms. Introduction of distorted "over-industrialized" production system to a new demand driven market caused vast changes in the structure of production and consequently in demand for production factors. All the Central and Eastern

European (CEE) Post-Soviet economies faced high job destruction rates and altered demand in terms of labour qualification. Although, the countries belonging to the Soviet sphere of influence were characterised by well educated labour force, some skills in the labour market became obsolete, some needed training re-training when the countries embarked on their economic transition (Jeong, Kejak, Vinogradov 2008). The supply side of the labour market faced problems responding to these changes, resulting in high rates of structural employment (Eamets 2001, p. 135).

Obviously, the factors shaping labour demand in CEECs have changed during the process of transition. The rapid adaption of the new rules of the game have turned the position of these countries to a normal middle-income countries' according to World standards and catching-up countries within the European context. The vast job destruction rates faced in the early phase of transition have been reduced, but the skill decomposition of employment is still changing (Commander and Kollo 2008 on the example of Hungarian firm-level data). The shift of the CEECs towards white-collar or tertiary educated workers has been documented in many studies (Kézdi 2002, Tarjáni 2007, Commander and Kollo 2008). Masso, Eamets and Philips (2006) find that the job turnover rates are still relatively high in Baltic States and that most of the movement of jobs takes place between sectors and not within sectors (Masso, Eamets and Philips 2006).

One explanation for these fast changes in labour demand is technological change or technological innovation. The impact of technological change can affect economy via laissez-fair or politically induced manner. First, the quick adaption of market reforms induced the free movement of technologies changing labour market in a laissez-faire manner. This has been an important aspect for these countries characterized by high openness to foreign trade and inward FDI that all contribute to the diffusion of technologies. Empirical estimations of these relations indicate that FDI and export are the strongest sources of technology diffusion (Keller 2004). Second, following the thought of endogenous growth theory or evolutionary theory it must be politically in-built to allocate resources to new technologies, R&D and innovativeness. New technologies create relative advantage to ensure the catching-up.

Freeman (2006) brings out that CEECs have been successful building national innovation system (NSI) in a broad sense, i.e. in terms of institutional reforms like opening economies to foreign investment and consultancy. But they have been less successful in building national innovation system in a narrow sense regarding the institutions directly related to R&D and allocating resources to R&D. The allocation of resources to this narrower NSI has been weak and this still holds a high potential in terms of facilitating technological change in these countries. (Freeman 2006) Hence CEECs have presumably benefited much from international technology diffusion, but have created little knowledge by themselves.

Most of the world economies have witnessed large increase in the relative demand for skilled workers since 1970s. The share of non-manual labour and their wages have increased in spite of the simultaneous increase in the supply of skilled labour.

There have been many explanations for this development. First, the skill-biased technological change (SBTC), i.e. technological change has been biased toward one production factor, skilled labour. The evidence of SBTC has been found on high- and low-income countries data (Berman, Bound, Machin 1998; Berman and Machin 2000). And it has been often related to the development of information and communication technologies (ICT) (Berman, Bound, Griliches 1994; Autor, Katz, Krueger 1998; Autor, Levy, Murnane 2003). The role of ICT on relative demand for skills has started to decrease in technology leading US economy (O'Mahony, Robinson, Vecchi 2008).

The second most common explanation has been the increased trade activity and lowered trade barriers. It has been estimated that increased trade activity with low-income countries has reduced the demand for low-skilled in high-income countries. This effect is estimated, however, to be much weaker compared to SBTC (Feenstra and Hanson 1999, Paul and Siegel 2001). Trade is also estimated to have interaction effects with SBTC, as trade diffuses technologies across countries (Paul and Siegel 2001). Third, organizational reorganisations together with ICT investments have been estimated to magnify the demand for skills (Bresnahan, Brynjolfsson, Hitt 2002) or stand as an individual component behind increased demand for skills (Caroli and Van Reenen 2001).

The same factors have presumably influenced the development of skill demand in post-communist transition countries. The SBTC has been estimated to have a dominating effect (Tarjáni 2007 on Hungarian data, Xu and Li 2008 on Chinese data). But expectedly, the trade interaction effect with SBTC has an important role to play. Keller (2004) suggests that the existing empirical literature indicates that foreign sources of technology have a major impact on local firms' productivity and that this effect is especially important for small countries. He also finds that there is more evidence on technology diffusion through import and FDI than through export (Keller 2004). In China, for instance, the direct effect of export on local firms' skill demand has been estimated to be negative. While the indirect effect through technology adoption has been positive as exporting firms witnessed SBTC and non-exporting did not. The technological change has been more skill-biased in companies with majority-foreign ownership and with private ownership (Xu and Li 2008).

According to Heckschler-Ohlin framework a country exports goods in which production factors it is abundant. Countries abundant in low-skill labour should export labour intensive products and countries abundant in high-skill labour should export skill intensive products. It is difficult to choose in which category CEECs should place oneself. From one side these countries are characterised by quite high share of tertiary educated workers, from other side their labour costs are considerably lower compared to their Western neighbours. In addition, Western Europe has outsourced part of their labour-intensive production to

Eastern Europe (Geishecker 2006) or moved their low-tech industries to Eastern Europe (Heidenreich 2008).

The empirical studies on developed economies indicate that changes in technologies have affected the overall employment growth at the firm level (Pianta 2005, Djellal and Gallouj 2007). The firms that implement innovations grow faster. This result may not be applied to the industry or country level as it is important to distinguish between whether the firm's innovation has caused larger market expansion or larger business stealing effect. The industry-level analysis indicates that industries with a lot of product innovation have witnessed employment increase and industries with a lot of process innovation have witnessed employment decrease (Greenan and Guellec 2001, Antonucci and Pianta 2002).

In sum, since 1970s technological changes have significantly shaped the labour market and have motivated large number of research papers. The effects are, however, not well investigated in the formerly centrally planned economies in Central and Eastern Europe (CEE). Papers by Kézdi 2002, Tarjáni 2007, and Commander and Kollo 2008 are some of the exceptions. There is probably several reasons why the impact of technological change has been less investigated among this country group. First, the transition process caused ample changes in the labour market of these countries and initially other factors had a more important role. Most of the movement of jobs took place between industries (Kézdi 2002, Masso *et al.* 2006) indicating that these movements are more attributable to the change in industry structure than to the change in technology. The phase of economic turmoil has been outlived for now and these countries have become tightly integrated to the World and especially European economic system, which all have increased the role and diffusion of technological changes.

Second, the technological changes or technological innovations have perceived to be far from the world technological frontier in these countries and hence have little ability to bring along significant change after implementation. This is partly true, since not much resources have been allocated to the local development of own R&D (Freeman 2006). The share of traditional low-tech industries is higher in CEECs. The low-tech industries are traditional users of new technologies produced in other industries/countries and invest little to R&D. But these low-tech industries benefit from R&D created in other countries (Ukrainski 2008). Hence, the smaller amount of R&D does not necessarily mean that the country is very far from the technological frontier.

The aim and research tasks

The aim of this thesis is to investigate the effect of technological change on labour demand in CEE countries. The analysis is undertaken at the country, industry and firm level. The thesis raises four research tasks. The first research task is to provide a theoretical background for the analysis. We discuss the adjustment processes after the implementation of technological changes and provide a historical overview of this relation in empirics. The second research task is the investigation of the role of technological change on skill composition on the sample of EU countries. The main focus in this task is on the comparison of Western European developed and Eastern European catching-up countries. We seek to explain the existing differences and the dynamic developments of skill structure across these country groups.

The third and fourth research tasks set up the analysis at the firm and industry level. The third research task is to investigate the impact of technological change or technological innovation on employment at the firm and industry level. We undertake the analysis on the case of the Estonian economy and employ a sample of firm level data. As an extension for this analysis we investigate whether the implemented technological changes have different effects on employment in high-, medium- and low-tech industries. The fourth research task is to investigate the impact of technological change or technological innovation on skill demand at the firm level. Again the Estonian economy and Estonian firm level data are employed to investigate this effect. This analysis is extended to investigate the effects of technology diffusion channels as foreign trade and FDI on skill upgrading. Every research task occupies one chapter in the thesis.

Data and methods used in the research

The essence of this thesis relies on the empirical analysis. Every section uses a different estimation strategy. We have sought to find the most suitable estimation strategy based on the inevitable data constraints. Chapter 2 proceeds from industry level data and uses a decomposition of shifts in data across countries and over time. Chapter 3 employs a sample of firm-level panel data and uses panel estimation methods. Chapter 4 makes use of a cross-section of the firm-level data and uses instrumental variables methods.

Chapter 2 employs a shift share analysis to decompose the European countries employment structure by occupation into the component of industry structure and the component of technological change. The component of technological change is proxied by within industry shifts in occupational groups. The analysis has been undertaken for 25 EU countries across the main occupational groups, one-digit ISCO level, and across the main industries, one-digit NACE level. The employed data includes Labour Force Surveys (LFS) of individual countries for 2000–2004. The LFS surveys have been collected by the statistical offices of each individual country and provided to Eurostat. The dataset employed in this thesis is based on the aggregated subset of these surveys and is provided by Eurostat.

Chapter 3 employs microeconometric panel data estimation methods to estimate firm-level labour demand equations. The Arellano and Bond (1991) and Arellano and Bover (1995) / Blundell and Bond (1998) dynamic panel data methods developed for panels with short time-series are used to estimate demand for jobs at firm level. We rely mostly on the Arellano and Bond (1991) GMM estimation method, as this method is more appropriate considering our data limitations. The technological change is divided into product and process innovation, respectively. The data set for this analysis has been constructed from three sources: Estonian Business register, the third Estonian Community Innovation Survey (CIS) and the fourth Estonian Community Innovation Survey (CIS). The resulting panel consists of more than two thousand of firms over the time-span of 2001–2003 and 2004–2005. We propose a novel estimation strategy for CIS data by merging the CIS surveys into a panel and implementing panel data estimation methods for the analysis.

Chapter 4 makes use of the cross-section estimation methods. We address the possible problem of an endogenous dependent variable by instrumentation and use 2SLS for estimation. We estimate the impact of technological change on the demand for high-skilled jobs. The technological change is proxied by product and process innovation and high-skilled jobs by the share of employees with higher education. The 3rd Estonian CIS data has been merged with the Estonian Business Register for the analysis. The dataset consists of more than two thousand firms.

Finally if should be emphasised that his thesis uses the notion of technological change and technological innovation interchangeably. We mean by technological change or technological innovation the implemented product or process innovation. Our notion of innovation is in line with the Schumpeterian view that innovation, unlike invention, is initiated by an entrepreneur and has commercial output (Fagerberg 2003, pp.131). But we use a somewhat narrower notion of innovation than Schumpeter's one (Fagerberg 2003, pp.130). We limit ourselves to *technological* innovation; i.e. product or process innovation, and exclude the discussion of organisational or marketing innovation. Another group of notions arise from the labour market side. We focus our discussion only on the demand side of the labour market. We do not focus on the adjustment process of the labour market via wages or labour supply, although these adjustments are potentially of importance. Since in empirical data we observe only the realised employment and do not observe the unsatisfied demand, we use the notions labour demand and employment interchangeably.

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1. THE THEORETICAL BACKGROUND FOR THE RESEARCH

There is a vast amount of research on the theoretical and empirical relation between technological change and employment or employment structure. There are two main frameworks that underly these discussions: evolutionary theory and neoclassical theory. We give a short description of the main discrepancies between these approaches based on a survey paper of evolutionary economics by Fagerberg (2003).

The evolutionary approach springs from Schumpeter's notion of evolution of economic process due to innovation. Schumpeter recognised the neoclassical Walrasian approach as the demonstration of “the power of equilibrating forces in the economy”, but he claimed that in reality the attained equilibrium is not stable or “would constantly be disrupted by innovation” (Fagerberg 2003, p. 129).

The main distinction between these approaches is that while the standard neoclassical framework depicts firms competing over *prices*, Schumpeter sees firms competing over *technologies*. Schumpeterian firms are competing over new ways of production or new products or better input factors or new markets or new ways of business organisation. Hence, Schumpeter’s notion of innovation is quite wide. With a successive innovation firm improves its market position, but this is not stable as other firms are imitating or developing new innovations until the attained market position vanishes. As the initial innovation induces imitators and new innovations in a particular market, some industries may grow temporarily faster than the whole economy and contribute to the cyclicality of the economy. Schumpeter claimed that these business cycles contribute to (but do not explain solely) the genesis of “long waves” in the economy that last around half a century. (Fagerberg 2003)

Schumpeter and evolutionary economists did not believe that formal equilibrium models can explain the historical economic development. The students of Schumpeter have developed and extended his ideas to explain the historical developments. The empirical research has extended Schumpeter's work in many areas as foreign trade, technology/innovation diffusion and the national system of innovation. (Fagerberg 2003) The analytical models of evolutionary and neoclassical approaches have converged somewhat over time. This concerns mostly the contributions to economic growth models and is related to the development of endogenous growth models from the neoclassical strand. (Verspagen 2005)

The formal analytical framework of this and the following chapters originate from the neoclassical tradition. This does not mean that we have taken a position in favour of either of the frameworks, neoclassical or evolutionary. We have benefited from both of them. The neoclassical framework offers a compact illustration of the adjustment process due to an occuring technological change or innovation. The adjustment feature of Walrasian equilibrium models was also appreciated by Schumpeter.

We do not concern ourselves with any direct testing of these analytical models. The neoclassical models are introduced to provide a tractable model of the adjustment process. The evolutionary ideas are used to broaden the interpretation and extend the empirical analysis. The evolutionary theory contributes as a source for various notions and ideas for empirical research. Among these notions the most important one is innovation, but also other phenomena as the diffusion of innovation, sectoral patterns of innovation, innovation interaction with foreign trade and FDI.

This chapter is an example of the mixture of evolutionary and neoclassical frameworks. We start with the historical perspective. For the sake of understanding the entrepreneurial function, the integration of historical and theoretical analysis was one of the methodological suggestions of Schumpeter (Fagerberg 2003). We go further in this chapter by the theoretical models originating from neoclassical strands. We limit ourselves only (or mostly) to theoretical models and the following chapters provide the empirical exercises altogether with the survey of empirical studies.

1.1. The historical perspective

The relationship between technological change and employment or employment structure has not been constant across different industrial revolutions. There have been technological innovations that have been skill-biased; de-skilling; labour-saving; labour-enhancing or starting completely new industries. We give an overview of these relations through the industrial revolutions.

The most common approach differentiates between three stages of industrial revolution. All of them have brought along different implications for employment and employment structure. In the following, we use the classification and description of industrial revolutions by Bruland and Movery (2005). This classification is based on the change in the innovation system and does not necessarily overlap with the Schumpeterian classifications based on "critical technologies". The critical technologies theory has been the origin for Shumpeter's "long wave" theory in business cycles. (Bruland and Movery 2005)

The First Industrial Revolution took place approximately from 1760 to 1850 and started from Great Britain. The First Industrial Revolution was characterised by shop-floor-driven technological innovation. The key innovation was the steam engine and many other process innovations that boosted the textile industry. The textile industry grew the most during this Industrial Revolution, but also other industries benefited from the vast technological changes, for example agriculture, mining and manufacturing of glass, iron, steel, chemicals, machinery and pottery.

The technological changes of this era were characterised by their labour-saving nature. This industrial revolution is described as a break out from the Malthusian trap – introduction of the innovation-based growth, leading to intensive growth in terms of output per head instead of extensive growth driven by population growth. (Bruland and Movery 2005) Nevertheless, the technological change was labour-saving; Deane (1979) brings out that due to the immense expansion of investments the total labour demand increased. The abundant cheap labour facilitated the increase of industrial output without a substantial rise of real wages. The labour supply was relatively inelastic during the period and labour market institutions did not protect the rights of employees. (Deane 1979)

The First Industrial Revolution has been found to be de-skilling. The skilled artisans were replaced by unskilled factory workers. In more detail, Chin, Juhn and Thompson (2006) find that the first waves of industrialisation changed the employment structure destroying the jobs in the so-called middle occupations. The skilled artisans were replaced by unskilled operatives and highly skilled engineers and managers. This regularity has been witnessed on the data of transoceanic marine transportation after the introduction of the steam engine. Although the application of the steam engine to transoceanic marine transportation takes place during the Second Industrial Revolution, the authors claim that these empirical finding have relevance also for the other industries that implemented steam engine during the First Industrial Revolution. (Chin *et al.* 2006)

The Second Industrial Revolution or the second phase of industrialisation took place between the late 19th century and in the early 20th century. The technological leadership started to move from Great Britain to United States and Germany. Bruland and Movery (2005) describe this period by the development of organised industrial R&D within the firm and development of scientific contacts between firms and universities. The key innovations of this period were various chemical products, the internal-combustion engine, industrial applications of electricity, telephone etc. This wave of technological innovation involved mostly industries such as chemicals and optics, but also gave rise to new industries like electrical equipment and electric power generation.

The effect of technological change on total employment during this era is unclear. Freeman and Soete (1997, p. 396) state that "the job creation effects have in the long run outstripped the job destruction, albeit accompanied by a steady reduction in working hours throughout the nineteenth and twentieth centuries." In terms of employment composition, the Second Industrial Revolution started to bring along technological changes that favoured more skilled workers. The technologically leading industries employed also more skilled workers and grew faster than other industries. Goldin and Katz (1998) argue that a complementarity of technology and skills emerged from the beginning of 20th century after the replacement of steam and water-power energy by electricity. Introduction of the electric energy reduced the demand for unskilled workers that were organised in the stocking and conveying of coal. The relative demand for skills increased, but the wage cap between white and blue collar workers first decreased and then remained stable in the US. This development has been assigned to the mass supply of educated workers during that time. (Goldin and Katz 1998)

Bruland and Movery (2005) classify as the "Third Industrial Revolution" the period after 1945. The technological leadership shifted from Western Europe to the USA. The international technology diffusion accelerated due to increased international trade and capital flows. This period is characterised by the inclusion of government institutions to the innovation process. The increasing public R&D was allocated to industry and academic research. The main inventions of this era come from the field of Innovation and Communication Technologies (ICT). New industries emerged: computers, semiconductors and biotechnology.

Unlike previous innovations like steam or lesser electricity power, the ICT technologies affected "every function within the firm as well as every industry and service" (Freeman and Soete 1997, p. 396). The technological changes that affect the entire economy are also called as general purpose technologies. Together with the quick international diffusion of new technologies during this era, it is difficult to estimate the net employment effect at the national level. It has been claimed that new technologies in 1950s and 1960s meant that North America, Western Europe and Japan experienced high productivity growth but even faster output growth due to employment growth and low unemployment. A similar pattern was later seen in Asian Tigers due to the IC technologies. (Freeman and Soete 1997)

The technological changes after 1945 have increased the relative demand for skilled workers. This has especially been the case for the more recent ICT inventions (Berman *et al.* 1994; Autor *et al.* 1998). Autor, Levy and Murnane (2003) found that computers have caused reduced of demand for routine manual and cognitive tasks and expansion of demand for non-routine cognitive tasks within industries. Their estimations proceeded from US data 1960–90s. The increase in the relative demand for skills has brought along various adjustment processes in 1980s and 1990s. The US has thus witnessed a decrease in the real wages of the least educated workers, while in Europe it has led to much higher unemployment rates of unskilled labour force. (Freeman and Soete 1997)

We go further by presenting some theoretical models on the relation between technology and labour demand. These models are all motivated from the era of the Third Industrial Revolution and the vast effects of ICT. Nevertheless, these basic frameworks are able to shed light on developments in earlier periods.

1.2. Technological change and demand for skills

There is a vast amount of models analysing the impact of technological change or technological innovation on skill demand. This section gives an overview of some of the basic models and their implication for Europe.

As mentioned earlier the developed and developing world has an witnessed increase in the relative demand for skills throughout the 20th century. The academic literature on these issues has exploded since the 1980s. The main factor behind the increased demand for skills since 1970 has been claimed to be the developments in Information and Communication Technologies (ICT). The nature of technological change that induces the use of skilled labour instead of unskilled labour is called a skill-biased technological change (SBTC). Hence, the main explanation for the relative demand increase of skilled labour since 1970s has been the SBTC.

Yet another factor has had an important role, the trade liberalisation and increased trade volumes between developed and less developed countries. The labour-augmenting production has shifted from developed countries to developing countries that are abundant with unskilled and less costly labour. According to this view, the increased labour-augmenting production in the less-developed countries has reduced the relative demand for skills in the less-developed countries and increased the relative demand for skills in the developed countries. This effect is estimated to be much weaker compared to SBTC on US data (Feenstra and Hanson 1999, Paul and Siegel 2001). The argument supporting the SBTC as the main factor behind skill-upgrading is that the developing world has witnessed similar increase in relative demand for skills and similar changes in industry skill composition (Berman *et al.* 1998, Berman and Machin 2000).

The trade effect and SBTC have also interaction effects as trade entails the technology diffusion across countries (see the survey by Chusseau, Dumont and Hellier 2008). Chusseau *et al.* (2008) bring out that the earlier estimates overestimated the importance of SBTC on skill upgrading due to various methodological factors and also because of not considering the interaction effect of technological change and trade.

This section gives an overview of three types of models to understand these mechanisms: 1) the models of SBTC; 2) the Heckscher-Ohlin type of models on the impact of trade on skill demand; 3) and of models combining both of these effects. The impact of trade on skill demand is not the aim of this thesis, but we discuss the impact of trade on skill demand to present the interaction effects. We rely on the Chusseau *et al.* (2008) on the basic derivation of SBTC and Heckscher-Ohlin models and complement the review by discussing the models more thoroughly.

The SBTC models are discussed in the subsection 1.2.1. The international trade models and the implications of the interaction of SBTC and international trade are discussed in the subsection 1.2.2. The subsection 1.2.3 previews the skill content in Europe and generalises the implications of the previously discussed models on the European content.

1.2.1. Skill-biased technological change

The skill-biased technological change (SBTC) denotes a situation in the economy where technological change induces a change in the relative demand for production factors independent of the prices of production factors. The SBTC may origin from the increased skill demand in skill-intensive industries, a sector-biased technological change; or from the technological change that induces the demand for skilled labour irrespective of the industry, a factor-biased technological change. (Chusseau *et al.* 2008) For example if we have two production functions, Cobb- Douglas (1.1) and constant elasticity of substitution (CES) (1.2) (Chusseau *et al.* 2008):

$$Y = AU^{\alpha_U} S^{\alpha_S}, \tag{1.1}$$

$$Y = A\left[(A_U U)^{(\sigma-1)/\sigma} + (A_S S)^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)} \tag{1.2}$$

where Y denotes production, S skilled and U unskilled labour and A is a Hicks neutral technical change. The sector bias is related to the change in total factor productivity. In the above specifications 1.1 and 1.2 the sector bias takes effect through A, the Hicks neutral technical change. If the overall productivity of skills is increased in sectors that are more skill-intensive, the resulting effect for the whole economy is sector-biased SBTC. The factor bias is related to the change in the productivity of a particular factor. This means that the share of α_S/α_U is augmented for Cobb-Douglas production and the share of A_S/A_U is augmented for CES production. If the productivity of skilled labour increases or the productivity of unskilled labour decreases, the ratio of productivities will be altered in favour of skilled labour inducing the increased relative demand for skills or the factor-biased SBTC. (Chusseau *et al.* 2008) Haskel (2000) generalises that labour economists tend to focus on factor bias, while trade economists to sector bias when analysing the SBTC.

The SBTC may arise from the increase of the use of other production factors. Another type of models analysing SBTC involve the argumentation that capital and skills being complementary. Acemoglu (2002a) generalises that capital and skills have been complementary since the very beginning of 20th century. He claims that: "Events since then support this notion. Personal computers, computer-assisted production techniques, and robotics appear to complement skilled workers, replacing many labor-intensive tasks." (Acemoglu 2002a, p. 8) Tarjani (2007) characterises that the capital accumulation has been increasing and that capital and skills have been complementary throughout the transition process in Hungary.

These types of models add the capital to the production function. If technological progress increases the utilisation of capital, the capital and skill complementarity and/or substitutability of capital and unskilled labour lead to increased relative demand for skills. The technical progress may increase the use of capital by many mechanisms. First, it may increase the factor bias of capital. Second, the sector bias may induce the productivity of capital-intensive industries; decrease the price of capital goods and capital; and increase the use of capital. (Chusseau *et al.* 2008) As it was brought out earlier, at least for developed world, the technological change has been claimed to be mostly labour and not capital augmenting (Acemoglu 2002b). Hence, the first argument is probably not valid for the developed world. Acemoglu (2002a) finds on US data over 1960s and1990s that the relative price of capital has had no role in skill upgrading. But this does not exclude the possibility that the capital-labour ratio has increased for some industries or for some group of countries.

These preliminary models on skill-biased technological change assumed that the technological change is exogenous. It was assumed that innovations like ICT just entered to the economy, changing the organisation of work; and that there were no economic incentives behind the introduction of these particular innovations. The more recent models on SBTC have devoted to endogenise technological change. Various mechanisms have been introduced; we give overview of the following: skill supply, technology adaption, life-cycle of the model. Acemoglu (1998) and Caselli (1999) models concentrate on the impact of SBTC on wage inequality. Nevertheless, these frameworks are also applicable to investigate the effect of SBTC on the skill demand.

Acemoglu (2002a) argues that technological change has not been exogenous and it is associated to a certain profit maximizing incentives. Or using his exact phrasing: “We can understand the behavior of technical change by recognizing that the development and use of technology is, at least in part, a response to profit incentives” (Acemoglu 2002a, p. 9). The technological innovations of the First and the Second Industrial Revolution, late 18th and 19th century, were deskilling because of the increasing migration of rural workers to English cities and increased supply of unskilled labour there. Contrarily the technological innovations of 20th century were skill-biased because of the rapid increase of the supply of skilled labour. The skill bias has accelerated within the last decades because of the increased supply of skills. (Acemoglu 2002a)

According to the model of Acemoglu (1998, 2002b) the skill supply gives incentives which types of technologies to develop. The model is built on the base of endogenous growth models with a two sectors of production: consumption goods production consisting of production of two intermediate goods produced by high-skilled and low-skilled labour; and knowledge accumulation. The new technologies are developed in knowledge accumulation production to fit the needs of a goods production market. If there are many skilled workers in the labour market, there is a larger demand for technologies that could make use of the skilled labour and more resources are allocated to develop these technologies. Acemoglu (1998) calls this phenomenon a directed technical change, the existing skill supply directs the type of technologies developed. (Acemoglu 1998)

Another need for the endogenisation of technological change arises from the adoption of the new technology. Caselli (1999) proposes a model where new technologies substitute the old ones. The adaption of new revolutionary technologies increases the demand for skilled workers, while the incremental technological change does not involve this impact. Technologies consist of machinery as well of the workers operating them. It is costly for workers to learn to operate the new machines. The technological revolution is skill-biased if the costs to learn to operate the new machinery are higher than were the costs to learn to use the old machinery. Contrarily, the technological revolution is de-skilling if the adaption to old machinery was more costly compared to the adaption of the new machinery. Caselli (1999) argues that examples of skill-biased technological revolutions are the steam engine[1], the dynamo and the ICT; while example of de-skilling technological revolution is the assembly line.

If the new technological revolution is skill-biased, the workers with a lower cost of learning accommodate the new machinery and workers with a high cost of learning remain attached to the old machinery. As the new machinery is more productive, more capital will be allocated to this machinery. Or by other words, capital moves from the low-skilled production to high-skilled production. Hence, the skill-biased technological revolution increases the demand for high-skilled labour because they have lower learning-costs and they are involved with more capital-intensive production.

Caselli (1999) finds support for his model from the development of US capital-labour dynamics. He claims that the variance of capital-labour ratios across industries increased since the late 1970s and those industries with higher capital-labour ratio growth witnessed higher growth in the proportion of non-production workers. The Caselli (1999) model provides similar implications as the one of exogenous capital increase leading to SBTC. He claims that his model may be interpreted as the explanation of mechanisms behind the capital-skill complementarity.

1.2.2. North-South trade and demand for skills

The second most important factor behind the skill upgrading is estimated to be the North-South trade. There the notion North depicts developed countries and South the emerging countries with large stock of cheaper unskilled labour.

[1] The steam engine is generally thought to be a de-skilling technology in the historical perspective, see Section 1.1. Chin *et al.* 2006 found on the empirical investigation that the steam engine changed the employment structure replacing skilled artisans by unskilled operatives and highly skilled engineers and managers. Hence the adoption of the new machinery was skill-biased in the top level of occupations and de-skilling in the lower level of occupations.

These types of models are usually built on the framework of Heckscher-Ohlin model. We use the Heckscher-Ohlin model set presented by (Chusseau *et al.* 2008).

There are two goods in the economy produced by two factors of production, *S* skilled and *U* unskilled labour. One of the goods is skilled labour intensive the other unskilled labour intensive. Two countries participate in the model: North and South. The North is abundant of skilled labour and the South is abundant of unskilled labour. Hence the North has a comparative advantage to produce a skill-intensive good and the South has a comparative advantage to produce the unskilled labour intensive good. The introduction of the North-South trade between these countries results in the following implications for the North (Chusseau *et al.* 2008):

1. The relative price of the unskilled labour intensive good and the relative wage of unskilled labour decrease (Stolper-Samuelson theorem). The latter effect depends on the labour market institutions and/or market failures related to wage adjustment. The lower wage adjustment brings along smaller effect of the following point (2) and results in increased unemployment of unskilled.
2. The decreased relative wages of unskilled labour reduce the relative skill demand in all of the industries of the North.
3. The share of skill-intensive industries in the North increases, inducing similar impact as the one of the sector biased technological change discussed above.

The implications of this model on the South are the opposite. The Stolper-Samuelson theorem (Stolper and Samuelson 1941) implies that under the constant returns to scale and perfect competition the increase in the relative price of a good leads to the increase in the relative returns of the production factor that is used the most in the production of the good. Hence, these factors gain of which the country is abundant. The introduction of trade bring along the increase of the relative price of unskilled labour intensive good and the increase of relative wage of unskilled in the South.

The basic Heckscher-Ohlin model takes many restrictive assumptions. The restrictions regarding the skill demand include the homogeneity of the technology in both countries, production of the entire good in one country and that only the final goods are tradable. These all have motivated the extension of the model. One of the most important extensions is international outsourcing. International outsourcing implies that the production process is segmented and some parts of the production are undertaken in other countries. Outsourcing includes the import of intermediate goods from both types of suppliers: own subsidiaries and other companies. (Chusseau *et al.* 2008)

Feenstra and Hanson (1996) argue from the viewpoint of North that: "If firms respond to import competition from low-wage countries by moving non-skill-intensive activities abroad, then trade will shift employment toward skilled workers within industries." They claim that previous studies have assumed that import competition changes the resource allocation between industries, but outsourcing may change also the resource allocation within industry. (Feenstra and Hanson 1996) The first empirical estimations used the skill decomposition analysis to investigate the effect of technological change on skill demand and skill wage cap. These studies divided skill upgrading into between and within industry effects (Berman *et al.* 1994 and 1998) and interpreted the within industry skill upgrading as a result of technological change. Hence, they may have overestimated the role of technological change. The Chapter 2 of this thesis uses the same methodology and discusses these shortcomings there.

Egger and Kreickemeier (2008) estimate the effects of international outsourcing, sometimes also called as international fragmentation, on relative skill demand. There are two inputs, skilled and unskilled labour and three sectors of production. The labour is mobile between sectors within the economy. There are three possible sectors of production, skill-intensive, non-skill-intensive and production with intermediate skill intensity. The outsourcing takes place only in the latter. In equilibrium the production takes place only in the sectors with intermediate skill intensity and in either of the skill-intensive or non-skill-intensive sector.

The Egger and Kreickemeier (2008) model is interpreted from the co called North point of view, while they do not use the North notion. The sector not subject to outsourcing is more skill intensive there. Outsourcing reduces unemployment if the non-outsourcing sector is more skill-intensive than the outsourcing sector. The intuition behind is that outsourcing leads to the expansion of non-outsourcing sector. Additionally, they differentiate countries by the type of wage schedule and the level of unemployment benefits. The egalitarian wage schedule means that preferences on the fairness are high. Outsourcing results in higher relative employment of skills in the countries with egalitarian wage schedule. The reductions of unemployment benefits to combat with unemployment are less effective under the outsourcing to low-wage countries.

The skill content of outsourcing may also take place through capital and skill complementarity. Chusseau *et al.* (2008) claim that as there are empirical evidences that capital is more substitutable for unskilled labour than skilled labour and that the relative price of capital over labour has decreased over time, the North faces increased relative demand for skills partly due to the interaction of capital and outsourcing. The unskilled labour is more substitutable for the production of intermediate goods. Hence the capital-labour ratios for the North are higher than for the South also due to outsourcing.

Last we discuss the interaction of international trade with technological change. We have discussed that trade and/or outsourcing have direct effect on skill demand. We have also discussed what are the mechanisms and motives behind the technological changes. Now we discuss how the trade of final and intermediate goods alter also the type of technologies developed for a particular group of countries and what may influence the international technology dissemination.

The exogenous technological change models previously discussed have also implications for cross-country skill demand. The exogenous SBTC model implies that if the countries experience similar changes in the factor and sector productivity, it indicates the international technology diffusion (Berman *et al.* 1998, Berman and Machin 2000). The skill demand may also vary across countries due to different capital-labour ratios. As these models are exogenous, they don't provide any deeper explanation for the realisation of international skill demand.

The endogenous SBTC models provide much more colourful explanations. The Acemoglu (1998) model implies that skill-abundant countries should develop skill-biased technologies. If technologically leading countries face high supply of skilled labour, they should develop technologies that are skill-biased. Acemoglu (2002a) claims that the skill-bias incentive of technological leaders determines the skill bias of world technologies. (Acemoglu 2002a)

Acemoglu (1998) shows on this endogenous technological change model that if South and North have similar patent systems, various technologies are developed in the North to meet the needs of these different groups of countries. While if the intellectual property rights protection is loose in the South, the North focuses on the development of skill-biased technologies. Meaning that if the R&D sector that develops new technologies cannot profit from the inventions developed for the South; it will concentrate only on the development of technologies benefiting the North.

The Caselli (1999) model implies that the countries with higher costs of learning associated to accommodate new technologies face lower technology diffusion. Generalising this result, the countries with relatively high share of skilled workers are more successful in accommodating new technologies and *vice versa*. If the skill endowment between the North and the South differ, the extent of technology diffusion will also differ across these groups of countries

1.2.3. Implications for Europe

In this thesis we undertake the empirical analysis at firm and country level. The country level analysis bring along two additional aspects for the analysis: the different incentives for different countries to innovate and the technology diffusion across different countries. As the aim of the thesis is to investigate and juxtapose the effect of technological change on labour demand in catching-up Europe, we distinguish between the two parts of Europe: the developed Western Europe and the catching-up Central and the Eastern European countries (CEEC) with the soviet background. We start with stylised facts on Europe and continue with the discussion on the implications of the above discussed theories on these two parts of Europe.

The data projections are organised as follows: beginning with discussion of the high-skilled employment shares and income level of the country; go further to investigate the skill upgrading across countries and finish by labour supply projections of workers with tertiary education. Dependent on the availability, we use also the USA data throughout this section for the comparison. There are two main proxies for skilled employment in the literature, the tertiary educated employment and the employment engaged in high-skilled occupations. This thesis uses the former in the following chapter on cross-country comparison and the latter in analysis on Estonian data in Chapter 4. These choices of proxies have been determined by the data limitations. As the more aggregated data on Europe is available for both of the indicators, we use the opportunity to provide the overview in terms of both of them.

Figure 1.1 plots the share of tertiary educated employment against GDP per capita for Europe and Figure 1.2 produces the same exercise in terms of high-skilled occupations. The pattern between educational division in employment and income is not very clear. The variation in the share of tertiary education employment decreases with the incomes of countries. The countries with relatively low income, below 20000 euros per inhabitant that also contain the group of CEECs have very variable shares of tertiary education.

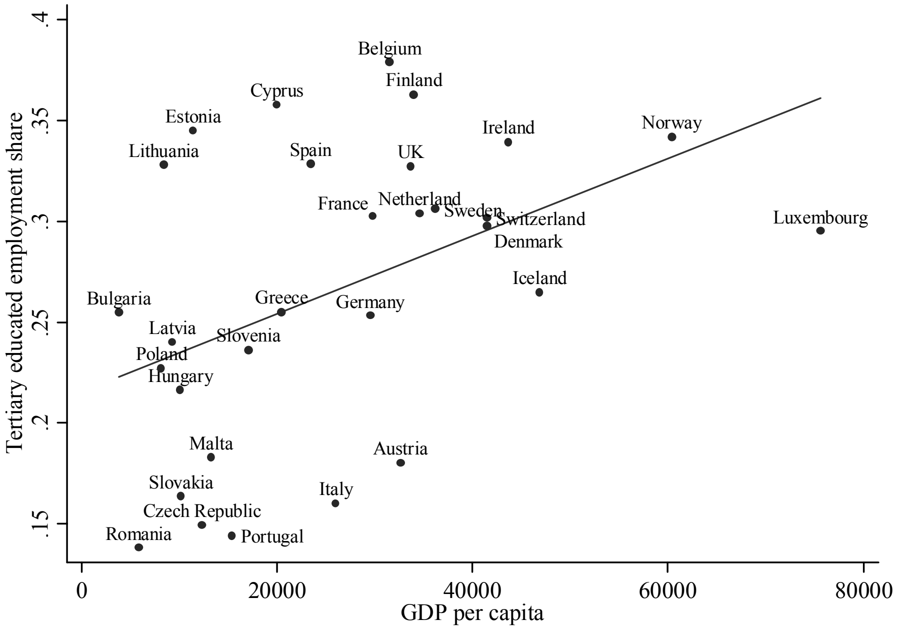

Figure 1.1. Tertiary education in employment and income per capita, 2007.

Source: Labour Force Surveys (Eurostat database 2009a), national accounts (Eurostat database 2009b), author's calculations.
Note: The GDP per capita is given in euros at current prices. The tertiary educated employment includes the workers with first and second stage of tertiary education (ISCED-97 groups 5 and 6).

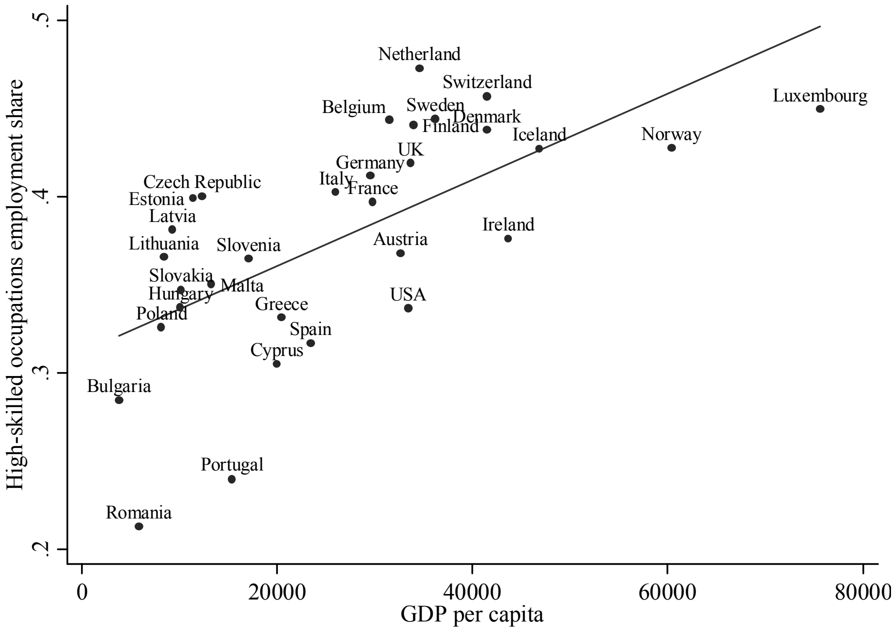

Figure 1.2. High-skilled occupations in employment and income per capita, 2007.

Source: Labour Force Surveys (Eurostat database 2009a, ILO database 2009a (for USA)), national accounts (Eurostat database 2009b), author's calculations.
Note: The GDP per capita is given in euros at current prices. The high-skilled occupations employment includes the workers from upper three groups of ISCO-88 classification (see Appendix A).

The overall trend between employment with tertiary education and income of a country is after all positive. In terms of high-skilled occupations employment the pattern is much clearer. High-income countries use more labour of the high-skilled white-collar occupations than the low-income countries. Interestingly, the US uses around 10 percentage points less workers in high-skilled occupations, compared to European countries with corresponding income per capita. One may also notice that the average utilisation of workers with tertiary education is higher than that of the workers employed in high-skilled occupations. Hence yet both of these proxies are related there are some discrepancies.

The overall trends showed that countries with higher income use more skills in production. We go further to investigate the skill accumulation across the same group of countries, see Figures 1.3 and 1.4. Both of these figures indicate that there is no trend between the skill accumulation and country's level of income. There is no evidence that the high-income countries witness faster skill accumulation as suggested by North-South trade hypothesis. The skill upgrading has taken place in the large majority of European countries over the last decade that indicates rather the validity of SBTC than the North-South trade hypothesis. If this is the result of SBTC as indicated by Berman *et al.* 1998 and Berman and Machin 2000, the SBTC have been pervasive all over the Europe.

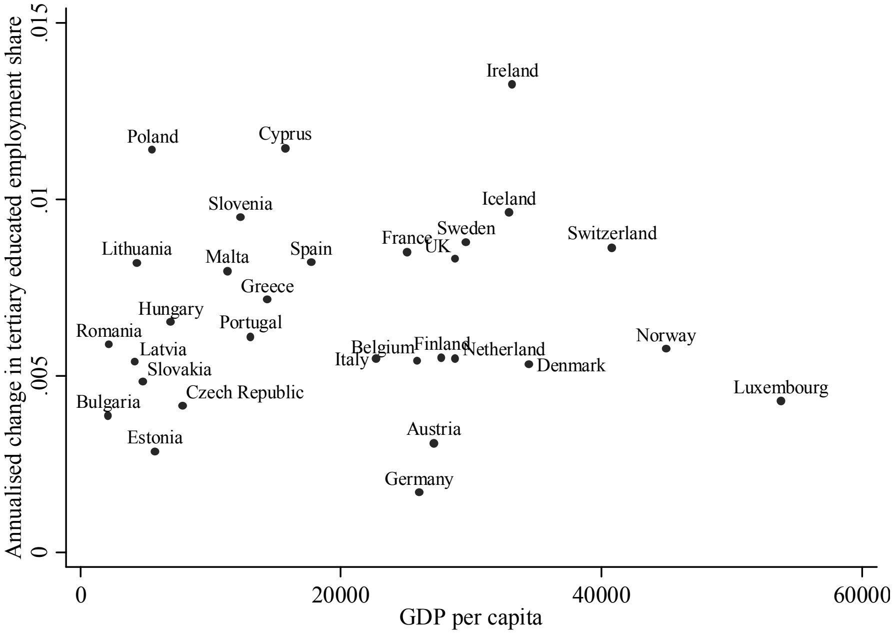

Figure 1.3. Tertiary education accumulation in employment and income per capita.

Source: Labour Force Surveys (Eurostat database 2009a), national accounts (Eurostat database 2009b), author's calculations.
Note: The GDP per capita is given in euros at current prices from 2002. The annualised change in the share of employment with tertiary education is based on the period 1998–2007; the series is shorter for some countries; for Lithuania and Sweden the year 2001, for Luxembourg the years 2003–2004 and for Austria the year 1999 are excluded due to statistical discrepancies.

Finally we illustrate the European supply of skills. The increasing relative supply of skills gives incentive to develop skill-biased technologies as sugges-ted by Acemoglu (1998). Figure 1.5 illustrates that the relative supply of skills has increased in Central and Eastern countries as in Western Europe and in US. The European and US data is not comparable in absolute terms, see the note under the Figure 1.5. The relative supply of skills has grown slower in CEECs than in Western Europe. This means that the incentives to take into use skill complementary technologies are stronger in Western Europe than in CEECs.

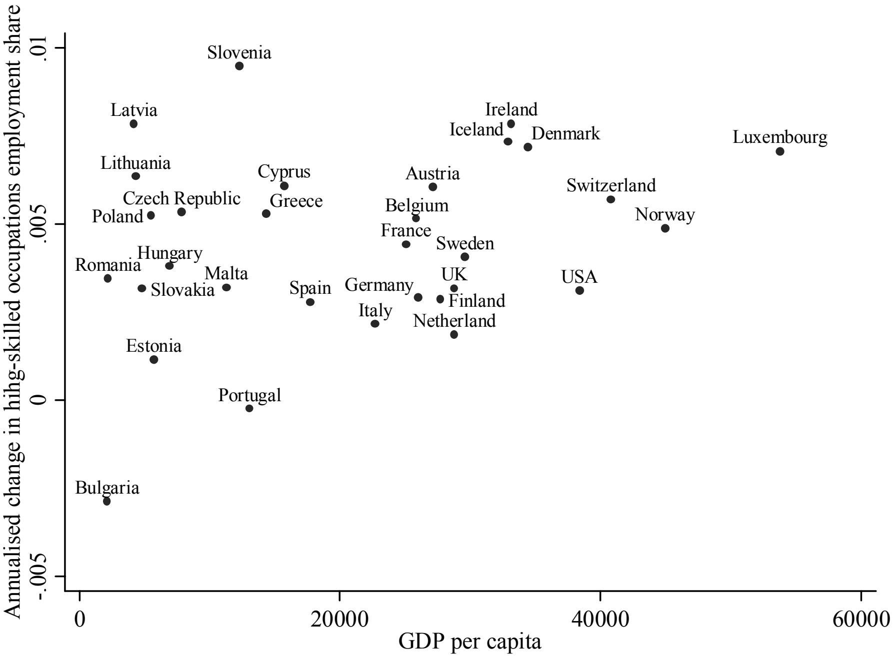

Figure 1.4. High-skilled occupations accumulation in employment and income per capita.

Source: Labour Force Surveys (Eurostat database 2009a, ILO database 2009a (for USA)), national accounts (Eurostat database 2009b), author's calculations.
Note: The GDP per capita is given in euros at current prices from 2002. The annualised change in high-skilled employment share is based on period 1998–2007. High-skilled employment denotes high-skilled white-collar employment (see Appendix A), the series is shorter for some countries, for Italy the years 2000 and 2004 are excluded due to statistical discrepancies.

Table 1.1 summarises the possible implications of various theoretical mechanisms for Europe. There are only two mechanisms, which effect on the skill demand is ambiguous over the group of Western Europe and CEECs, the factor and sector bias of the technological change. The former of them entail probably similar effects for Western and Eastern Europe, there is no reason to believe that the relative productivity of skills differ substantially across Europe. The latter, the sector bias, bring along probably more changes in skill demand for the CEECs than Western Europe. The sector bias depends on the different total factor productivity across industries, because the total factor productivities across industries are probably more dynamic in the catching-up countries.

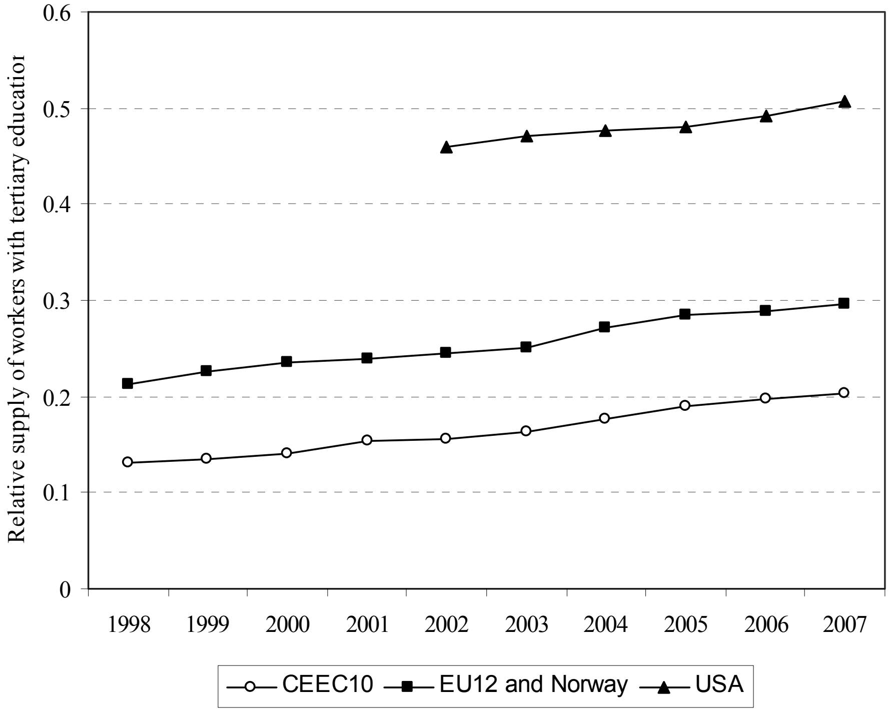

Figure 1.5. The relative supply of tertiary education.

Source: Labour Force Surveys (Eurostat database 2009a, ILO database 2009b (for USA)), author's calculations.
Note: The relative supply of skills is the ratio of population with tertiary and less than tertiary education. The data on Europe and USA is not comparable in absolute terms. European data is based on population aged 15–74; the US data origins from ILO database and is based on population 25 and over. In addition the US data is based on a wider definition of tertiary education (based on ISCED-76).

All the other theoretical mechanisms have different implications for Western and Eastern Europe. Higher share of high-skilled workers and higher relative supply of skills implies lower new technology adoption costs and incentive to develop skill-biased technologies in Western Europe. The trade with lower-income countries induces the abolishment of low-skill jobs. These factors imply a pressure for skills upgrading. Already large share of skill-intensive industries and slower capital accumulation implies lower skills upgrading for Western Europe compared to CEECs. The knowledge spillover from trade is probably also less important for Western Europe.

Table 1.1. Technology-related mechanisms affecting skill demand in Europe.

Mechanism	Impact on skill demand	
	Western Europe	CEECs in Europe
Factor-biased technological change	Higher/lower relative productivity of skilled labour → faster/slower skills upgrading	
Sector-biased technological change	Higher/lower total factor productivity growth in skill-intensive industries → faster/slower expansion of skill-intensive industries → faster/slower skills upgrading	
Capital accumulation growth	Lower productivity of capital → slower increase in the capital stock ↔ capital skill complementarity → slower skills upgrading	Higher productivity of capital → faster increase in the capital stock ↔ capital skill complementarity → faster skills upgrading
Increasing supply of skills	High growth of supply of skills → development of skill complementary technologies → skills upgrading	High growth of supply of skills → adoption of skill complementary technologies from the West → skills upgrading
Adoption costs	Higher share of high-skilled workforce → lower adoption costs → faster technology diffusion and faster skills upgrading	Lower share of high-skilled workforce → higher adoption costs → slower technology diffusion and slower skills upgrading
North-South trade	Exposition to trade with low-income countries → increase in relative prices of skilled labour intensive good → increase in relative wages and demand of skilled workers	Exposition to trade with high-income countries → increase in relative prices of unskilled labour intensive good → increase in relative wages and demand of unskilled workers
Outsourcing	Displacement of labour-intensive parts of production to low-income countries → skills upgrading	FDI oriented on labour-intensive production → reduced demand for skills

Source: Author's tabulation.

Contrarily, the CEECs have more capacity for skills upgrading due to the lower share of skill-intensive industries and faster growth of capital accumulation. Higher adaption costs and North-South trade involve lower skill upgrading compared to Western Europe. The trade with technologically more advanced countries entail a high potential for knowledge spillover and technology diffusion. Lower the new technology adoption costs, stronger the effect of new skill-biased technologies developed in the West to CEECs.

The theories discussed in this section are empirically tested in Chapters 2 and 4. The Chapter 2 investigates whether the skill upgrading in Europe has been factor or sector biased and whether there is an evidence of technology diffusion in Europe. This analysis is undertaken at the country and industry level. The Chapter 4 investigates the effect of technological change on skill upgrading and the interaction effects with trade in a CEE country. This analysis is performed on the firm-level data on Estonia.

1.3. Technological change and labour demand

The purpose of this section is to present the pattern how innovation affects employment. As we are interested in the outcome of innovation, we do not investigate the innovation process itself. We differentiate between product and process innovation as these bring along different implications. This is a different approach from the one we use in the Chapter 3. But the purpose here is to provide a wider background how different innovations affect firm. Nevertheless the resulting labour demand is similar to the one we use in the Chapter 3.

A suitable model for this purpose is the one proposed by Greenan and Guellec (2001). They assume that firms produce homogenous good under the Cobb-Douglas production function. Hence, we assume that under the constant elasticity of substitution (CES) production function (or the function used in Chapter 3) the production factors are moderately substitutable with the elasticity of substitution equal to one. Greenan and Guellec (2001) propose a Cobb-Douglas production:

$$Ys = AK^{\alpha_1}L^{\alpha_2}, \tag{1.3}$$

where K denotes capital, L labour and A is a Hicks neutral technical change. The technical change parameter consist of two parts $A = A'T^{\alpha_0}$, where A' denotes the common technology in the economy and T^{α_0} represents the production technology used in the firm. If $\alpha_0 > 0$, the improvement in the production technology in the firm or process innovation in the firm increases the productivity of a firm and the amount of production, if the amount of production inputs are unchanged. Hence, process innovation acts as a positive supply shock. The firm minimizes its costs with respect to given output. This optimization problem results in the following cost function:

$$C = ZA'^{-1/e}T^{\alpha_0}{}^{-1/e}R^{\alpha_1/e}W^{\alpha_2/e}Ys^{1/e}, \tag{1.4}$$

where R denotes price of capital, W price of wages; and $Z = (\alpha_1/\alpha_2)^{(\alpha_2-\alpha_1)/(\alpha_1+\alpha_2)}$ and $e = \alpha_1 + \alpha_2$.

The firm faces a constant elasticity demand function:

$$Yd = BP^{-\beta}, \tag{1.5}$$

where P denotes prices, β the elasticity of substitution, $\beta > 1$; and B the novelty or quality of the goods on the market. The novelty or quality of the goods on the market consist of two parts $B = B'G^{\beta_0}$, the novelty or quality common to the economy and the novelty or quality of the goods supplied by the firm. If $\beta_0 > 0$ the improvement of a good in the market at given prices increase the demand for the good. Or otherwise, product innovation acts as a demand shock for firm.

Greenan and Guellec (2001) assume that firm acts as a monopoly and sets price with a constant mark-up over marginal cost. The monopoly profit maximising price equals $P(Ys) = C'(Ys)/(1-1/\beta)$. The firm sets prices dependent on its' marginal cost of production (that may vary across firms) and the elasticity of a demand curve. Deriving marginal cost from the equation 1.4 and substituting it to the monopoly price set equation yields:

$$P(Ys) = \frac{1}{e(1-1/\beta)} ZA'^{-1/e} T^{\alpha_0^{-1/e}} R^{\alpha_1/e} W^{\alpha_2/e} Ys^{(1-e)/e} \tag{1.6}$$

The firm produces the amount demanded at the profit maximising price. Inserting 1.6 to 1.5 and denoting the produced (*Ys*) and demanded amount (*Yd*) by *Y*, reveals firm's supply curve:

$$Y = \frac{B'G^{\beta_0}}{(e-e/\beta)^{-\beta}} \left[ZA'^{-1/e} T^{\alpha_0^{-1/e}} R^{\alpha_1/e} W^{\alpha_2/e} Y^{(1-e)/e} \right]^{-\beta} \tag{1.7}$$

Solving for *Y*, results in the reduced form of firm production (see Equation 1.8). Inserting 1.8 to the price equation 1.6 gives reduced form of price, Equation 1.9. Solving for the firm cost minimisation problem and substituting out firm production via Equation 1.8 reveals the reduced form of factor demand equations. The impact of innovation on factor demands is identical across production factors in this case, because innovation enters to the production function via Hicks neutral technical change. As the impact of innovation on capital demand is not of a vital interest of this thesis, we will skip the capital demand equation. Equation 1.10 presents the labour demand. Equations 1.8, 1.9 and 1.10 depict the behaviour of the firm. Variables are logarithmic (logarithms are presented in lowercase letters) and differentiated with respect to time.

$$\dot{y} = c_y + \frac{e\beta_0}{\theta}\dot{g} + \frac{\beta\alpha_0}{\theta}\dot{t} - \frac{\beta\alpha_1}{\theta}\dot{r} - \frac{\beta\alpha_2}{\theta}\dot{w} \tag{1.8}$$

$$\dot{p} = c_p + \frac{(1-e)\beta_0}{\theta}\dot{g} - \frac{\alpha_0}{\theta}\dot{t} + \frac{\alpha_1}{\theta}\dot{r} + \frac{\alpha_2}{\theta}\dot{w} \tag{1.9}$$

$$\dot{l} = c_l + \frac{\beta_0}{\theta}\dot{g} - \frac{(1-\beta)\alpha_0}{\theta}\dot{t} + \frac{(1-\beta)\alpha_1}{\theta}\dot{r} - \frac{(1-\beta)\alpha_1 + \beta}{\theta}\dot{w}, \tag{1.10}$$

where $\theta = e + \beta(1 - e)$ and is positive under conventional parameter values. If firm operates under constant returns to scale production ($e = \theta = 1$), then process innovation reduces prices, under lower prices the amount demanded is larger and labour demand increases. Under the same conditions product innovation does not affect prices, but expands demand resulting in enlarged production and labour demand. The adjustment process is rather robust on the size of e or returns to scale. The only exception is that under the increasing returns to scale also the product innovation reduces prices and under decreasing returns to scale the product innovation increases prices. Table 1.2 summarises how innovation impacts labour demand.

Table 1.2. Impact of innovation on labour demand at the firm level.

	Adjustment process	Impact on labour demand
Product innovation	Product innovation elasticity of demand (β_0) is large, high improvement of quality or novelty of new goods → large expansion of demand	Labour demand increases
	Product innovation elasticity of demand (β_0) is small, new goods replace the old ones, novelty of goods is low → demand increases moderately or remains unchanged	Labour demand increases moderately or is unchanged
Process innovation	Process innovation elasticity of productivity (α_0) is low, new technology improves moderately the efficiency of production and price elasticity of demand is large ($\beta > 1$) → expansion of demand due to price reduction compensates the factor saving effect	Labour demand increases
	Process innovation elasticity of productivity (α_0) is large, the improvement in the efficiency of production is large and the price elasticity of demand is low [a)] → production factors are saved and demand does not expand much due to the price reduction	Labour demand increases moderately, is unchanged or decreases

Source: Author's tabulation based on the model by Greenan and Guellec (2001).
[a)] This conclusion does not result from the model by Greenan and Guellec (2001) as they assume monopolistic price setting and monopolist would not participate in the market with price elasticity of demand lower than one.

The impact of innovation on labour demand is robust to the returns to scale. The impact of product innovation on labour demand depends on the product innovation elasticity of demand. If new products induce improved novelty or quality and do not just replace the old products in the market; the product innovation elasticity of demand should be positive and so the impact of innovation on labour demand. The impact of process innovation on employment depends on the process innovation elasticity of productivity and price elasticity of demand. If new processes enhance productivity and lower prices, and the price elasticity of demand is large ($\beta > 1$); the impact of process innovation on labour demand is positive.

Smolny (1998) sets up a more sophisticated model taking into account also the effect of competitors' innovation and capacity constraints. The competitors' innovation reduces the demand and reduces firm's employment. The capacity constraints increase the variance in prices, but reduce the variance in output and employment. Similarly to the model by Greenan and Guellec (2001) the model by Smolny (1998) imbeds that product innovation expands demand and process innovation reduces costs. There are no significant differences between these models in the adjustment of process due to process innovation. In terms of product innovation, the model by Smolny (1998) assumes that firm innovation affects also the elasticity of demand; it predicts that product innovation decreases the elasticity of demand and hence reduces competition. If product innovation brings along the smaller uncertainty about the demand; the variation in output and prices decrease, while output and employment increase.

The model by Smolny (1998) provides also implications for the industry level analysis. Sectors with a lot of product innovation are more monopolistic, firms change prices less often. These industries face also lower demand uncertainty; products are specialised and competitors' innovation has smaller effect on firms' demand. Hence, industries dominated by product innovation have lower variance in prices. Sectors with a lot of process innovation experience a tight price competition and higher price elasticity of demand. Both of these effects bring along larger variance of prices.

In sum, the model by Smolny (1998) leaves the effect of industry or firm level product or process innovation on employment ambiguous. The model by Greenan and Guellec (2003) predict under conventional parameter values positive impact of product and process innovation on employment at the firm level. The results of a particular theoretical model depend on the assumptions or simplifications taken. The main lesson of this section is that nevertheless it is possible to show analytically how product or process innovation impact firm's labour demand, the effect depends on many factors and is hardly predictable from theoretical model. We test these effects empirically in Chapter 3 on Estonian data.

2. SKILLS STRUCTURE OF EU COUNTRIES: RESULT OF DEVELOPMENTS IN INDUSTRY STRUCTURE OR TECHNOLOGICAL CHANGE

2.1. Introduction

Many countries have witnessed a marked increase in the demand for skilled workers since the 1970s. These developments have been registered in high-income as well as in developing countries. The most common explanation for these developments has been skill-biased technological change (SBTC) stemming from progress in, for example, Information and Communication Technologies (ICT) (Autor, Katz, Krueger 1998; Kelly 2007). Positive relations have been found also between demand for skills and research and development expenditures, innovation or other technology proxy variable. Alternative explanations for these upgrading of skills have been globalisation via foreign trade (Paul and Siegel 2001), including outsourcing (Geishecker 2006; Minondo and Rubert 2006); and organisational change (Caroli and Van Reenen 2001; Piva *et al.* 2005).

The empirical literature investigating skill-biased technological change has mostly concentrated on high-income countries[2], but some recent contributions have investigated the issue for less developed countries (Kijima 2006 for India; Kang and Hong 2002 for Korea). The cross-country analysis of skills upgrading usually proceeds from shift-share analysis. The shift-share analysis disentangles a country's skills upgrading into between industry and within industry effects. Between industry effects capture changes in the skill structure due to shifts in the industry composition, while within industry effects capture changes due to shifts in individual industries' skill structure. The within industry developments in the demand for skills are mostly attributed to technological change, but organizational change and trade could also play a role. The cross-country comparative studies have also limited themselves to developed OECD countries (Berman *et al.* 1998) or added a scattered selection of developing countries around the world (Berman and Machin 2000).

From this it follows that under a straightforward decomposition, a country's skills structure is a combination of the developments between industries and within industries. Reallocation of labour between industries is usually related to the level of economic development in a country. Raiser *et al.* (2004) have summarized the cross-country studies on the relationship between employment structures and economic development. They concluded that the richer the country, the smaller its employment share in agriculture and industry, and the

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[2] E.g. Autor *et al.* 1998, Paul and Siegel 2001, Baltagi and Rich 2005 for the US; Berman, Bound and Machin 1998 for the US, UK and selected developed countries; Gera *et al.* 2001 for Canada; Edwards 2004 for South Africa; Salvanes and Førre 2003 for Norway; Sakurai 2001 for Japan; Kelly 2007 for Australia.

larger its employment share in services. Elsewhere, developments in within-industry skill structures were found to be similar in high and middle income countries (Berman and Machin 2000). Continuing along this line of thought, countries at different levels of economic development should display similar developments in skill structures within industries, but independent developments between industries.

In 2004, the European Union entered a new era, because ten new less-developed countries joined the union, of which eight were Post-Soviet states. The long-term goal of the EU is not only to become the most competitive economy in the world (Blanke 2006), but also the convergence of the Member States' income levels (The Council of the European Union 1999). One of the key factors behind economic growth is the amount and quality of the production factors. Labour decomposition in a country provides a straightforward picture of where the country is standing in terms of its industry structure and within-industry skill use. The target of income convergence for countries cannot be achieved if some countries operate with less advantageous industry structures or production technology. Investigation of the dynamic developments in skill structures makes it possible to explain past developments and provide input for future developments. Expectancies about future developments in skill structures again provide essential input for educational and labour market policies.

The purpose of this chapter is to investigate developments in skill structures in EU countries. We will address the question whether countries at different levels of development undergo similar or different developments in skill decomposition between and within industries. To do so, we will classify the components of the developments in skill structures for 25 EU Member States in a static and a dynamic framework. We will also test the simultaneity of within industry skills upgrading across countries, tracking down technology spillovers across EU members. Two definitions of skilled workers will be used: the employment share of non-production occupations and the employment share of high-skilled non-production occupations[3]. In terms of time, we will take the period of 2000–2004 for the dynamic analysis and the year 2004 for the static analysis.

Our study contributes to the literature in two areas. First, we cover the skill structure of a broad range of countries at different stages of development, but from one geographical region. Both the post-communist new EU countries and the “old” high-income Western EU members are included in the study, which enables us to compare the results across two groups of countries. The strong points of our study are representativeness and comparability of the data as we

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[3] Alternative measures of skills could be the wage bill share of non-production workers, the share of university degree workers or a codification of a special skill (e.g. cognitive) in a particular occupation. Despite minor differences between the occupational classifications used in different countries, the International Standard Classification of Occupations (ISCO-88) is considered to be consistent across countries at the aggregated level (Elias and McNight 2001).

proceed from methodologically comparable labour force surveys of individual countries. Second, unlike the existing literature, we also provide a static analysis of the countries' skill structures. Contrary to the dynamic analysis, the individual countries are not compared to their mean over time, but to the average of the group of countries. This approach is an effective tool, providing a straightforward explanation as to why any particular country lacks behind in skill use: whether it is due to the industry structure or to the within industry skill composition. This methodology is a potential tool for similar studies using cross-sectional data of countries with diverse economic backgrounds.

Our results suggest that in a static framework the between industry effects explain most of the differences in the countries' skill structures. In a dynamic analysis, similarly to previous studies, we find that the within industry effect is behind most of the changes in skills structure, likely as a result of skill-biased technological change. Within industries skills upgrading is, especially in high-income EU members, similar in the same industries across countries, possibly reflecting the technology diffusion over the EU.

The chapter is organized as follows. The next section provides some background information and an overview of previous empirical studies. Section 2.3 describes the data. Section 2.4 presents the static analysis of EU skill structures in 2004. Section 2.5 presents the changes in EU occupational structures over the period 2000–2004 and discusses the correlations between the within industry developments. The last section summarizes the results.

2.2. Background

The countries under investigation in this chapter have very diverse economic backgrounds. The group of countries includes all Members States of the EU in the year 2004, including the 10 new Member States (NMS10) that joined in 2004, of which eight were Post-Soviet countries. In terms of macrovariables, in 2002, labour productivity in the new EU countries was approximately 50% of that of the old EU15 members. The new members' GDP per capita in purchasing power parity adjusted terms amounted to 46.4% of the EU15 average, and the unemployment rate was almost twice as high (14.7% compared to 7.7%) as the EU15 average (European Commission 2003a, p. 44).

The differences in the relative prices of labour and capital are also noticeable. Labour costs in the new Member States were considerably lower than those in the EU15 countries. In 2003, monthly labour costs in the EU15 were 3,333 EUR, while the labour costs in NMS10 amounted to only approximately one fourth of this amount, or 887 EUR (Eurostat database 2005). Capital costs were also in favour of the new members, although the differences in capital costs are not comparable to those in labour costs. The implicit tax rate on capital income for EU15 was 19.2%, whereas for new members it was 12.8%; the average statutory tax rate on corporate income was 30.1% for old members and 20.6% for new members (European Commission 2005, pp. 88, 93).[4]

According to the Heckschler-Ohlin model, the new Member States that witness a lower relative price of labour should be net exporters of labour-intensive goods, whereas the old Member States should be net exporters of capital-intensive goods (see e.g. Leamer 1984; 1992). Taking into account the complementarity of capital and high-skilled labour, and the substitutability between capital and low-skilled labour, the occupational structure of the new members compared to the old members should be inclined towards low-skilled labour.

However, the coexistence of diffusion of technology from the new to the old members and the witnessed skill-biased technological change in the old Member States, should over time lead to skills upgrading for both country groups. The diffusion of new technologies may take place via both international trade and capital flows, in particular via foreign direct investments (FDI). Barrell and Pain (1997) estimated the role of FDI in the process of technological change in developed Europe, proceeding from FDI instead of total capital flows as the former are "intimately connected to the transfer of technologies between nations" (Barrell and Pain 1997, pp. 1770–1771). In 2001–2003, the accumulated FDI inflow from outside the EU25 countries to new member countries (then accession countries) amounted to only 17% of the total flows to accession countries (Eurostat 2005, p. 52). Thus, a large share of the new members' FDI originates from the EU15 countries.

Berman *et al.* (1998) found evidence for a skill-biased technological change (SBTC) in both developed and developing countries. They carried out a cross-country analysis, based on the argument that due to modern international communication and trade, the technological change occurring in one country (notably the USA) is quickly adopted in other countries. Moreover, the more intensive use of labour-saving technologies decreases the demand for low-skilled workers all over the world. They tested their hypothesis by decomposing the differences in the employment share of non-production workers (which they considered to be skilled) into between industry and within industry components. According to their cross-country comparison of manufacturing sectors in the world's 12 richest countries (in terms of GNP per capita), the share of skilled workers increased in all of the investigated countries during the 1970s and 1980s, amounting on average to a 0.4 and 0.3 percentage point increase per year, respectively. The increase is largely attributed to the within effect, which accounted for 84% and 92% of the change in the respective decades. Thus, the increase in the share of skilled workers was mostly the result of shifts towards skilled workers within industries, instead of a different employment allocation

[4] Many observations on implicit tax rates are lacking for the new member countries. The countries included in the NMS10 figures are the Czech Republic, Estonia, Lithuania and Slovakia. One should also notice that the tax bases could differ across countries.

between industries (Berman *et al.* 1998, pp. 1257–1258). This within industry effect towards skilled labour can be interpreted as evidence for skill-biased technological change. Similarly, the above-mentioned authors found that the increase in the share of skilled workers, in spite of increasing or stabilized relative wages for these workers, indicated SBTC in developing countries (Berman *et al.* 1998, p. 1271).

Empirical research on skill-biased technological change has used two methods to detect similar trends across countries in skill-biased technological change (Berman and Machin 2000, p. 18). One method tests whether skills upgrading has occurred in the same industries across countries. The other method tests for technology transfers as correlations between skills upgrading and some global input indicator of technological change (computer usage, R&D intensity, see e.g. Machin and Van Reenen (1998)). In this chapter, the first method is used. In addition to testing the simultaneous spread of the technological change also the correlations between countries' within industry skills upgrading are investigated (see Berman and Machin 2000).

2.3. Data

The analysis of this chapter employs micro data from Labour Force Surveys for each of the 25 countries being members of the EU since May 2004. The data have been collected in each of the EU Member States and are supplied to Eurostat by each Member State. Member States have the obligation to provide data compatible with EU definitions and to follow the same quality standards (European Commission 2006).

The sampling design of EU Labour force surveys varies across the Member States, but the results are weighted so as to represent the working age population of a country. The working age population has been defined in most of the countries as the age group “15+” or “15–74”. Most of the surveys are quarterly rotating panel surveys with an average sampling rate of 0.49% per quarter in second quarter of 2004. (European Commission 2006) Labour Force survey estimates per year have been used for this chapter. Because, first, changes in skill structure are time consuming and quarterly data do not provide any additional insights about the problem and, second, yearly data increases the reliability of the estimates.

The queries for the data sets used in this chapter were made in Eurostat and were provided to the authors. For each country the data set includes the employment distribution across industries and occupations. The occupational distribution of EU Labour Force surveys follows the ISCO88 classification, i.e. International Standard Classification of Occupations of the International Labour Organization (ILO). The ISCO occupational groups were provided to authors at the one-digit level, containing 10 major occupational groups and one group where occupation was unknown (see appendix A). The industry distribution of

EU Labour Force surveys follows the NACE Rev. 1 classification, i.e. Statistical Classification of Economic Activities in the European Community. Again the industry classification was provided at the one-digit level including 17 major industries plus one group where industry type was unknown (see appendix B), cf. European Commission (2003b).

Both of the classifications are also comparable outside the EU. The ISCO is as ILO reference classification internationally well recognised and widely used. The NACE classification is closely related to the ISIC Rev. 3 classification, i.e. United Nations (UN) International Standard Industrial Classification of All Economic Activities. The latter is a UN reference classification that is a product of international agreement and has been followed by many countries internationally (see European Commission: CIRCA 2008).

Eurostat provided these survey estimates of industries' occupational distribution as yearly employment volumes, all further calculations have been made by the authors. The time span is reduced to 2000–2004 as for this period data were available for all of the 25 countries which were EU members from May 2004.

2.4. Static analysis, 2004

2.4.1. Cross-country shift-share analysis

This section investigates the cross-country differences of the occupational structures in the EU25 countries for one year, 2004. The static cross-country shift-share analysis is used to distinguish between the between and within sectors effects. The methodology is adopted from Esteban (2000), who used the methodology to decompose EU regional productivity differentials.

The number of countries, k, in the analysis is 25, $k = 1, \ldots, 25$. The occupational shares are based on the one-digit ISCO classification level ('major groups'), $j = 1, \ldots, 11$, with one occupational group added to account for the share of unknown occupations (see Appendix A). The industry shares are presented at the one-digit NACE classification level, $i = 1, \ldots, 18$, where again one sector includes all unknown economic activities (see Appendix B).

The deviation of a particular country's occupational structure from the average occupational structure in the EU countries has been decomposed into three effects: the *between* effect (I_j^k), the *within* effect (II_j^k) and the *interaction effect* (III_j^k). The between effect is also referred to as the *industry mix component*, or the *industrial effect*, whereas the within effect is also labelled as the *occupational effect* or the *technology effect.*

The difference between country k's share of occupation j and the EU25 cross-country average share of occupation j is denoted as d_j^k. This difference is the sum of the *between, within and interaction effects:*

$$d_j^k = o_j^k - \overline{o}_j = I_j^k + II_j^k + III_j^k, \qquad j = 1, \ldots, 11 \tag{2.1}$$

The variable o_j^k denotes the share of occupation *j* of total occupation in country *k*. The variable $\overline{o}_j$ is the EU25 cross-country average of the share of occupation *j* of total occupation and is calculated as follows: $\overline{o}_j = \sum_k o_j^k / 25$, $k = 1, \ldots, 25$.

The shares of each occupation sum up to one for each country *k* and also for the EU average, i.e. $\sum_j o_j^k = 1$ and $\sum_j \overline{o}_j = 1$. The shares of each occupation for each industry and the shares of each industry sum up to one for every country, i.e. $\sum_j o_{ij}^k = 1$ for every industry *i* and country *k*; $\sum_i \overline{o}_{ij} = 1$ for every industry *i* and $\sum_i s_i^k = 1$ for every country *k*, $\sum_i \overline{s}_i = 1$ for the cross-country average, where $\overline{o}_{ij} = \sum_k o_{ij}^k / 25$ and $\overline{s}_i = \sum_k s_i^k / 25$.

The *between effect* (I_j^k) captures the differences in the occupational structures due to the differences in the employment allocation between sectors:

$$I_j^k = \sum_i \overline{o}_{ij} \left(s_i^k - \overline{s}_i \right) \tag{2.2}$$

The variable $\overline{o}_{ij}$ denotes the EU average of the share of occupation *j* in industry *i*, s_i^k is the employment share of industry *i* in country *k*, and $\overline{s}_i$ is the EU average of the employment share of industry *i*. If the occupational structure within the production sectors of a country were equal to the EU average for every economic activity, then the differences in the country's overall occupational structure would be wholly accounted for by the differences in employment allocation between the production sectors. In other words, if the technology in use within a production sector were the same for all the EU countries, the occupational structures of individual countries could still differ because of the different importance of each production sector.

The *within effect* (II_j^k) shows the differences in the overall occupational structure due to the different occupational structures of each production sector:

$$II_j^k = \sum_i \left(o_{ij}^k - \overline{o}_{ij} \right) \overline{s}_i \tag{2.3}$$

The variable o_{ij}^k denotes the share of occupation *j* in industry *i* in country *k*, $\bar{o}_{ij}$ is the corresponding variable for the EU, and $\bar{s}_i$ is the employment share in industry *i* for EU. If the industry structure in terms of employment were the same across the EU countries, a country's overall occupational structure could differ because of the different occupational structures within industries. Thus, the within effect reflects the differences in occupational structures due to differences in the technologies used in the same production sectors.

The *interaction effect* (III_j^k) accounts for the effect of the interaction between the share of occupation *j* across industries and the employment shares of industries. The interaction effect is positive if, compared to the EU average, a particular country's occupation *j* is more important for the sectors that the country is specialized in, or occupation *j* is unimportant for the sectors that the country is not specialized in. The opposite holds if occupation *j* is unimportant for the sectors that a country is specialized in, or occupation *j* is important for the sectors that the country is not specialized in. The interaction effect is derived as follows:

$$III_j^k = \sum_i \left(o_{ij}^k - \bar{o}_{ij}\right)\left(s_i^k - \bar{s}_i\right) \qquad (2.4)$$

The sum of the *between*, *within* and *interaction* effects for a particular occupation in a country is equal to the total difference between the share of the occupation in the country and the cross-country average share of the occupation in the EU25 (see equation 2.1).

2.4.2. Shift-share analysis, 2004

The differences between the employment shares of each occupation in individual countries and the corresponding EU average for 2004, are shown in Appendix C. A positive (negative) sign implies that a country's share of an occupation is above (below) the EU25 average. The armed forces (isco 0) and the unknown occupational group are left out of the discussion for the rest of the analysis (see Appendix A for the isco classification). Occupation groups isco 1–3 comprise the high-skilled non-production occupations: legislators, senior officials and managers (isco 1), professionals (isco 2), technicians and associate professionals (isco 3). For isco 1, the UK and Ireland are clearly above the cross-country average, whereas Cyprus is significantly below. For isco 2, Belgium and the Netherlands have the highest occupational shares, whereas Portugal has the lowest share. For isco 3, Austria and Germany have the highest shares, and Ireland and Greece the lowest.

The groups isco 4 and 5 represent the low-skilled non-production occupations: clerks (isco 4) and service workers as well as shop and market sales workers (isco 5). Belgium and Luxembourg have the highest, and Lithuania and Estonia the lowest shares in isco 4. For isco 5, Sweden has the highest, and Italy and Belgium the lowest shares. The groups isco 6 to 8 represent the skilled production occupations: skilled agricultural and fishery workers (isco 6), craft and related trades workers (isco 7), and plant and machine operators together with assemblers (isco 8). Poland has by far the highest share in isco 6. The Czech Republic and Slovakia have the highest shares in isco 7, while the Netherlands has the lowest share in this occupational group. Slovenia has the highest, and Cyprus the lowest share in isco 8. Finally, for the unskilled production occupations in isco 9 (elementary occupations), Cyprus and Spain have the highest, and Slovenia and Sweden the lowest shares.

It is difficult to draw general conclusions by comparing country's every isco group shares to the cross-country EU averages. This also holds when for each occupational group the total differences between the national and the EU averages are decomposed into the industrial, within and interaction effects. These effects are shown in Appendix D, and will not be discussed further. Instead Tables 2.1 and 2.2 present the results of a shift-share analysis for the year 2004 with the number of occupational groups reduced to two, in order to facilitate the presentation of the results. The major occupational groups have been aggregated into two occupational classes in two different ways:

1) Non-production *versus* production occupations.
2) High-skilled non-production *versus* all other occupations (i.e., low-skilled non-production and production).

The first division, the non-production *versus* production division, is widely used in the literature of skill-biased technological change, although until now only for dynamic analyses (Berman *et al.* 1998, Berman *et al.* 2000). The second division, the high-skilled non-production *versus* the remaining occupations, is used to check whether the results are robust to different definitions of skills.

It follows that the new Member States employ fewer workers in non-production (Table 2.1) and high-skilled non-production (Table 2.2) occupations than the old Member States. The correlation between the share of non-production occupations or the share of high-skilled non-production occupations and a dummy variable characterizing the country type (old or new member), is significant at the 1% level. Among the old Member States, Greece, Portugal and Spain have a low share of non-production and high-skilled non-production occupations, even by comparison with the new Member States. Therefore the variation is high within the old Member States group; the standard deviation is 0.069 for non-production and 0.059 for high-skilled non-production occupations. Within the EU15 group, the Netherlands has the highest share of non-production and high-skilled non-production occupations, while Portugal has the lowest shares. The NMS10 group is more homogeneous, with standard deviations of 0.038 and 0.029, respectively. Only Lithuania and Poland stand out with low shares of non-production occupations, whereas Cyprus has a very low share of high-skilled non-production occupations.

Tables 2.1 and 2.2 show that the between effect dominates the within effect for both country groups and both skill classifications. However, there is no statistically significant correlation between either of the effects and the country type. Figure 2.1 shows the results of the shift-share analysis for the non-production occupations, while Figure 2.2 shows these results for high-skilled non-production occupations. The figures summarize the results in Tables 2.1 and 2.2. The abbreviations of the countries used in the figures are included in the first column of Tables 2.1 and 2.2. For the old Member States of the EU15, the results are more or less similar, the exceptions being Greece, Portugal and Spain. In general, the old Member States employ more workers in high-level occupations, because their industrial structure is inclined towards the sectors that use more high-skilled workers, and because their industry production technologies rely more intensively on high-skilled workers. In this group, only the between effect for Ireland and the within effect for the UK depend on the choice of one or the other division.

Greece, Portugal and Spain among the old Member States, and Latvia, Lithuania, Poland and Slovakia among the new Member States employ fewer workers than on average in high-level occupations. This is due to their industry structure being inclined towards the sectors that employ more low-skilled workers, as well as production technology that intensively uses low-skilled workers. Malta is the only country consistently entering the category where the industry structure is inclined towards high-skilled workers, although the production technology is inclined towards low-skilled workers. The Czech Republic and Slovenia belong in both divisions to the group with a low-skill intensive industry structure and high-skill intensive production technology. The rest of the NMS10 group clearly employs more workers in industries that intensively use low-skilled workers, whereas the magnitude of the within effect (the technology in use) is dependent on the choice of measure of skilled occupations, i.e. high-skilled non-production occupations or all non-production occupations.

Table 2.1. Shift-share decomposition of non-production occupations in the EU in 2004.

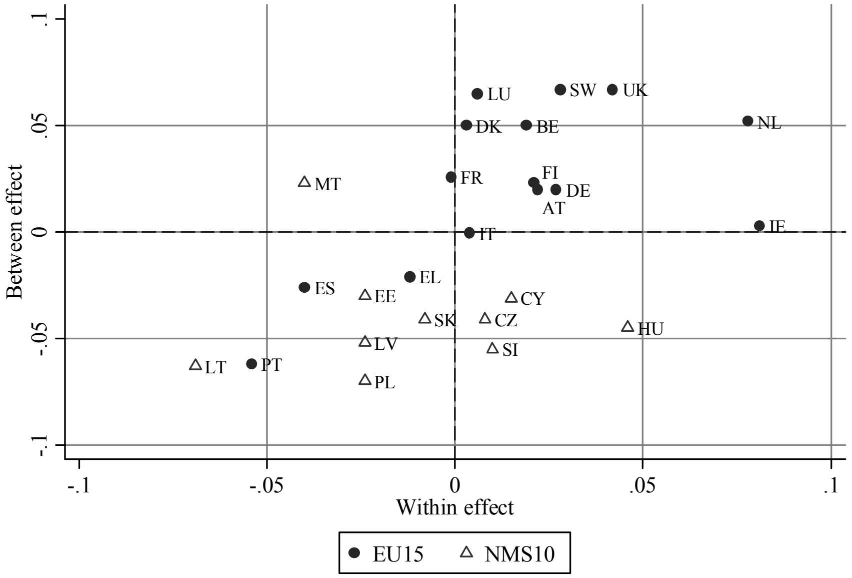
	Share in 2004	Difference from EU25 cross-country average share	Between effect (size and share, %)		Within effect (size and share, %)		Interaction effect (size and share, %)	
Belgium (BE)	0.690	0.071	0.050	70	0.019	26	0.003	4
Austria (AT)	0.656	0.038	0.020	53	0.022	58	-0.004	-11
Denmark (DK)	0.676	0.057	0.050	86	0.003	5	0.005	9
Finland (FI)	0.658	0.040	0.023	58	0.021	53	-0.004	-10
France (FR)	0.638	0.020	0.026	130	-0.001	-5	-0.005	-25
Germany (DE)	0.669	0.051	0.020	40	0.027	52	0.004	8
Greece (EL)	0.580	-0.038	-0.021	-55	-0.012	-30	-0.006	-15
Ireland (IE)	0.694	0.076	0.003	4	0.081	107	-0.008	-11
Italy (IT)	0.620	0.002	$-0.5e^{-3}$	-25	0.0039	195	-0.001	-70
Luxembourg (LU)	0.683	0.065	0.065	84	0.006	8	0.006	8
Netherlands (NL)	0.743	0.125	0.052	42	0.078	62	-0.005	-4
Portugal (PT)	0.492	-0.126	-0.062	-50	-0.054	-43	-0.010	-7
Spain (ES)	0.545	-0.073	-0.026	-35	-0.040	-56	-0.007	-9
Sweden (SW)	0.723	0.105	0.067	64	0.028	27	0.010	9
UK (UK)	0.717	0.099	0.067	68	0.042	42	-0.009	-9
Czech Republic (CZ)	0.578	-0.040	-0.041	-103	0.008	20	-0.007	-18
Cyprus (CY)	0.585	-0.033	-0.031	-94	0.015	45	-0.018	-55
Estonia (EE)	0.557	-0.061	-0.030	-49	-0.024	-39	0.007	11
Hungary (HU)	0.571	-0.047	-0.045	-96	0.046	98	-0.048	-102
Latvia (LV)	0.539	-0.079	-0.052	-66	-0.024	-30	-0.003	-4
Lithuania (LT)	0.475	-0.143	-0.063	-44	-0.069	-48	-0.012	-8
Malta (MT)	0.605	-0.013	0.023	177	-0.040	-308	0.003	23
Poland (PL)	0.506	-0.112	-0.070	-62	-0.024	-21	-0.019	-17
Slovakia (SK)	0.556	-0.062	-0.041	-66	-0.008	-13	-0.014	-22
Slovenia (SI)	0.565	-0.053	-0.055	-104	0.010	19	-0.008	-15
EU15 average	0.650	0.032	0.021	67	0.011	33	0	0
NMS10 average	0.534	-0.084	-0.052	-61	-0.021	-26	-0.011	-13
EU25 average	0.633	0.015	0.0105	71	0.0040	27	0.0003	2
EU25 cross-country average	0.618							

Source: Labour Force Surveys from 25 EU countries, authors' calculations.

Table 2.2. Shift-share decomposition of high-skilled non-production occupations in the EU in 2004.

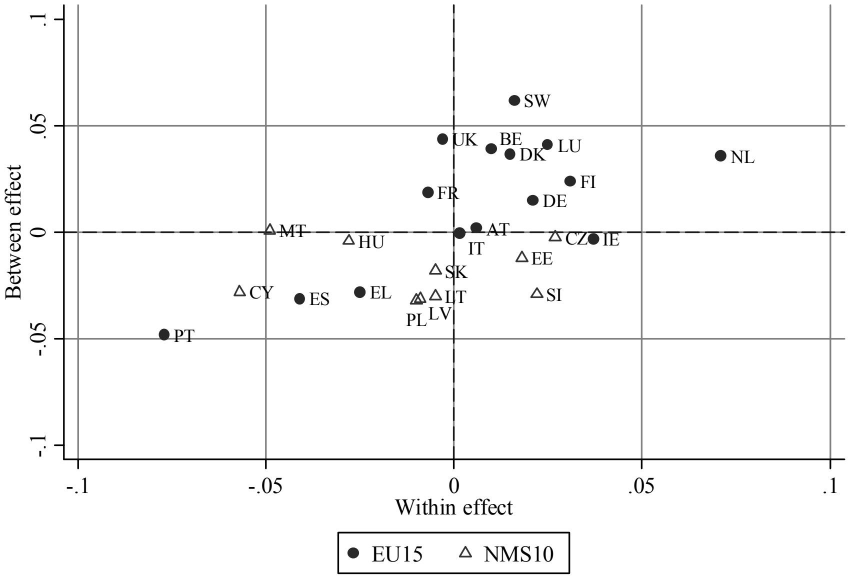
	Share in. 2004	Difference from EU25 cross-country average share	Between effect (size and share, %)		Within effect (size and share, %)		Interaction effect (size and share, %)	
Belgium (BE)	0.425	0.045	0.039	87	0.010	22	-0.004	-9
Austria (AT)	0.387	0.007	0.002	29	0.006	86	-0.001	-14
Denmark (DK)	0.427	0.047	0.037	79	0.015	32	-0.005	-11
Finland (FI)	0.427	0.047	0.024	51	0.031	66	-0.008	-17
France (FR)	0.384	0.004	0.019	475	-0.007	-175	-0.008	-200
Germany (DE)	0.421	0.041	0.015	36	0.021	53	0.005	11
Greece (EL)	0.326	-0.054	-0.028	-52	-0.025	-46	-0.001	-2
Ireland (IE)	0.412	0.032	-0.003	-9	0.037	116	-0.002	-6
Italy (IT)	0.395	0.015	$-0.3e^{-3}$	-2	0.0016	11	-0.001	-7
Luxembourg (LU)	0.454	0.074	0.041	55	0.025	34	0.008	11
Netherlands (NL)	0.486	0.106	0.036	34	0.071	67	-0.001	-1
Portugal (PT)	0.261	-0.119	-0.048	-40	-0.077	-65	0.006	5
Spain (ES)	0.309	-0.071	-0.031	-44	-0.041	-58	0.001	1
Sweden (SW)	0.440	0.060	0.062	103	0.016	27	-0.018	-30
UK (UK)	0.406	0.026	0.044	169	-0.003	-12	-0.015	-58
Czech Republic (CZ)	0.375	-0.005	$-2.4e^{-3}$	-48	0.027	540	-0.008	-160
Cyprus (CY)	0.284	-0.096	-0.028	-29	-0.057	-59	-0.011	-12
Estonia (EE)	0.384	0.004	-0.012	-300	0.018	450	-0.002	-50
Hungary (HU)	0.341	-0.039	-0.004	-10	-0.028	-73	-0.007	-17
Latvia (LV)	0.333	-0.047	-0.031	-67	-0.009	-18	-0.007	-15
Lithuania (LT)	0.323	-0.057	-0.030	-54	-0.005	10	-0.022	-38
Malta (MT)	0.335	-0.045	0.001	2	-0.049	-109	0.003	7
Poland (PL)	0.317	-0.063	-0.032	-50	-0.010	-16	-0.021	-34
Slovakia (SK)	0.353	-0.027	-0.018	-68	-0.005	-18	-0.004	-14
Slovenia (SI)	0.360	-0.020	-0.029	-145	0.022	110	-0.013	-65
EU15 average	0.393	0.013	0.013	100	0.0002	2	$-0.7e^{-3}$	-5
NMS10 average	0.336	-0.044	-0.025	-56	-0.008	-19	-0.011	-25
EU25 average	0.384	0.004	0.007	175	-0.003	-75	$-0.1e^{-3}$	-3
EU25 cross-country average	0.380							

Source: Labour Force Surveys from 25 EU countries, authors' calculations.



Source: Labour Force Surveys from 25 EU countries, authors' calculations.

Figure 2.1. The between and the within effects of the share of non-production occupations, 2004.



Source: Labour Force Surveys from 25 EU countries, authors' calculations.

Figure 2.2. The between and the within effects of the share of high-skilled non-production occupations, 2004.

In sum, all the new member countries (except for Malta) employ relatively fewer skilled workers than the EU average because their industry structures are biased towards less skill-intensive industries. For the Post-Soviet countries, this could be the continuing impact of the distorted Soviet industrial system, which relied extensively on agriculture and heavy industries. For cross-country comparison, the overall trend is that the countries that employ more (less) skills do so because they use more (less) skill-intensive production technologies and because they rely more (less) on skill-intensive industries. Referring to the graphical description, this means that countries tend to locate around the 45° line. However, the differences in the shares of (high-skilled) non-production workers are rather dominated by the between (industrial) effect.

2.5. Dynamic analysis, 2000–2004

The time scale for the dynamic analysis comprises the period 2000–2004, i.e. four years before the accession of 10 new members and the year of the accession. The aim of this section is not to investigate directly the impact of the enlargement of the EU, but the development and possible convergence of the countries' skill structures under the ongoing process of European integration. Two exercises are undertaken to track the developments in EU skills structure. First, the upgrading of skills has been decomposed into between industry and within industry effects. Second, the similarities in within industry skills upgrading of individual industries has been examined.

2.5.1. Shift-share analysis 2000–2004

In this section, we will consider the changes over time in the occupational structures of skilled occupations for the 25 countries, which comprised the European Union after the 2004 accession. Again, the indication of skilled occupations is the employment share of non-production occupations and the employment share of high-skilled non-production occupations.

For decomposition of the aggregate changes in the occupational structure, we distinguish between developments within industries and between industries (see e.g., Berman *et al.*1994, Berman *et al.* 1998 or Berman and Machin 2000). Therefore, the change in the share of (high-skilled) non-production occupations between 2000 and 2004 is given as:

$$\Delta s = \sum_i \Delta s_i \bar{o}_i + \sum_i \Delta o_i \bar{s}_i \ , \qquad (2.5)$$

where o_i indicates the employment share of non-production (high-skilled non-production) occupations in industry employment, and s_i indicates the employment share of a production sector in total employment. The production sectors are indicated by subscript i, i=1, …, 18 (see Appendix B). A bar above the variables reflects an average over time. The change in the share of non-production (high-skilled non-production) occupations is equal to the sum of the *between* and the *within* effects. The between effect accounts for the changes in the occupational structure due to the changes in employment across industries, and the within effect for the changes due to developments within industries.

Table 2.3 reports the shares of non-production occupations and Table 2.4 the share of high-skilled non-production occupations in the EU countries for 2000 and 2004, and the decomposition of the changes. The main trend is that the share of skilled occupations has increased over the time investigated (see the fourth column in Tables 2.3 and 2.4). The share of non-production occupations increased in particular for Austria, Greece and Portugal. Also the share of high-skilled non-production occupations increased for these countries as well as for Luxembourg, Slovenia and Italy.[5] In many NMS countries the increase has been less than the EU15 average. The degree of, skills upgrading measured by the non-production occupations has been strong in Poland relative to the other NMS countries. The same holds for Slovenia with respect the high-skilled non-production workers. This implies that Greece, Portugal and Poland are catching up with the EU15 average as to their skill structure. Only in three out of 25 countries the shares of non-production or high-skilled non-production workers have decreased.

The decomposition analysis indicates that the within effect contributes most to the change in the share of high-skilled non-production employment (last column in Table 2.4). The cross-country average share of the within effect in the total change is 71% (in EU15 71% and in NMS10 72%, the six countries with a negative within effect are excluded). This is consistent with most of the literature on skill-biased technological change; see for instance Berman *et al.* (1998) for developed countries, and Berman *et al.* (2000) and Kang (2002) for developing countries. For example, Berman *et al.* (1998) estimated the within effect of the change in the share of non-production workers to be 84% in the 1970s, and 92% in the 1980s in selected OECD countries. Most of the literature in this field proceeds from the production/non-production division. In the current analysis, the within effect accounts for 58% of the change in the share of non-production employment in EU25 countries (again, the five countries with a negative within effect are excluded) (see the last column in Table 2.3). For the NMS10 group the importance of within effect is a bit higher, accounting for 64% of the change, while the within effect accounts for 54% of the change in the EU15 countries. This may indicate the decreasing role of skill-biased technological change in skills upgrading for a wider group of skilled workers.

[5] The large growth of high-skilled non-production occupations in Italy is probably to a large extent due to a major revision in classifying workers into high-skill occupations in the Italian survey.

Table 2.3. Share of non-production occupations in the EU in 2000–2004.

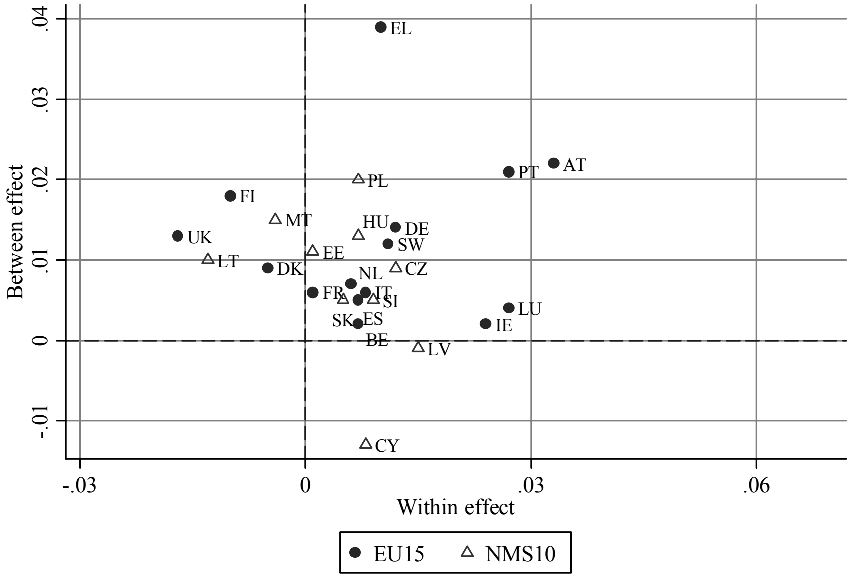
	Share in. 2000	Share in 2004	Difference between 2000–04	Between effect (size and share, %)		Within effect (size and share, %)	
Belgium (BE)	0.681	0.690	0.009	0.002	26	0.007	74
Austria (AT)	0.601	0.656	0.055	0.022	41	0.033	59
Denmark (DK)	0.672	0.676	0.004	0.009	225	-0.005	-125
Finland (FI)	0.650	0.658	0.008	0.018	225	-0.010	-125
France (FR)	0.631	0.638	0.007	0.006	91	0.001	9
Germany (DE)	0.643	0.669	0.026	0.014	55	0.012	45
Greece (EL)	0.531	0.580	0.048	0.039	79	0.010	21
Ireland (IE)	0.668	0.694	0.026	0.002	10	0.024	90
Italy (IT)	0.606	0.620	0.014	0.006	46	0.008	54
Luxembourg (LU)	0.652	0.683	0.031	0.004	13	0.027	87
Netherlands (NL)	0.730	0.743	0.013	0.007	52	0.006	48
Portugal (PT)	0.444	0.492	0.048	0.021	44	0.027	56
Spain (ES)	0.533	0.545	0.012	0.005	41	0.007	59
Sweden (SW)	0.700	0.723	0.023	0.012	54	0.011	46
UK (UK)	0.721	0.717	-0.004	0.013	325	-0.017	-425
Czech Republic (CZ)	0.557	0.578	0.021	0.009	43	0.012	57
Cyprus (CY)	0.590	0.585	-0.005	-0.013	-260	0.008	160
Estonia (EE)	0.543	0.557	0.012	0.011	90	0.001	10
Hungary (HU)	0.551	0.571	0.020	0.013	65	0.007	35
Latvia (LV)	0.525	0.539	0.014	-0.001	-7	0.015	107
Lithuania (LT)	0.478	0.475	-0.003	0.010	333	-0.013	-433
Malta (MT)	0.593	0.605	0.011	0.015	136	-0.004	-36
Poland (PL)	0.479	0.506	0.027	0.020	73	0.007	27
Slovakia (SK)	0.546	0.556	0.010	0.005	50	0.005	50
Slovenia (SI)	0.550	0.565	0.014	0.005	36	0.009	64
EU15 average*	0.636	0.650	0.014	0.011	78	0.003	22
NMS10 average*	0.512	0.534	0.022	0.016	72	0.006	28
EU25 average*	0.617	0.633	0.016	0.012	76	0.004	24

* Weighted average based on employment volumes.
Source: Labour Force Surveys from 25 EU countries, authors' calculations.

Table 2.4. Share of high-skilled non-production occupations in the EU in 2000–2004.

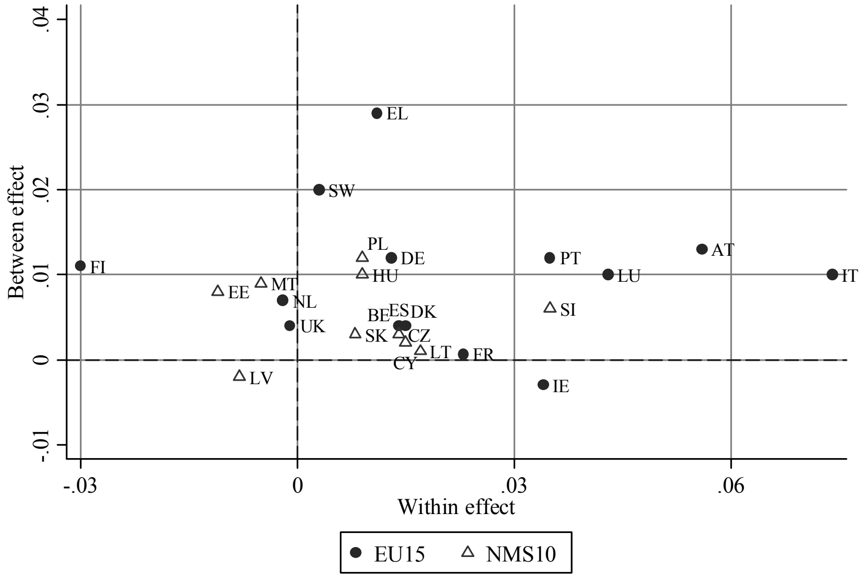
	Share in. 2000	Share in 2004	Differ-ence between 2000-04	Between effect (size and share, %)		Within effect (size and share, %)	
Belgium (BE)	0.407	0.425	0.018	0.004	25	0.014	75
Austria (AT)	0.318	0.387	0.069	0.013	20	0.056	80
Denmark (DK)	0.408	0.427	0.019	0.004	23	0.015	77
Finland (FI)	0.446	0.427	-0.019	0.011	58	-0.030	-158
France (FR)	0.360	0.384	0.024	0.001	3	0.023	97
Germany (DE)	0.396	0.421	0.025	0.012	47	0.013	53
Greece (EL)	0.286	0.326	0.040	0.029	73	0.011	27
Ireland (IE)	0.381	0.412	0.031	-0.003	-10	0.034	110
Italy (IT)	0.311	0.395	0.084	0.010	13	0.074	87
Luxembourg (LU)	0.401	0.454	0.053	0.010	19	0.043	81
Netherlands (NL)	0.481	0.486	0.005	0.007	140	-0.002	-40
Portugal (PT)	0.214	0.261	0.047	0.012	26	0.035	74
Spain (ES)	0.291	0.309	0.018	0.004	25	0.014	75
Sweden (SW)	0.417	0.440	0.023	0.020	84	0.003	16
UK (UK)	0.403	0.406	0.003	0.004	133	-0.001	-33
Czech Republic (CZ)	0.358	0.375	0.017	0.003	19	0.014	81
Cyprus (CY)	0.267	0.284	0.017	0.002	13	0.015	87
Estonia (EE)	0.387	0.384	-0.003	0.008	267	-0.011	-367
Hungary (HU)	0.322	0.341	0.019	0.010	54	0.009	46
Latvia (LV)	0.343	0.333	-0.010	-0.002	-24	-0.008	-76
Lithuania (LT)	0.305	0.323	0.018	0.001	7	0.017	93
Malta (MT)	0.331	0.335	0.004	0.009	225	-0.005	-125
Poland (PL)	0.296	0.317	0.021	0.012	59	0.009	41
Slovakia (SK)	0.342	0.353	0.011	0.003	28	0.008	72
Slovenia (SI)	0.319	0.360	0.041	0.006	14	0.035	86
EU15 average*	0.366	0.393	0.027	0.008	28	0.019	72
NMS10 average*	0.317	0.336	0.019	0.010	52	0.009	48
EU25 average*	0.358	0.384	0.026	0.008	32	0.017	68

* Weighted average based on employment volumes.
Source: Labour Force Surveys from 25 EU countries, authors' calculations.



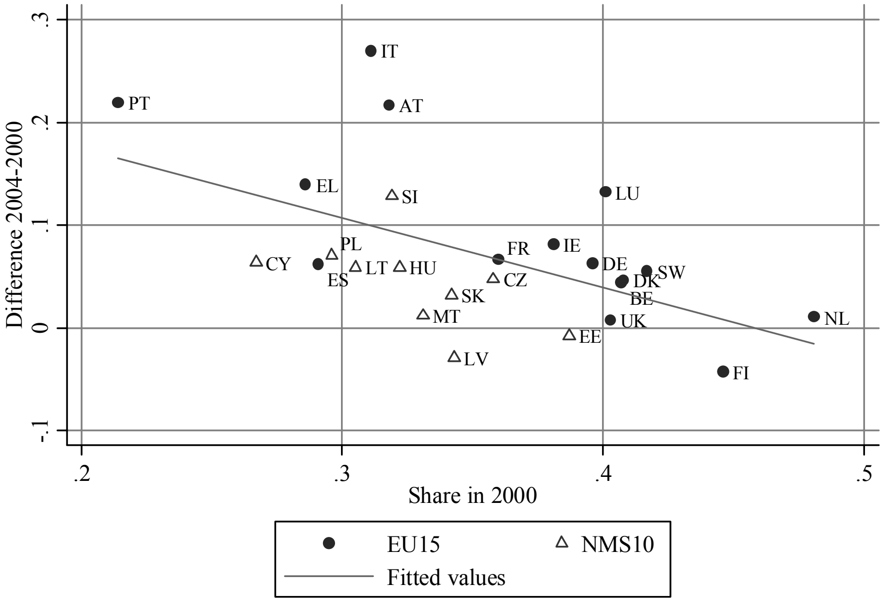
Source: Labour Force Surveys from 25 EU countries, authors' calculations.

Figure 2.3. Between and within effects of the employment shares of non-production occupations, 2000–2004.



Source: Labour Force Surveys from 25 EU countries, authors' calculations.

Figure 2.4. Between and within effects of the employment shares of high-skilled non-production occupations, 2000–2004.



Source: countries' Labour Force Surveys, authors' calculations.

Figure 2.5. The share of high-skilled non-production occupations in 2000 and the differences over 2000–2004.

The decomposed between industry and within industry effects are also mapped in Figures 2.3 and 2.4. The picture is clear in the sense that most of the countries have experienced skills upgrading due to both skill favouring industry and within industry shifts (most of the observations lie in the upper right section of the Figures 2.3 and 2.4). This pattern is more evident under the narrower definition of skills, i.e. for high-skilled non-production workers. Within industry developments have clearly a stronger impact on skills upgrading for high-skilled non-production employment shares (notice the scaling of the horizontal axis of the Figures 2.3 and 2.4). A comparison of country groups does not provide a particular pattern, although NMS10 group tends to have effects of a smaller magnitude (situated closer to the origin).

Figure 2.5 shows that for the high-skilled non-production occupations, the initial level in 2000 and the difference over time are significantly correlated. This suggests that convergence has taken place among the EU25 countries: the countries with a higher share of skilled occupations have a lower increase in the relative demand for skills. This, however, is not the case for the share of non-production employment. The results indicate a diffusion of increased skill demand within industries across countries and convergence of the share of high-skilled non-production employment.

2.5.2. Technology diffusion in the EU

An additional exercise for testing the pervasiveness of skills upgrading across countries is by testing for skills upgrading within the same production sectors across countries. Technology is often presumed to be a public good, which is expected to spread quickly from country to country. If skills upgrading is really the result of skill-biased technological change, one should observe within-industry skills upgrading in similar industries across countries. In this respect, the European Union is a good example for analysis; although the countries' levels of development vary, they have similar institutional environments, and also trade intensively with each other within a close geographical range.

Berman *et al.* (1998) showed the existence of skills upgrading in similar industries among developed OECD countries. They observed that the within effects of the change in non-production employment of different industries were tightly and positively correlated across eight OECD countries. They interpreted this result as an indication of technology diffusion across countries. Berman *et al.* (1998) observed 33 out of 36 positive correlations and 11 out of 36 positive statistically significant correlations at the 5% level. Extending the same exercise to developing countries revealed similar results in within industry skill shifts between developed and middle-income countries, but not between developed and low-income countries (Berman and Machin (2000)). A similar approach is used in this chapter. We undertake the analysis for two country groups: (1) the more developed group of countries defined as the EU12, which consists of the EU15, excluding Greece, Portugal and Spain, and (2) all EU25 countries.

Table 2.5 presents the correlations between individual countries within industry shifts in non-production workers. Again the number of industries used is 18 (see appendix B). Similarly to Berman *et al.* (1998), the within effects of all countries are found by multiplying each country's within sector skills upgrading by the over-time average of European average employment shares (in the second term of equation 2.5, the $\bar{s}_i$ is now not just the country's over-time average, but the over-time average of the European cross-country average). The purpose of this weighting is to ensure cross-country comparison of the countries' within effects by eliminating the impact of the country-specific industry structure.

Our results for the EU12 countries indicate that for the non-production employment share, 55 out of 66 correlations are positive and 20 out of 66 correlations are positive and significant at the 5% level (see Table 2.5). For example, Belgium's within-industry skill shifts correlate at the 5% level with within industry shifts in Austria. The respective numbers for the high-skilled non-production employment shares are 45 out of 66 and 15 out of 66 (see Table 2.6). Now the correlation coefficient between Belgium and Austria within industry skills upgrading is still high, but insignificant at 5% level. For the EU25 countries, the relative number of positive and significant correlations is lower, namely 205 out of 300, and 54 out of 300 for the non-production employment share, and 188 out of 300 and 61 out of 300 for the high-skilled non-production employment share.

Berman and Machin (2000) found that 31% of the within industry shifts in skills demand are positively and significantly correlated in selected OECD countries. Our results show this share to be 30% for the EU12 countries' non-production employment. Hence, skills upgrading or technology diffusion appears to be pervasive for the most developed EU countries. As expected, for a wider group of countries, the shifts in skill use within industries are less correlated indicating lower technology diffusion.

A shortcoming of the shift-share methodology, as used also in this chapter, is pointed out by Berman *et al.* (1998, pp. 1260–1262). They argue that the assumption of homogeneous products within industries is questionable at a high aggregation level of industries. There is a danger of interpreting the within industry shift from the production of low-skill intensive products to high-skill intensive products as skill-biased technological change. However, they find that their estimations of the within effects of 28 manufacturing industries did not differ much from the estimations using plant-level data. The lack of more disaggregated data for all countries does not allow us to test whether the results differ for more disaggregated or firm-level data. This may be an important point for further research, since Berman *et al.*, 1994) show that there may be some overestimation of the within effect at the more aggregated level.

On several occasions, the positive within industry effect, in spite of increasing relative wages, could be the result of some other factors than SBTC (Berman *et al.* 1998, pp. 1260–1262):

- Skills upgrading could be the result of capital investments with complementary shifts to high-skilled labour.
- Plant-level demand increases in skill-intensive goods. In high-income countries this could be the result of increased openness to non-skill-intensive goods from developing countries, which increases the relative price of skill-intensive goods.
- Plant-level outsourcing of low-skilled occupations. Berman *et al.* (1998) estimate that in the USA, outsourcing could account at most for 16% of the decrease in unskilled workers between 1973 and 1987.

There may be factors other than skill-biased technological change driving skills upgrading in the developed world, with outsourcing as a prime possibility. Geishecker (2006, p. 580) estimates for Germany that outsourcing to Central and Eastern European countries is an important factor that decreases the demand for production workers in Germany, while technological change is still the most important factor, but to a somewhat lesser extent.

Table 2.5. Correlations[1)] of within industry shifts in non-production employment shares, EU12 and EU25[2)], 2000–2004

	BE	AT	DK	FI	FR	DE	IE	IT	LU	NL	SE	UK	EL	PT	ES	CZ	CY	EE	HU	LV	LT	MT	PL	SK
AT	**0.51**	1																						
DK	0.25	**0.50**	1																					
FI	0.21	**0.60**	**0.60**	1																				
FR	-0.08	0.46	0.34	**0.63**	1																			
DE	0.44	**0.78**	**0.55**	**0.73**	**0.66**	1																		
IE	0.18	**0.75**	**0.66**	**0.69**	**0.79**	**0.87**	1																	
IT	-0.37	-0.25	0.10	0.00	0.35	0.02	0.19	1																
LU	-0.21	0.06	0.22	0.16	0.38	0.29	0.38	**0.72**	1															
NL	0.15	**0.73**	**0.62**	**0.65**	0.45	**0.79**	**0.83**	-0.02	0.23	1														
SE	-0.20	-0.07	0.41	0.35	0.28	0.15	0.11	0.25	0.12	0.08	1													
UK	0.43	0.40	0.45	0.40	-0.22	0.30	0.23	**-0.57**	-0.25	0.44	-0.11	1												
EL	-0.22	0.32	0.45	0.21	**0.53**	0.45	**0.69**	0.32	0.32	**0.61**	0.33	0.03	1											
PT	0.04	0.33	0.24	-0.02	0.45	0.43	**0.55**	0.32	0.28	0.39	0.22	-0.16	**0.86**	1										
ES	0.05	**0.61**	0.26	0.37	**0.51**	**0.67**	**0.67**	0.07	0.35	**0.72**	0.00	-0.02	**0.61**	**0.61**	1									
CZ	-0.03	0.41	0.40	0.40	**0.49**	0.45	0.44	-0.08	0.19	**0.51**	**0.52**	0.01	**0.49**	0.41	**0.62**	1								
CY	-0.17	0.43	0.26	**0.51**	**0.70**	**0.64**	**0.77**	0.04	0.11	**0.75**	0.07	0.16	**0.73**	**0.50**	**0.62**	0.44	1							
EE	-0.33	0.15	**0.47**	0.30	0.03	0.13	0.25	0.13	0.01	0.40	0.10	0.26	0.21	-0.02	0.12	-0.07	0.19	1						
HU	-0.13	0.37	0.32	0.00	0.21	0.22	0.46	0.22	0.36	0.45	0.04	0.17	**0.75**	**0.72**	**0.52**	0.37	0.35	0.21	1					
LV	-0.27	-0.38	0.08	-0.01	0.39	0.03	0.17	**0.52**	0.34	-0.23	0.26	-0.25	0.32	0.28	-0.18	-0.22	0.19	0.00	-0.03	1				
LT	0.12	-0.27	0.04	-0.32	**-0.55**	-0.37	-0.38	-0.39	-0.16	-0.24	-0.19	0.45	-0.35	-0.39	-0.46	-0.07	-0.41	-0.12	0.01	-0.21	1			
MT	-0.30	-0.30	0.11	0.17	0.17	0.07	0.19	0.09	0.03	0.29	-0.04	0.16	0.27	-0.01	0.13	0.11	**0.54**	0.18	-0.03	0.29	0.12	1		
PL	-0.16	**-0.64**	**-0.51**	**-0.70**	-0.33	**-0.53**	**-0.49**	0.08	0.02	**-0.59**	-0.05	-0.29	-0.08	0.05	-0.42	-0.19	-0.29	**-0.64**	-0.01	0.26	0.46	0.07	1	
SK	0.15	-0.39	-0.17	-0.13	-0.26	-0.05	-0.29	-0.20	-0.07	-0.15	-0.02	-0.07	-0.36	-0.37	-0.09	-0.01	-0.14	-0.37	**-0.66**	0.00	0.19	0.36	0.26	1
SI	-0.16	-0.34	0.07	-0.22	-0.18	-0.17	-0.18	-0.11	0.14	-0.10	0.43	0.05	0.19	0.12	0.03	**0.49**	-0.08	-0.32	0.15	0.06	**0.49**	0.25	**0.55**	0.44

1) Correlation coefficients in bold print reflect statistical significance at 5% level.
2) For country abbreviations, see Tables 2.1, 2.2, 2.3 or 2.4.
Source: Labour Force Surveys from 25 EU countries, authors' calculations.

Table 2.5. Correlations[1)] of within industry shifts in high-skilled non-production employment shares, EU12 and EU25[2)], 2000–2004

	BE	AT	DK	FI	FR	DE	IE	IT	LU	NL	SE	UK	EL	PT	ES	CZ	CY	EE	HU	LV	LT	MT	PL	SK
AT	0.31	1																						
DK	-0.04	0.17	1																					
FI	0.45	**0.52**	-0.11	1																				
FR	0.34	**0.66**	0.35	**0.55**	1																			
DE	0.45	**0.57**	**0.56**	0.30	**0.84**	1																		
IE	0.41	**0.63**	0.26	0.41	**0.81**	**0.85**	1																	
IT	0.06	-0.08	-0.42	-0.38	-0.35	-0.39	**-0.48**	1																
LU	-0.27	0.12	0.26	0.19	0.31	0.26	0.16	**-0.50**	1															
NL	0.29	-0.37	-0.45	-0.01	-0.24	-0.07	0.19	-0.10	-0.30	1														
SE	0.13	-0.02	0.21	0.18	0.08	0.14	0.22	**-0.53**	0.24	0.03	1													
UK	**0.66**	**0.62**	0.02	**0.70**	**0.58**	**0.49**	**0.62**	-0.16	-0.28	0.12	0.20	1												
EL	-0.20	-0.07	**0.61**	-0.33	0.28	**0.53**	**0.50**	**-0.55**	0.17	0.16	0.13	-0.09	1											
PT	0.11	0.42	**0.59**	0.04	**0.59**	**0.72**	**0.53**	-0.37	0.45	-0.36	0.17	0.24	**0.47**	1										
ES	**0.62**	0.31	-0.05	**0.59**	**0.64**	**0.59**	**0.71**	-0.42	0.20	0.33	0.36	**0.54**	0.15	0.15	1									
CZ	-0.03	**0.74**	0.38	0.44	**0.67**	**0.53**	**0.53**	-0.24	0.29	-0.35	-0.20	0.36	0.24	0.28	0.25	1								
CY	**0.49**	**0.56**	0.12	0.38	**0.57**	**0.62**	**0.66**	-0.06	-0.05	0.07	0.37	**0.71**	0.07	0.27	**0.54**	0.35	1							
EE	-0.09	0.27	-0.16	**0.56**	0.09	0.06	0.09	-0.36	**0.54**	0.09	-0.02	0.12	-0.17	0.01	0.16	0.38	0.09	1						
HU	**0.60**	**0.51**	0.02	**0.72**	**0.62**	**0.51**	**0.58**	-0.12	0.11	0.17	0.18	**0.69**	-0.15	0.07	**0.66**	0.46	**0.69**	0.30	1					
LV	0.20	-0.44	-0.32	0.28	0.15	-0.09	0.08	-0.14	-0.14	0.47	0.20	0.17	-0.04	-0.29	0.42	-0.31	0.01	-0.21	0.29	1				
LT	-0.26	-0.10	**0.78**	**-0.55**	-0.08	0.15	-0.17	0.05	0.05	**-0.47**	0.05	-0.36	0.44	0.23	-0.39	0.16	-0.10	-0.40	-0.26	-0.43	1			
MT	0.22	-0.40	-0.28	0.47	-0.08	-0.26	-0.22	-0.11	0.00	0.34	0.09	0.12	-0.33	**-0.54**	0.32	-0.15	-0.03	0.22	0.39	**0.68**	-0.34	1		
PL	-0.21	-0.34	**0.58**	**-0.51**	-0.23	-0.02	-0.16	-0.07	-0.17	-0.16	0.27	-0.34	0.44	-0.06	-0.28	-0.13	-0.13	**-0.55**	-0.25	-0.02	**0.81**	-0.12	1	
SK	0.38	-0.03	-0.16	**0.65**	0.45	0.14	0.16	-0.13	0.14	0.07	0.19	0.43	-0.31	-0.03	**0.55**	-0.01	0.24	0.09	**0.61**	**0.74**	-0.43	**0.72**	-0.31	1
SI	0.00	0.01	0.38	-0.26	0.24	0.36	-0.04	0.23	0.21	-0.42	-0.17	-0.13	0.22	0.34	0.01	0.23	0.19	-0.11	-0.09	-0.27	**0.51**	-0.16	0.19	-0.06

1) Correlation coefficients in bold print reflect statistical significance at 5% level.
2) For country abbreviations, see Tables 2.1, 2.2, 2.3 or 2.4.
Source: Labour Force Surveys from 25 EU countries, authors' calculations.

2.6. Summary

In this chapter, we employed Labour Force Survey data for the EU25 countries to decompose the shifts in the countries' occupational structures into the within industry and between industries effects. We carried out two types of analyses: a static analysis for the year 2004, and a dynamic analysis for the period 2000–2004. Both of these analyses were implemented proceeding from two different definitions of skilled workers: the employment share of non-production workers, and the employment share of high-skilled non-production workers.

The main conclusion is that the old Member States, except Greece, Portugal and Spain, are characterized by a more skill-intensive occupational structure than the new Member States. This is the case irrespective of whether skill intensiveness is measured by the share of non-production workers or by the share of high-skilled non-production workers. In 2004, the EU15 countries (except Greece, Portugal and Spain) used more skilled workers because of both the industrial (between) and the technological (within) effects. This implies that these countries have a more skill-intensive industry structure and their production technology within industries is more intensively based on skills, while the new member countries' (except Malta's) industry structure is clearly biased towards less skill-intensive industries. In general, the differences in the shares of (high-skilled) non-production workers between countries are dominated by the between (industrial) effect.

The dynamic analysis of 2000–2004 showed that changes in the share of high-skilled non-production workers are mostly driven by within-sector changes, which are probably related to skill-biased technological change. Also, the developments in the share of the total group of non-production workers are larger for the within (technology) than for the between (industrial) effect, although less evidently than for the high-skilled non-production workers in our study and the non-production workers in the study by Berman *et al.* (1998). These results could also indicate the slowdown of the implications of skill-biased technological change for non-production vs. production composition of the workforce.

The diffusion of the increased demand for skills within sectors has been witnessed for the EU12 country group, but less strongly for the EU25 country group. Overall, the convergence of the share of high-skilled non-production workers is apparent. The differences in skill use between the new and old Member States can mostly be accounted for by differences in their industry structures. Similar trends in the countries' within effects support the idea that skill demand in the new member countries is catching up, while the structural developments that could equalize the industry mix of the new and old member countries are related to increased domestic demand and will probably take time.

The shift-share analysis of this chapter can be used to forecast the employment growth of occupations in the EU Member States. If forecasts of the countries' sector employment levels are made, for instance, by means of a macroeconomic forecasting model, the between effect represents the impact of the predicted changes in the industry composition on the occupational structure within countries. Moreover, changes of the occupational mix within sectors follow from the within effect. This effect can be predicted by extrapolating the time trends of skills upgrading within sectors of industry. If possible, the occupational upgrading should be related to exogenous variables that can explain the extent of occupational upgrading.[6]

Data availability implied that we proceeded only from the occupational structure. An alternative measure of the skill structure can be obtained from data on educational attainment.[7] An interesting avenue of future research would be a comparative analysis of information on occupational structure and educational attainment.

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[6] See e.g. Dekker *et al.* (1990) and Cörvers and Dupuy (2006) for the Netherlands, and Briscoe and Wilson (2003) for the UK.

[7] See Winchester *et al.* (2006) for a comparison of these two approaches and the implementation of cluster analysis to combine wage and educational information of occupational groups with the aim of deriving a composite measure of skills.

3. THE IMPACT OF INNOVATION ON EMPLOYMENT: FIRM- AND INDUSTRY-LEVEL EVIDENCE FROM ESTONIA

3.1. Introduction

The level of employment is a combination of various supply and demand side factors. We focus ourselves on the effect of technological innovation (technological changes) on employment. The empirical evidence from developed economies usually finds a positive relationship between employment and innovation; see Pianta (2005) and Djellal and Gallouj (2007) for literature surveys. Distinguishing between product and process innovation allows for a more thorough investigation of the relationship in question. Pianta (2005 p. 572) quoted Schumpeter who defined product innovation as "the introduction of a new good…or a new quality of a good," and process innovation as "the introduction of a new method of production… or a new way of handling a commodity commercially." Most of the empirical studies have found a positive relationship between product innovation and employment at the firm level (Van Reenen 1997; Greenan and Guellec 2001; Harrison, Jaumandreu, Mairesse, Peters 2008). In terms of process innovation the results are more varied. Greenan and Guellec (2001), Fung (2006) and Harrison *et al.* (2008) found the relationship to be positive, Van Reenen (1997) found there to be a weak positive or no significant relationship, while Evangelista and Savona (2003) found this relationship to be negative.

These results are sensitive on the method and data used and the type of economy analysed. The purpose of this chapter is to investigate the implication of technological innovation on employment in transition economy. We use the firm-level data of Estonia. Estonia is the former member of the Soviet Union and is performing moderately in economic terms within the group of new members of the EU. It joined the EU in 2004 and similarly to other countries from this new members group had a rapidly developing catch-up economy in the sample period. This makes Estonia as an average case of the group of post-communist catch-up countries in the Central and Eastern Europe (CEE).

This chapter contributes to the literature in two respects. Firstly, it proceeds from the data of a catch-up country instead of a high-income country and provides a comprehensive analysis about firm- and industry-level effects. The innovations are smaller in scale and scope in lower income countries, which may cause different implications regarding the employment effect. For example, in lower income new EU Member States the R&D expenditures as share of GDP were less than half the level in the high-income EU15 countries, viz. 0.81% versus 1.91% in 2006 (Eurostat 2008a). This also means that the size of high-, medium- and low-tech sectors is different in these lower income countries. The low-tech industry companies have relocated from high-income Western Europe to lower income Central and Eastern Europe and these industries are characterised mainly by process innovation (Heidenreich 2008).

Most of the empirical studies of this topic concentrate on the high-income countries; exceptions are Lundin, Sjöholm, Ping and Qian (2007); Yang and Lin (2008); and Benavente and Lauterbach (2008). There are only few studies analysing the impact of innovation on employment at both the firm and industry level; the main exceptions are studies by Greenan and Guellec (2001) and Evangelista and Savona (2003). Many effects of innovation as business stealing or market expansion cannot be controlled for at a firm-level analysis. This underscores the need for a comprehensive analysis at the firm and industry level.

Secondly, this chapter suggests a new estimation strategy for the widely used Community Innovation Survey (CIS) data in a panel form. We develop a unique database merging two rounds of CIS data with Business Register data. The possession of wider and longer data allows us to employ a more advanced estimation strategy compared to a popular estimation scheme for CIS suggested by Jaumandreu (2003).

Our results indicate that overall innovation activity has a positive and statistically significant employment effect at the firm and industry levels; the effect seems to be stronger at the firm level. Process innovation has a significant positive effect on employment at the firm level and product innovation at the industry level. These results confirm the firm- and industry-level results from high-income countries (Greenan and Guellec (2001) and Evangelista and Savona (2003)). Surprisingly, the innovation has no impact on employment in high-tech sector, while process innovation has strong positive effect on employment in low-tech sector.

The chapter is organized as follows: The next section gives an overview of the literature and compares innovation activities in Western and Eastern European countries. Section 3.3 derives a labour demand function and presents the estimation strategy. Section 3.4 introduces and describes the data. Section 3.5 presents the results of the empirical estimations and, finally, Section 3.6 summarizes the results.

3.2. Literature and background

3.2.1. Related literature, firm-level studies

As already mentioned, the usual conclusion of the studies on the impact of innovation on employment is that there is a positive relationship between innovation and employment. This result could differ depending on the theoretical specification, empirical estimation methods and data characteristics. See Appendix E for a tabulation of results from industry-level studies.

In terms of theoretical derivation the mainstream approach is to assume some type of production function (usually exhibiting constant elasticity of substitution (CES)), derive from there the corresponding labour demand function and proxy all the technological change terms with proxies of technological change. The range of technological change proxies includes innovation inputs like R&D expenditures or innovation outputs like patent or count of implemented innovations. Examples of this approach are Van Reenen (1997); Piva and Vivarelli (2005); Fung (2006), Lachenmaier and Rottmann (2007) and Yang and Lin (2008).

The results of these studies indicate usually a positive impact of innovation on employment, but the magnitude and statistical significance of the effect varies. The impact of overall innovation on employment has been found to be significant and positive on UK, Italian and Taiwan data (Van Reenen (1997); Piva and Vivarelli (2005); Yang and Lin (2008)). The impact of product innovation has been found to be positive and significant (Van Reenen (1997); Yang and Lin (2008)), while the impact of process innovation has been found to be weaker positive (Yang and Lin (2008)) or insignificant (Van Reenen (1997).

The advantage of this approach is its simplicity and straightforward interpretation. The disadvantage is that the diverse nature of technological change, like product or process innovation, is not fully incorporated. The structure of the model does not take into account their distinct interaction with supply and demand side factors.

The mechanisms through which product and process innovation influences employment can differ substantially. The result of process innovation is greater efficiency in production, and as a result, production inputs can be saved or production prices reduced. The usual outcome is a decrease in employment, but when product quality is increased or the output price is reduced, it can also result in higher employment due to increased demand. New products or services, radical innovation or imitation, usually enhance quality and the variety of goods opening new markets as well as increasing production and employment. The result can also be opposite, new goods are innovated to reduce costs and in this way have similar effects to process innovation. Product innovation can also have no effect on employment, such as when new products replace old ones with minor economic effects (Pianta 2005, pp. 572–573, Smolny 1998, pp. 365–366).

Alternative theoretical derivation treats the mechanisms how product and process innovation affect employment separately. Greenan and Guellec (2001), for instance, assume that process innovation affects the production function of a firm, while product innovation affects the demand for its products. The firm maximizes profits not only by choosing factor demands but also by choosing its prices and level of production. The reduced form of price and production equations are combined to produce an equation system consisting of three equations: sales (price times production), labour and capital demand.

Greenan and Guellec (2001) find that firms introducing process innovation undertake price reduction that lead to increased demand. If the demand would not have changed, the firms' employment would have diminished, but since the demand reacts, firms' employment increases. Product innovation generates increased demand and consequently higher employment. Surprisingly, the positive effect of process innovation on employment is larger than the effect of product innovation. This result is an uncommon one in this literature; usually the effect from product innovation is larger. The result is unlikely dependent on their estimation strategy, as they find the same result when regressing employment growth directly on product and process innovation.

Results by Greenan and Guellec (2001) indicate that the theoretical mechanisms described above also work empirically. Nevertheless their approach allows them to investigate what is behind the direct impact of innovation on employment; this approach has not found many followers. This may be a result of additional complications related to the estimation of a system, e.g. identification problems or that specification errors spill over to other equations when the system estimation methods are used. Researchers may just focus on the direct effects of innovation on employment because they trade off the additional knowledge for additional complications.

Lastly, we discuss the theoretical derivation proposed by Jaumandreu (2003). This approach is constructed to fit the characteristics of innovation survey data suggested by the OECD and European Commission in Oslo manual 1997 or 2005, also called the Community Innovation Surveys (CIS). This type of survey is widely used internationally to collect information on innovation. Jaumandreu's (2003) estimation strategy has found many followers; cf. Peters (2004) on German data, Harrison *et al.* (2008) on data for four European countries, Hall, Lotti and Mairesse (2008) on Italian data; and Benavente and Lauterbach (2008) on Chilean data.

The CIS data collects information about the current year and two years before that, enabling to introduce growth over two years but limiting the data set to a cross section when only one wave of the survey is used. Jaumandreu (2003) proposed two production functions for the production of old and new products and combined labour demand function from the cost function of either of the products. He assumed that the marginal cost with respect to wage is the same across new and old products, and derived the total change in labour demand as a combination of change in labour demands for either of the products. The resulting specification for the estimation is quite simple; change in employment depends only on output growth due to new products and efficiency growth due to process innovation.

The empirical results following this framework usually confirm a positive relation between employment growth and product innovation, whereas the effect from process innovation on employment is mostly negative but always insignificant (Harrison *et al.* (2008); Hall *et al.* (2008)). This consensus seems not to depend on the income level of the country under investigation. In addition to France, Germany, Spain, UK and Italy, Benavente and Lauterbach (2007) find very similar results for Chile.

This overwhelming consensus in results may also be a result of an over-simplification in specification. The disadvantages of this approach are related to the limitations of the data set it has introduced to suit for. First, as CIS data does not comprise information on investments or capital stock, other factors of production except for labour are omitted. Therefore it is restrictively assumed that the growth of firms' capital stock is the same within industries (cf. the inclusion of industry and year dummies in the panel data estimations). Second, the assumption that the marginal cost with respect to wage is constant across product novelty enables elegantly to avoid wages in the estimated employment growth specification. Although, an elegant simplification in the theoretical derivation, this may result in an omitted variable bias in empirical estimation as employment, wages and innovation are empirically interrelated. Third, the impact of innovation on employment persists over several years (see Van Reenen (1997), Lachenmaier and Rottmann (2007)). Hence the cross-section with two-year differences may underestimate the impact of innovation on employment. The CIS data also brings about some other measurement problems, which will be discussed in the section about data.

There is also a set of empirical studies that do not specify any theoretical model behind their empirical estimations. These studies usually possess information on firms' own estimation how innovation has impacted their labour endowment and estimate discrete or binary choice models dependent on various explanatory variables. Rennings, Ziegler and Zwick (2004); and Evangelista and Savona (2003) are examples of this type of studies.

In terms of economic sectors, the high-tech or R&D intensive sectors usually have stronger positive effect on employment from innovation activities (Yang and Lin 2008; Greenhalgh *et al.* 2001; both of the studies proxy innovation by R&D). Results across manufacturing and services tend to diverge for process innovation, but there is no clear pattern to which direction (Peters 2004 and Harrison *et al.* 2008).

In terms of the type of economy analyzed, empirical investigations usually proceed from the data of high-income countries. Among the low income economies, Lundin *et al.* (2007) found there to be no effect of science and technology investments on employment in China, whereas Yang and Lin (2008) and Benavente and Lauterbach (2008) found positive effects of innovation on employment on Taiwan and Chilean data, similarly to the effects found for high-income countries.

We purpose to contribute to the very limited literature of analysis on low-income countries. This chapter employs Estonian CIS data. Estonia is a middle-income country according to world standards. We address a number of the limitations of CIS surveys and suggest an alternative estimation strategy by merging the CIS data with the whole population of the Estonian Business Register data. This enables us to widen our set of variables and to construct panel data sets from two consecutive CIS surveys. The wider set of variables enables us to avoid the simplified specification proposed by Jaumandreu (2003) and to control for capital and wages as suggested by Van Reenen (1997). Panel data is the supreme type of data for this kind of firm level analysis. It enables, compared to cross-section data, to control for firm-specific fixed effects and thus to achieve more reliable estimates. Most of the studies in this literature, except for CIS data studies, utilize panel data econometrics. The usual dynamic panel data estimation methods are difference GMM (GMM-DIF) by Arellano and Bond (1991) and system GMM (GMM-SYS) by Arellano and Bover (1995) and Blundell and Bond (1998).

3.2.2. Related literature, industry-level studies

The net effect of innovation on employment at the aggregate industry level can differ from firm-level results. The firm-level analysis usually does not allow extending these results to the whole industry. There are several reasons why these firm-level results cannot be applied to the industry level (Harrison *et al.* 2008, Piva and Vivarelli 2005):

- it is not possible to distinguish between market expansion and the business stealing effect; or otherwise, it is not observable whether the employment of other firms will increase or diminish as a result of innovation in the firm;
- the entry and exit of firms is not observed, innovators may close down non-innovators;
- and totally new economic branches may surface and create completely new jobs.

Piva and Vivarelli (2005) gave an overview of the advantages and disadvantages of microeconometric estimation of the employment effects of innovation. The main disadvantage was that the results of the micro studies cannot be generalized to the whole economy, because all the sectoral and macroeconomic effects were not captured. For instance, if one uses a sample with only innovating firms, "business stealing" effects will be neglected.

There is evidence that innovation has a positive effect on employment at the sectoral level as well at the firm level. The Appendix F tabulates a selection of industry-level studies. Innovative firms and sectors create more employment compared to non-innovative ones (Greenan and Guellec 2001, on a French panel). Greenan and Guellec (2001) found that the positive effect of process innovation dominates at the firm level and the positive effect of product innovation dominates at the industry level (the possible effect of market expansion). Similarly, Antonucci and Pianta (2002) found on a panel of manufacturing industries of the high-income European countries that process innovation had a negative effect on employment, while product innovation had a positive, but insignificant effect. Evangelista and Savona (2003) found that in the Italian service sector the positive employment effects of innovation were larger in firm-level estimations than in industry-level estimations.

In sum, the simultaneous surveys on firm and industry levels do not give the same results across the level of analysis undertaken, especially when distinguishing between product and process innovation. The impact of process innovation on employment tends to be more negative at industry level.

Different methodologies have been used to analyse the impact on employment of industry-level innovation. If information about the direct effect of innovation on employment was available, the weighted share of firms with a positive effect per industry could be calculated easily. This estimation strategy was used by Evangelista and Savona (2003) on Italian services CISII (1993–95) data. They found a positive employment effect in knowledge-intensive industries and a negative impact in traditional service sectors. Their firm-level results were much more positive in terms of employment.

Unfortunately, direct information about the impact of innovation on employment is often lacking from the data. Hence, the consequent strategy is to calculate industry-level employment changes and test these against an industry's innovation activity. The identification of the innovation effect is the bottleneck in this approach. Antonucci and Pianta (2002) employed this strategy on 8 high-income EU countries manufacturing CISII data. They estimated the industry's rate of change of employment for 1994–99 depending on innovation and other control variables from 1994–96. They found a negative impact of innovation on European manufacturing employment.

Alternatively, one can use more advanced measurement of an industry's employment change. Greenan and Guellec (2001) disentangled the industry's employment growth rate into a job creation and a job destruction rate. They used the calculation of job flows suggested by Davis and Haltiwanger (1992). There are clear advantages to this approach compared to conventional industry employment growth. Let us take an example where an industry experiences a zero net employment change, but a positive number of jobs are created and destroyed in the industry. Consequently, the net employment change is not related to any of the industry's innovation variables; the jobs created in the industry might be due to product innovation and the jobs lost might be due to process innovation. Without a distinction between job creation and job destruction, we could easily underestimate the role of innovation in total employment reallocation in the labour market.

In this chapter, we proceed from the latter approach. Similarly to Greenan and Guellec (2001), the Davis and Haltiwanger (1992) method will be used to calculate an industry's job creation and job destruction rates. The advantage of this approach is that the resulting rates are interpretable as ordinary growth rates. The disadvantage is that by definition there is a much higher probability of having larger job flows in smaller firms. If, for instance, a worker's job is destroyed in one firm, the probability of finding a new job in the same firm is much lower in the case of a small firm. The way out is to divide industries into groups by firm size (Greenan and Guellec, 2001); this strategy will be used also in this chapter, we will distinguish between three size groups.

3.2.3. Innovation patterns of high- and middle-income countries

The purpose of this section is to investigate the position of Estonia in international rankings of innovativeness and economic development. According to endogenous growth theory and evolutionary growth theory, innovativeness enhances economic growth. (See Mulder, De Groot and Hofkes (2001) for a comparison of these two theories.) Empirical cross-country studies have not been very successful in confirming this relationship. The reasons for that are different for endogenous growth theory and evolutionary growth theory. In line with endogenous growth models according to so called "Jones critique", empirically the increase in the number of R&D workers does not lead to higher growth rates. While the evolutionary economics still suffers under lousy properties for empirical testing. (Verspagen 2005, pp. 506–507, 509)

Testing of a particular growth theory is not an objective of this chapter. We investigate the relationship between innovativeness of a country and GDP per capita on the cross-section data of European countries. The differences in cross-country innovativeness can also be a result of different industry mixes in these countries. Antonucci and Pianta (2002) concluded based on a sample of European countries' manufacturing industries that the same industries across countries were characterised by similar shares of new or improved products in sales or share of process innovation in sales. In other words, the distribution of countries between product and process innovativeness can be explained by industry specificity rather than by country factors (Antonucci and Pianta 2002, p. 300). We do not go further to consider innovation patterns at country and industry level.

Figure 3.1 presents the relation between the share of product and process innovative firms and the countries' income in the 25 European countries. There is a positive relation between the share of product and process innovative firms, but the relation seems to be non-linear. The share of process innovative firms increases faster at lower levels of innovativeness and the share of product innovative firms increases faster at higher levels of innovativeness. These country-level observations are weighted by countries' GDP *per capita* in euros; the larger the country marker is in Figure 3.1, the higher the country's GDP per capita. Evidently, countries with a higher level of income tend to have more innovative firms and tend to create more product rather than process innovations.

Three groups of countries emerge from the figure. The first group comprises countries with a fixed low level of product innovation and varying low level of process innovation. These countries all have relatively low income levels in the European context and consist of Bulgaria, Hungary, Malta, Slovakia, Romania, Poland and Lithuania. The second group contains countries with middle levels of product and process innovation. This group includes countries where process innovation dominates and which are characterised by middle and high levels of income: Spain, Italy, France, Portugal, Cyprus and Greece. There are also countries in the second group where product innovation dominates and this group includes high income countries: The Netherlands, Norway, Finland, and as an outlier, the Czech Republic. The final group comprises countries with high innovativeness dominated by product innovation. This group contains high income countries such as Denmark, Belgium, Sweden, Austria, Luxembourg, Germany and Ireland. Ireland is an exception that possesses a remarkably high share of process innovative firms. The country under investigation in this chapter, Estonia, is also a part of this group. Estonia is a clear outlier in the group as the country has high rates of innovativeness, but a low level of income.

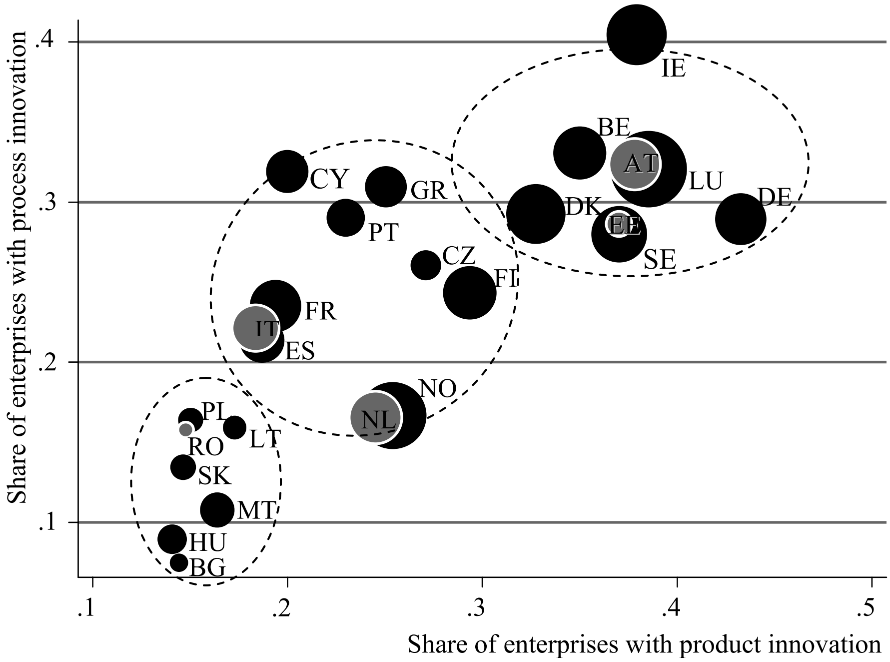

Figure 3.1. Relationship between product and process innovativeness, weighted by GDP per capita (2004, in euros).

Source: IV European Community Innovation Surveys, 2002–04; author's calculations (Eurostat 2008b).
Note: The process innovation numbers drawn from the Eurostat database do not contain process innovation created jointly by firms and outside partners. For country abbreviations, see Tables 2.1, 2.2, 2.3 or 2.4.

The implemented innovation is only one indicator of innovativeness, the amount of innovation expenditures or the structure of these expenditures may enrich the observed relationship between countries innovativeness and income. We go further by investigating the structure of innovation expenditures across European countries in Figure 3.2.

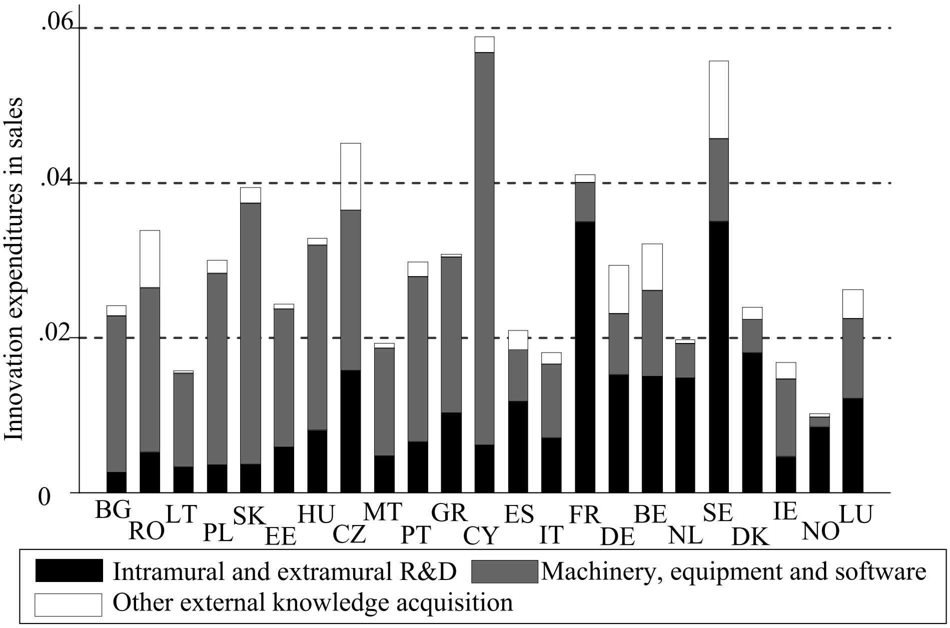

Figure 3.2. Innovation expenditures in sales, countries ordered by GDP per capita (2004, euros).

Source: IV European Community Innovation Surveys, 2002–04; author's calculations (Eurostat 2008b).
Note: For country abbreviations, see Tables 2.1, 2.2, 2.3 or 2.4.

Figure 3.2 shows that while there is no clear relation between a country's innovation expenditures and income, there are peculiarities in countries structure of innovation expenditures. Countries with higher GDP per capita dedicate significantly more resources to R&D among innovation expenditures. This trend holds especially for a low-income European countries, they all do little R&D nevertheless their often large innovation expenditures. The low-income new EU members spent as much as 74% of their innovation expenditures just for the acquisition of machinery, equipment and software, while the same share was only 36% in high-income European countries in 2004 (Eurostat 2008b). This suggests that most of the innovations are close to conventional capital investment in low-income new EU members, including Estonia.

In sum, what concerns the data of this chapter, one must keep in mind that in spite of many innovative enterprises in Estonia, the innovations of these firms are probably far from major technological shifts. This regularity is also confirmed by another EU-wide innovation survey, the European Innovation Scoreboard. This also ranks Estonia as one of the most innovative countries among the lower-income new EU members, but characterised by a very unbalanced innovation system. Estonia has developed its innovation drivers (tertiary education), innovation and entrepreneurship (SMEs innovation activity) well, but performs poorly in transferring these into knowledge creation (low R&D activity) (Pro Inno Europe 2007).

3.3. The labour demand function of firms

The empirical literature investigating the employment effects of innovation (or technological change) often proceeds from the neoclassical production theory assuming a specific functional form of the production function. The labour demand is derived from profit maximizing conditions and estimated using various econometric methods.

The specification used in this paper proceeds from the one employed by Van Reenen (1997). A constant elasticity of substitution (CES) production function has been used to derive the labour demand function. A perfectly competitive firm operates according to a CES production function:

$$Y = A\left[\left(A_L L\right)^{(\sigma-1)/\sigma} + \left(A_K K\right)^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)}, \qquad (3.1)$$

where Y is output, A is the Hicks-neutral technology parameter, A_L is labour augmenting Harrod-neutral technology, A_K is the Solow-neutral technical change, L is employment, and K is capital. In a perfectly competitive world without distortions, the marginal product of labour should equal real wages (W/P). Proceeding from this assumption and solving for labour demand results in the following labour demand function:

$$\log L = \log Y - \sigma \log(W/P) + (\sigma - 1)\log A_L \qquad (3.2)$$

Next, equalizing the marginal product of capital with the real price of capital and substituting via this condition for the output in the labour demand function (3.2), gives the following labour demand function:

$$\log L = (\sigma - 1)\log(A_L / A_K) - \sigma \log(W/P) + \log K + \sigma \log R \qquad (3.3)$$

Next, van Reenen (1997) replaced the unobserved technology terms with innovation and produced a stochastic form of the labour demand function. The replacement of technology terms by innovation is a reasonable truncation as Acemoglu (2002b) argued that technological change has been mostly labour augmenting over the last 150 years and not capital augmenting. This indicates that the technological change should enter to the estimations mostly through A_L; and the distinction between A_L and A_K is empirically not important. Our labour demand function is derived as follows:

$$l_{it} = \alpha_1 INNO_{it} + \beta_3 w_{it} + \beta_4 k_{it} + \tau_t + u_{it} \,. \tag{3.4}$$

Lower case letters stand for logarithms, *INNO* indicates innovation, τ_t represent time dummies, and u_{it} is a white noise error term. The superscript *i* indicates the firm and *t* the time period. The price of capital is assumed to be constant across firms, but variable over time; i.e., proxied by time dummies.

In empirical studies the latter static specification of labour demand should be extended with dynamic adjustment for employment and innovation. The database used for this paper reports innovation as a discrete variable over two 3-year periods, 1998–2000 and 2002–04. Hence, the simultaneous introduction of the yearly lagged innovation variables is not possible here as $cor(INNOV_{it}, INNOV_{it-1}) = 1$. Assuming that any adjustment in employment due to a technology change is gradual, the technology variable is lagged by three time periods. This is also motivated by the fact that it is not known in which year the innovation took place and lagging the innovation variable by three periods prevents the estimation of the impact of future innovations on current employment. After counting for employment persistence[8] the following labour demand equation results:

$$l_{it} = f_{\mathrm{i}} + \alpha_1 INNO_{it-3} + \beta_1 l_{it-1} + \beta_2 l_{it-2} + \beta_3 w_{it} + \beta_4 k_{it} + \tau_t + u_{it} \,, \tag{3.5}$$

where the constant f_i represents a unified constant for every firm at every period of time and two AR terms of employment have been added. As usual in panel data models, the residual u_{it} has two components, a traditional white noise one and a firm specific part.

3.4. Data

This paper uses data from three sources: The Estonian Business Register (register) of 1994–2006, the third Community Innovation Survey of 1998–2000 (CIS3) and the forth Community Innovation Survey of 2002–04 (CIS4). The Estonian Ministry of Justice collects the register-based data and as it is compulsory for enterprises to report their economic indicators correctly, this database is taken likely the most reliable one. Thus, when a variable like employment is reported in both databases (in both the register and innovation surveys), the register data has been used.

The data of the Estonian Community Innovation Surveys is collected by Statistics Estonia. The methodology of the Estonian CIS surveys proceeds from the methodology recommended by the European Commission (see European

[8] The lagged time periods up to 2 periods are used as employment lags become insignificant after this lag length (yearly estimates).

Commission Oslo manual 1997 or 2005 for details). The first waves of CIS surveys were conducted every 4 years and this is the case in our CIS3 and CIS4 surveys. The first wave of CIS survey was launched in a large number of European countries already in 1990–92 (European Communities 2001, p 18). In Estonia, the first survey was conducted for 1998–2000 (see Kurik *et al.* (2002); Viia *et al.* (2007) for the summary of Estonian CIS3 and CIS4 surveys).

In this paper information on innovation comes from the CIS data, while register data provided information on capital and employment costs. Employment was covered in both data sets; primarily register data was used. If an observation was not available in the register data but was available in the CIS, then the information from the CIS was used. We present the data by first discussing possible measurement errors as well as selection and sample biases, followed by descriptive statistics of the main variables used in the empirical analysis.

There are some difficulties related to the measurement of innovation in CIS surveys. First, the innovativeness is reported as a binary variable. This may bring along measurement errors as some innovative firms undertake multiple innovative activities and others only undertake one within the observed period of time. Innovation count data would, of course, be a superior measure. For the second complication of the innovation variable, it is self-reported. Enterprises are asked to report information on their innovation activities retrospectively; i.e., reporting innovation activity from 1998 to 2000 in 2000, and innovation activity from 2002 to 2004 in 2004 etc. Although a phenomenon like innovation should not give respondents any incentives to misreport its occurrence, there may be some differences across firms on the understanding or interpreting this concept. Third CIS surveys measure innovations over three years without specifying the exact year in which the innovation took place. In sum, the innovation variable in CIS surveys may be described as something like "maximizing over three years the minimum innovation activity within a year".

Considering the measurement of our innovation variable, we compute an innovation variable that takes the value 1 for every year within the 3-year period being considered if the firm was innovating and takes the value 0 for every year within the 3-year period if the firm was not innovating. We lag our innovation variable by three time periods to alleviate the third measurement issue. But there is nothing to be done with the two first ones and this should be kept in mind when interpreting the results.

The selection bias is a concern in all surveys. Our construction of the panel may miss-specify the impact of innovation on employment if firms drop out from the sample due to their innovation activity. For example if the innovation causes a firm to be closed down, we do not take this firm's negative employment effects of innovation into account and overestimate the positive impact of innovation on employment. We checked for the selection bias by observing the innovation behaviour of firms that exited the Business Register or market after the CIS3. 8.9% of these firms that were in the sample of CIS3 exited the market afterwards (between 2001 and 2005). But a *t*-test showed that there was no difference in these exiting firms' average innovation activity in CIS3. This suggests that selection bias is not a serious issue in our sample.

Another issue is a possible sample bias. The CIS survey sample has been made selecting firms by the size and the field of their activities. The field of activities included are mining and selected manufacturing and service sectors (the traditional public sectors in services sectors are excluded). Not all production sectors are included in the innovation surveys as agriculture, construction, hotels, education, and health care are excluded (see Table 3.1)[9]. Thus, the CIS survey does not represent the whole population of Estonian enterprises in terms of their field of economic activity. Nevertheless, employing a comparable methodology in different countries (following the Oslo manual) ensures the comparability of data across countries (Kurik *et al.* 2002, p. 21; Viia *et al.* 2007, p. 18).

Table 3.1. Distribution of Estonian enterprises by field of activity, Estonian Business Register and Community Innovation Surveys [a)].

NACE [b)]	Register 1999		CIS 1998–2000		Register 2003		CIS 2002–2004	
	Count	Share	Count	Share	Count	Share	Count	Share
A	1727	4.45			2359	4.64		
B	171	0.44			163	0.32		
C	103	0.27	24.5	0.79	97	0.19	198	1.13
D	5103	13.16	1490	48.19	6046	11.89	8839	50.59
E	301	0.78	104.0	3.36	281	0.55	498	2.85
F	2593	6.69			3884	7.64		
G	13859	35.75	517.8	16.75	14623	28.76	3702	21.19
H	1544	3.98			1811	3.56		
I	2977	7.68	396.2	12.81	3962	7.79	2956	16.92
J	530	1.37	102.6	3.32	1226	2.41	244	1.40
K	7724	19.92	456.7	14.77	13412	26.38	1033	5.91
L	0	0			5	0.01		
M	404	1.04			511	1		
N	521	1.34			876	1.72		
O	1211	3.12			1591	3.13		
Total	38768	100	3161	100.00	50847	100	1747	100.00

Source: Estonian Business Register, CIS3 and CIS4, own calculations.
[a)] The numbers for CIS are weighted by weights supplied by data collectors (later estimates proceed from unweighted numbers).
[b)] Appendix B supplies the explanation for NACE field of economic activity acronyms.

[9] This does not mean that the representatives of some of these uncovered industries are not present in the survey. The firms' actual and codified field of activity is a somewhat dynamic variable and sometimes firms unintentionally end up in a sample.

Table 3.2. Descriptive statistics, 1998–2000 and 2002–04.

	All firms		Innovators		Non-innovators	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Share of innovative firms [a)]	0.377	0.485				
Share of firms with product innovation [a)]	0.276	0.447				
Share of firms with process innovation [a)]	0.266	0.442				
Employment	58	243	87	334	40	162
Real wage [b)]	92	219	105	88	85	269
Real capital stock [c)]	19.3	266.6	36.9	419.6	8.6	85.4
Number of observations	9885		3727		6158	
Number of groups	2783		1134		1926	

Source: Estonian Business Register, CIS3 and CIS4, own calculations.

[a)] We have excluded these firms from our sample that started their activity within the response period of CIS. Firms established between 1998 and 2000 were excluded from CIS3 and those established between 2002 and 2004 were excluded from CIS4.

[b)] Yearly remuneration costs per employee in thousands of Estonian kroons (EEK) (1 EEK = 1/15.65 EUR), deflated by GDP deflator.

[c)] Capital stock equals the sum of tangible fixed assets and intangible fixed assets, minus goodwill. Presented in millions of Estonian kroons (EEK) (1 EEK = 1/15.65 EUR) and deflated by GDP deflator.

The capital stock is calculated by summing tangible fixed assets and intangible fixed assets, and subtracting goodwill. The capital stock measure is in the prices of the year 2000. The GDP deflator at the one-digit NACE level has been used to deflate the capital stock. The NACE codes are taken from the register data; in cases where register data is missing, observations have been drawn from CIS data. The wage is calculated by dividing total remuneration costs of the enterprise (including social security and pension payments) by the number of workers in the firm. The real wage is calculated by deflating with GDP deflator at the one-digit NACE level. All the variables are reported at the firm level.

The number of observations after merging the CIS and register databases is 3161 for CIS3 and 1747 for CIS4. The number of enterprises that are covered in both CIS rounds is 1122. The empirical analysis uses unbalanced panel; hence the number of observations differs from that. The larger and innovative firms are somewhat overrepresented in this data set. The descriptive statistics of these firms that were interviewed in CIS3 or CIS4 and reported their employment, wages and capital stock are presented in Table 3.2. The share of firms with any innovative activity amounts almost to 40%. The share of product and process innovators is of the same magnitude, below 30% in the sample. The innovative firms are bigger in terms of the number of employees and capital stock; and their remuneration costs per employee are higher compared to non-innovators.

3.5. Empirical results

3.5.1. Firm-level evidence

This chapter proceeds from a labour demand specification similar to Van Reenen (1997), see Section 3.3. A simple OLS estimation of the labour demand in equation 5 will lead to a biased coefficient estimate of the lagged dependent variable as the firm specific part of the error term will be positively correlated with the lagged dependent variable. The standard solution is to use within group estimation or model in differences to get rid of firm-specific effects. However, neither of these strategies will give satisfactory estimates for our dynamic labour demand equation. For the within group estimator, the transformed lagged employment (deviation from within group mean) would be negatively correlated with the transformed error terms (deviation from within group mean). This bias, also called the Nickell bias, diminishes when $T \rightarrow \infty$ (Nickell 1981), but in our sample T is small. Estimating the dynamic panel model in differences would again give a correlation between lagged differenced employment and the error term, but this correlation can be addressed by introducing instruments to lagged differenced employment.

Considering the above complications, instrumental variable techniques are the most preferable ones for dynamic panel data estimations. The Arellano and Bond (1991) and the Arellano and Bover (1995) / Blundell and Bond (1998) dynamic panel data GMM estimation methods are developed for panels with small T and large N. The former method proposes an instrumental variable estimation for the first-differenced dynamic panel data specification. The lagged differenced dependent variable and other predetermined or endogenous variables are instrumented by their earlier values in levels and by other strictly exogenous or additionally specified instruments. This approach is also often called as a difference GMM estimator (GMM-DIF). The latter method by Arellano and Bover (1995) and Blundell and Bond (1998) propose similar method; but estimating system where to the specification in first differences the specification in levels has been added. The specification in levels uses variables' earlier values in first differences as instruments. This method is often called system GMM (GMM-SYS). The system GMM has theoretical advantages over the difference GMM. Blundell and Bond (1998) show that the system GMM has better finite sample properties in the case of short panels with moderately persistent series (autoregressive term around 0.8 and 0.9).

Table 3.3 presents the results of the panel estimates. The technology variable, innovation, has been lagged by three years due to the measurement of this variable in CIS surveys. The CIS survey collects the information on innovation activity of a firm over the three-year period, but does not ask in which year the innovation(s) took place Hence, to avoid the estimation of the effect of the future innovations on current employment, we lag the innovation by 3 years.

Table 3.3. Innovation impact on employment, 2001–2006.

	OLS (pooled) a)		Within estimator a)		Two-step GMM-DIF a) b)		Two-step GMM-SYS a) c)	
	Coef.	Robust S. E.	Coef.	Robust S. E.	Coef.	Robust S. E.	Coef.	Robust S. E.
Innovation $(t-3)$	0.033***	0.010	0.027*	0.014	0.022***	0.008	0.133***	0.0412
Employment $(t-1)$	0.870***	0.035	0.337***	0.042	0.319***	0.053	0.991***	0.054
Employment $(t-2)$	0.058*	0.033	0.095***	0.032	0.062***	0.015	-0.002	0.042
Real wages	-0.05***	0.017	-0.44***	0.061	-0.40***	0.099	-0.75***	0.143
Real capital	0.050***	0.004	0.097***	0.012	-0.028	0.046	0.105***	0.017
Sargan test (31) (38)					32.3		100.3***	
p-value					0.405		0.000	
Difference Sargan (13)							46.1***	
p-value							0.000	
AR(1): no autocorrelation					-2.47**		-3.76***	
p-value					0.014		0.000	
AR(2): no autocorrelation					0.35		-	
p-value					0.725		-	
No. of observations	7317		7317		6910		7317	
No. of groups			2452		2376		2452	

a) Time and industry dummies (see Appendix G) have been used as additional explanatory variables.
b) GMM-DIF, estimation on differences. The set of instrumented variables includes: lagged differenced employment, differenced real wages and differenced real capital stock. The set of exogenous variables includes: innovation, time and industry dummies. The set of instruments includes: lagged employment, real wages, real capital and exogenous variables. The maximum lag length of instruments is limited to 3 years as the error of Sargan test tends to increase together with the number of instruments (see the discussion in Roodman (2006)).
c) GMM-SYS, system estimation. The estimation on differences imposes variable and lag set as in GMM-DIF, except excluding dummy variables from the list of instruments. The estimation on levels instruments lagged employment, real wages and real capital by differenced lagged employment, real wages, real capital and dummy variables in levels. The maximum lag length of instruments is limited to 3 years for the estimation in differences and 2 years for the estimation in levels. The two-step estimation makes use of Windmeijer (2005) correction of standard errors.
***, ** ,* denote the significance at, respectively, the 1%, 5%, and 10% levels.

This lagging is broadly in accordance with the literature that has found that the effect of innovation on employment is sluggish. Van Reenen (1997) estimates the peak effect to take place 6 years after the introduction of the innovation. Lachenmaier and Rottman (2007) find that the effects of lagged process innovation are stronger than that of the lagged product innovation[10].

The choices on capital and wages can affect next period's employment decisions, so capital and wages are treated as endogenous[11]. Sargan tests indicated the use of a maximum of three years of lags for employment and endogenous predetermined variables as instruments. For instance, differenced employment in 2003 is instrumented by employment levels in 2002, 2001 and 2000, plus other instruments arising from predetermined endogenous variables and exogenous variables introduced by the same logic.

As predicted, the OLS should overestimate and within group estimation underestimate the coefficient of lagged employment. The GMM estimators should lie between the upward biased OLS coefficient and the downward biased within group coefficient. The Table 3.3 presents that this is not the case in our estimations. The difference GMM seems to underestimate the lagged employment and other endogenous variable coefficients, while system GMM tends to overestimate the lagged employment coefficient. As Blundell and Bond (1999, p. 10) note: "If the instruments used in the first-differenced estimator are weak, then the difference GMM results are expected to be biased in the direction of within groups." Although, the Sargan test does not reject our choice of instruments ($p=0.434$), it does not exclude the weak instruments problem. The system GMM provide sensible estimators, but there the Sargan test clearly rejects the choice of instruments. The difference Sargan test that tests the validity of all instruments against the subset of difference GMM instruments, gives the same result rejecting the choice of system GMM instruments.

---

[10] The innovation variable is measured over three years and other variables are measured yearly. One can improve the estimations by controlling for this different frequency problem. Hence, one can introduce a panel in first differences over two years where $\Delta X(t)=X(t)-X(t-2)$ and X denotes whatever variable in the panel except for innovation. The resulting panel has the same frequency across all the variables. We have undertaken the experiment with this differenced panel and the results are available from authors upon request. Our short panel maintains the frequency problem as the data is not available for all the three years after the CIS4 (we have 2005–2006 instead of 2005–2007). Nevertheless, except for somewhat larger coefficient on innovation the coefficients remain relatively similar to the ones reported in Table 3.3 GMM-DIF and GMM-SYS columns.

[11] The choice on innovation may also be endogenous. Unfortunately our measurement of innovation variable does not enable to investigate that. For example, treating innovation as endogenous in GMM-DIF model requires to use the first differences of innovation variable for instruments. While the first differences of our innovation variable end up in a series of zeros with no variation (see the data section for the description of innovation variable), it is not feasible due to data limitations to treat innovation as endogenous in this framework. The exercise on the endogeneity of innovation is undertaken in Chapter 4 on a cross-section data.

We use Roodman's (2006) xtabond2 command for Stata in our GMM-SYS estimation. The problem of this command is that it does not enable to specify separately dummy variables to prevent them from first differencing. This confuses our control for the economic activity and the evaluation of the impact of innovation on employment. The first differencing of our innovation variable results in a numerous series of zeroes without any variation. Altogether with the rejection of the validity of instruments, this sets the system GMM as a valid estimation method for us under doubt. Hence, we proceed from the difference GMM and keep in mind that the estimators are probably downward biased.

The results indicate that innovation has positive and significant impact on employment. We doubt the extremely large innovation coefficient from system GMM. Other estimation methods indicate that innovation(s) increases three years after implementation employment growth by 2–3%. Those, innovating firms faced higher employment growth compared to firms that did not implement innovation. Due to the peculiarities of our innovation variable, the short run effects of innovation are not directly estimated and it is not possible to estimate the total long run effect of innovation on employment. Since, the employment lags up to two years are introduced as explanatory variables, some of the short run effect of innovation may show up there. This means that the overall impact of innovation on employment growth may even be larger.

Innovation was taken to be exogenous because the measurement of the variable does not enable to take first differences from it. The latter is necessary for the instrumentation in xtabond command of Stata (see the footnote no. 10). Overall the coefficients are in a reasonable magnitude, except for real capital stock. Blundell and Bond (1999) discuss why this very persistent variable is not always suitable for difference GMM estimation and system GMM should be preferred. Our system GMM estimation gives a bit more sensible coefficient for real capital stock, but in absolute terms real wages have larger effect on employment compared to real capital stock. This result indicates that capital formation has had little role in employment formation that is possibly related to the characteristics of transition economy. The investments into capital have been large and these are often introduced to update the production and the link to employment is probably hazier than in high-income economies. The coefficient of real wages may be interpreted as the elasticity of substitution (see the derivation in Section 3.3). This means that in our case the elasticity of substitution lies somewhere between 0.3 and 0.7.

We go further by distinguishing between process and product innovation and separating sample by technology intensiveness of industries. We use OECD / Eurostat classification of technology and knowledge-intensive sectors (OECD 2007, Eurostat 2008c). The Appendix H presents the OECD / Eurostat classification of industries by their technology and knowledge-intensiveness. This classification belongs to the widely used group of classifications that divide industries into groups of high-, medium- and low-technology by their R&D intensiveness. Table 3.4 presents various innovation indicators based on this classification of high-, medium- and low-tech sectors. The high-technology sector firms invest the highest rates into R&D and implement much more product innovations compared to the medium- and low-tech sectors.

Table 3.4. Sectoral differences in innovation, 1998–2000 and 2002–04.

	Whole sample [b)]	High-tech sector	Medium-tech sector	Low-tech sector
Share of R&D expenditures in turnover [a)]	0.009	0.065	0.011	0.002
Share of innovation expenditures in turnover [a)]	0.027	0.095	0.032	0.015
Share of innovative firms	0.377	0.610	0.355	0.361
Share of firms with product innovation	0.276	0.515	0.239	0.270
Share of firms with process innovation	0.266	0.363	0.275	0.247
Number of observations	9885	716	3651	5518
Number of groups	2783	233	1100	1646

Source: Estonian Business Register, CIS3 and CIS4, own calculations.
[a)] Data on R&D and innovation expenditures was collected only for 2000 and 2004.
[b)] The sample coincides with the sample of Table 3.2. Hence, only these observations are included where information on innovation, employment, wages and capital is reported.

The share of innovative firms is not much different across medium- and low-tech industries, while the R&D or innovation investments are much smaller in low-tech sector. This may indicate that the inputs for innovation differ across these sectors, while in medium-tech sector the research necessary for innovation is performed within the firm, the low-tech sector firms use the R&D performed in other sectors or in other countries. Heidenreich (2008) finds on European data that the low- and medium-low-tech sector is characterised by the type of firms denoted as supplier dominated by Pavitt (1984). These firms in low-tech sector implement mostly process innovation and have: "…weak internal innovation capabilities and a strong dependence on the external provision of machines, equipment and software. /…/ An increased range of goods and services and access to new markets are less important than improved flexibility of production or reduced labour costs." (Heidenreich 2008, p. 11)

The estimation results are presented in Table 3.5. Both product and process innovation are positively related to employment, but process innovation has stronger and significant effect. This may partly be a result of long time lags of innovation variables, as the effect of process innovation may be more sluggish (stronger position in the market due to increased price competitiveness).

Table 3.5. Product and process innovation impact on employment by type of economic activity, 2001–2006.

	Whole sample a) b)		High-tech sector a) b)		Medium-tech sector a) b)		Low-tech sector a) b)	
	Coef.	Robust S. E.	Coef.	Robust S. E.	Coef.	Robust S. E.	Coef.	Robust S. E.
Product innovation ($t-3$)	0.010	0.010	-0.006	0.017	0.011	0.015	0.001	0.012
Process innovation ($t-3$)	0.017*	0.009	-0.016	0.019	0.020*	0.011	0.021*	0.011
Employment ($t-1$)	0.320***	0.053	0.300***	0.082	0.323***	0.071	0.325***	0.058
Employment ($t-2$)	0.061***	0.015	0.024	0.025	0.055**	0.024	0.051***	0.015
Real wages	-0.396***	0.099	-0.680***	0.124	-0.312**	0.139	-0.406***	0.094
Real capital	-0.029	0.046	0.130***	0.042	0.032	0.047	0.044	0.053
Sargan test (31)	32.4		22.3		33.6		51.6**	
p-value	0.340		0.871		0.345		0.011	
AR(1): no autocorrelation	-2.51**		-1.27		-2.19**		-2.72***	
p-value	0.012		0.205		0.028		0.007	
AR(2): no autocorrelation	0.36		0.58		-1.27		0.32	
p-value	0.722		0.564		0.203		0.752	
No. of observations	6910		448		2510		3771	
No. of groups	2376		166		899		1386	

a) Time and industry dummies have been used as additional explanatory variables.
b) Estimation method is GMM-DIF. The set of instrumented variables includes: lagged differenced employment, differenced real wages and differenced real capital stock. The set of exogenous variables includes: innovation, time and industry dummies. The set of instruments includes: lagged employment, real wages, real capital and exogenous variables. The maximum lag length of instruments is limited to 3 years as the error of Sargan test tends to increase together with the number of instruments (see the discussion in Roodman (2006)).
***, ** ,* denote the significance at, respectively, the 1%, 5%, and 10% levels.

Separating sample by technology intensiveness of economic sectors gives somewhat surprising results. Innovations in the high-tech sector have insignificant negative effect on employment. The innovations in high-tech sector were characterised as the most R&D intensive (Table 3.5). The high-tech sector has a reputation of economic engine and other studies have found there to be the strongest relation between technological change proxies and employment (Greenhalgh *et al.* 2001, Yang and Lin 2008).

The process innovation has significant positive effect on employment in the medium- and low-tech industries. While product innovation has some positive but insignificant impact on employment in medium-tech sector, it has almost non-existent effect on employment in low-tech sector. This indicates that firms in the low-tech sector benefit the most from investments to the efficiency of production. Latter coincides with the discussion above on the Pavitt's (1984) concept of supplier dominated firms in low-tech sector. There the increased range of goods is less important than the reduced production prices.

The theoretical models from Section 1.3 indicated that the impact of product innovation on employment arise from the demand expansion due to the improvement of novelty or quality of the products. Product innovations are seen to act as a demand shock and have a little impact on the supply side. The empirical evidence on Estonian data shows that the impact of product innovation on employment is rather modest. This indicates to the low degree of improvement in the good novelty or quality. The Section 3.2.3 already discussed that Estonian low R&D expenditure but high innovation activity points to the incremental manner of innovation. This section confirms this story. Surprisingly, the high-tech industries that invest remarkably to R&D and implement a lot of product innovations are not able to internalise their product innovations into a positive demand shock and increased labour demand.

The impact of process innovation on employment depends on the trade off between two effects: employment disposal due to increased efficiency of production and demand increase due to lowered prices. The empirical exercise indicates that process innovation has significant positive effect on employment; hence the demand expansion compensates the factor saving effect. This could indicate the high price elasticity of demand, which could be the case in low-tech industries where the production is more price-sensitive.

3.5.2. Industry-level evidence

The firm-level effect of innovation may not coincide with the industry-level effects as firm-level analysis does not take into account possible market expansion or business stealing effects. In sake of completeness we go further to the industry-level analysis. We distinguish between 22 industries (see Appendix G) and 3 size groups, i.e. less than 25 employees, 25–149 employees and 150+ employees. The total number of groups is 63, while some groups remain empty due to a lack of observations. The job flow rates are calculated as follows (this designation has been adopted from Greenan and Guellec (2001)):

$$g_{st}^{pos} = \sum_{\substack{e \in E_{st} \\ g_{et} > o}} \frac{x_{et}}{x_{st}} g_{et} \tag{2.6}$$

$$g_{st}^{neg} = \sum_{\substack{e \in E_{st} \\ g_{et} < o}} \frac{x_{et}}{x_{st}} \left| g_{et} \right| \tag{2.7}$$

$$g_{st}^{net} = g_{st}^{pos} - g_{st}^{neg} \tag{2.8}$$

Where g_{st}^{pos} indicates the job creation rate, g_{st}^{neg} the job destruction rate and g_{st}^{net} the net job flow. The latter equals the conventional sector's employment growth. Subscript *e* denotes the firm, *e* = *1*, …, *E*; subscript *t* denotes the time, *t* = 2001, …, 2006; and subscript *s* denotes the sector (by industry and firm size), *s* = 1, …, 63. The firm's average employment, x_{et}, has been calculated as $x_{et} = (L_{et} + L_{et-1})/2$ where L_{et} represents the firm's employment. The sector's average employment, x_{st}, has been calculated as $x_{st} = \sum_{e \in Est} x_{et}$. Finally, the firm's employment growth rate, g_{et}, has been calculated as $g_{et} = (L_{et} - L_{et-1})/x_{et}$.

The job creation and destruction rates are essentially size weighted averages of the growth rate of growing firms and an absolute value of negative growth rates of diminishing firms. One should notice that the calculated flows underestimate actual job flows as employment is reported on a yearly basis so that the flow rates do not include job flows within a year (Greenan and Guellec, 2001). Job flows are found to be higher in transition economies than in high-income countries (Masso, Eamets and Philips 2006). Thus, even if the employment has been relatively stable, the labour reallocation rates have still been high. This is inevitable to accommodate the transition process. For Estonia, and also for other post-communist CEE countries, it has been found that labour reallocation origins mostly from the reallocation between industries (Masso *et al.*, 2006). This means also that the factors driving positive or negative job flows may differ and this is not evident from the net job flow indicators.

Table 2.6 presents the results of the analysis at the industry level. For the sake of comparability, the same sample and similar specification (see Equation (2.5)) have been used as at the firm-level analysis. We limit ourselves to OLS estimation. The data is already in differences that controls for the firm-specific effects. We do not use the difference or system GMM estimation as compared to firm-level analysis the number of objects is now relatively small. Hence, the coefficient of lagged differenced employment and probably also the ones on capital and wages may be biased.

Table 2.6 shows that the impact of innovation on various job flows differs substantially. Industry's innovation has an insignificant role in creating negative job flows, but product innovation is related positively and process innovation negatively to positive job flows. The innovation impact on net employment is weaker, but rather similar to the one of positive job flows. Hence, innovations have had insignificant role to diminish industry's employment, probably other factors like structural changes across industries have had more important role. While there is evidence that product innovations have played significant role to increase industry-level employment.

Table 2.6. Innovation impact on employment at the industry-level, 2001–2006.

	g^{pos} a) b)		g^{neg} a) b)		g^{net} a) b)	
Job flow growth (t-1)	0.053 (0.121)	-0.041 (0.132)	0.039 (0.058)	0.039 (0.059)	0.067 (0.050)	0.055 (0.051)
Job flow growth (t-2)	0.414** (0.193)	0.317* (0.175)	0.144 (0.158)	0.143 (0.159)	0.250* (0.134)	0.214 (0.131)
Innovation (t-3) c)	-0.004 (0.030)		-0.014 (0.037)		0.012 (0.052)	
Product innovation (t-3) c)		0.118*** (0.043)		-0.022 (0.044)		0.100 (0.074)
Process innovation. (t-3) c)		-0.125** (0.053)		0.004 (0.040)		-0.077 (0.081)
Real wage growth	-0.088** (0.039)	-0.113*** (0.034)	0.055** (0.022)	0.058** (0.023)	-0.133*** (0.044)	-0.153*** (0.037)
Real capital stock growth	0.024 (0.026)	0.031 (0.023)	-0.058** (0.027)	-0.057** (0.027)	0.091** (0.040)	0.092** (0.038)
No. of observations	153	153	159	159	152	152

a) The estimation method is OLS. Coefficients are reported above, robust standard errors below in parenthesis.
b) The set of control variables includes firm size and time dummies.
c) The innovation in a sector by firm size groups is a sum of each firm's innovation weighted by firms' employment relative to the total employment in a sector and size group (again the weighting scheme from (6)–(8) is followed). One must remind that due to the peculiarities of the CIS survey our innovation variable is constant over time periods 1998–2000 and 2002–04.
***, ** ,* denote the significance at, respectively, the 1%, 5%, and 10% levels.

We do not carry out similar analysis for high-, medium- and low-tech industries, because within these groups the number of observations for some industries is very small (especially for 3-digit NACE industries) and additional differentiation in terms of size groups is not possible. Nevertheless we undertake a graphical exercise plotting industry innovativeness against industry employment growth. Figures 3.3–3.5 present the relation between innovation and employment growth by industries and technology groups. Industries' innovativeness is weighting by firm employment. This means that larger firms in the sample have larger influence on the industry average innovativeness. Industries' employment growth is calculated as average of yearly growths in 2005 and 2006. Each industry's averages are compared against the whole economy average across industries; see the dashed line on figures.

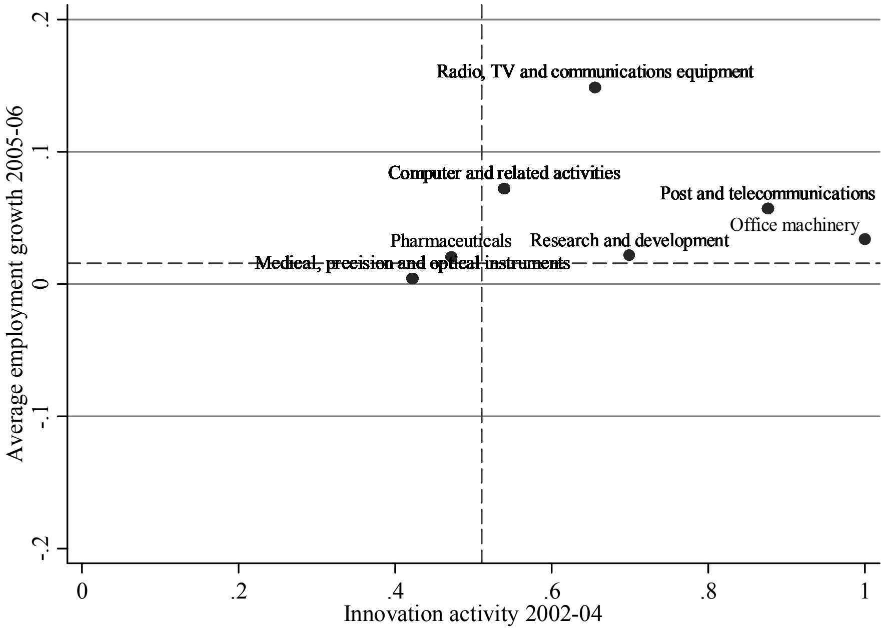

Figure 3.3. Innovation and employment in high-tech industries, Estonia.

Source: Estonian IV Community Innovation Survey and Business Register; author's calculations. Note: Dashed lines indicate average innovativeness (0.51) and employment growth (0.016) across industries; Appendix H provides the NACE categories of high-tech industries.

The most innovative, high-tech industries have faced the highest employment growth compared to medium- and low-tech industries. The low-tech industries are less innovative and less prosperous in terms of employment growth. This enriches the results from the firm-level analysis. While the high-tech industries have witnessed the highest employment growth rates and innovativeness; innovation has had no role on the employment growth in these industries at the firm level. The opposite is true for the low-tech industries. Nevertheless of the mostly negative employment growth rates in low-tech industries, innovation has played important role in increasing the employment at the firm level. The positive effect of process innovation at the firm level vanishes at the industry level due to business stealing effect. High industry-level product innovativeness is increasing industry employment via market expansion effect.

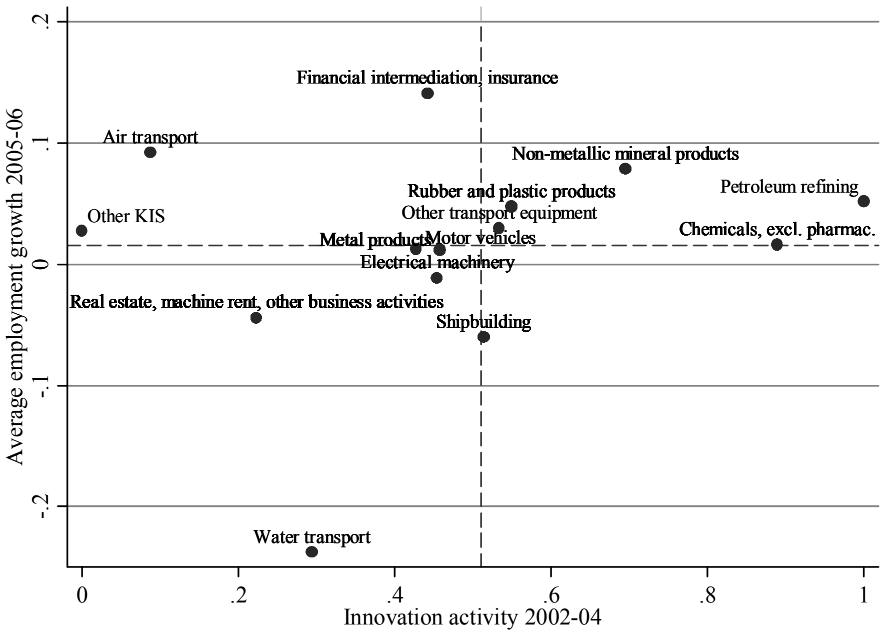

Figure 3.4. Innovation and employment in medium-tech industries, Estonia.

Source: Estonian IV Community Innovation Survey and Business Register; author's calculations.
Note: KIS denotes knowledge-intensive services; dashed lines indicate average innovativeness (0.51) and employment growth (0.016) across industries; Appendix H provides the NACE categories of medium-tech industries.

The industry-level results complement the firm-level results. In both cases innovation tends to have a positive effect on employment, but the effect is somewhat more significant at the firm level. Process innovation has strong positive impact on employment at the firm level, while product innovation has strong positive effect on employment at the industry level. The former may be a result of our long time-lags introduced for innovation variables, as unlike to product innovation the effect of process innovation is not that direct and takes longer time. The industry level positive innovation impact on employment is intuitive as market expansion of an economic activity is attributable rather to new goods than to new ways of production.

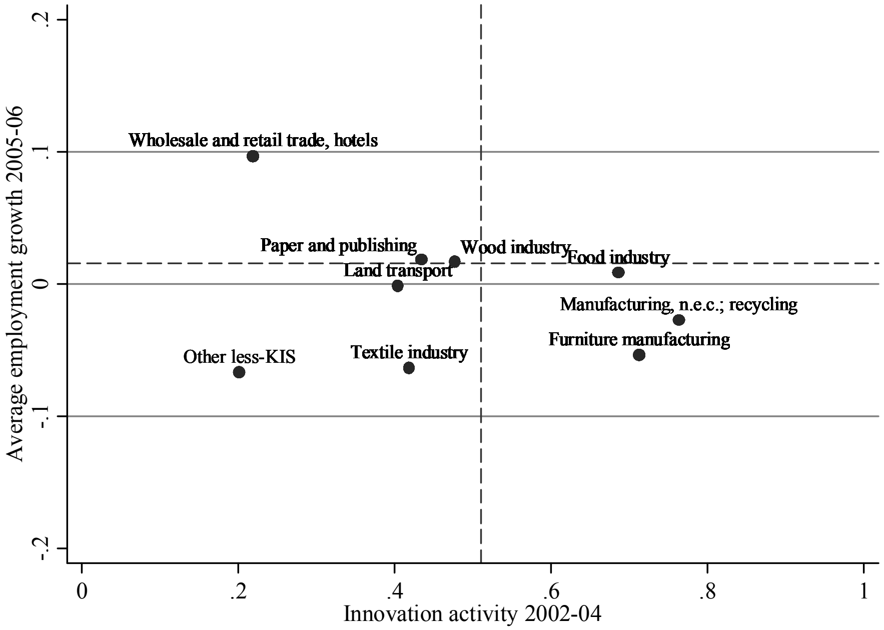

Figure 3.5. Innovation and employment in low-tech industries, Estonia.

Source: Estonian IV Community Innovation Survey and Business Register; author's calculations. Note: KIS denotes knowledge-intensive services; dashed lines indicate average innovativeness (0.51) and employment growth (0.016) across industries; Appendix H provides the NACE categories of low-tech industries.

These results are in line with the literature dealing with high-income countries. Evangelista and Savona (2003) found on Italian data much more positive innovation effects at the firm level than at the industry level. Greenan and Guellec (2001) found on French data the process innovation effect to be stronger at the firm level and the product innovation effect to be stronger at the industry level.

In sum, the industry-level analysis indicates that higher product innovativeness in a sector is related to a higher job creation rate and weakly to the net employment growth. Contrarily, process innovation is related negatively to job creation rate and has insignificant negative effect on industry's net employment growth.

3.6. Summary

In this chapter, the effect of innovation on employment was investigated at the firm- and industry-level. A dynamic panel of Estonian firms was constructed proceeding from 3rd and 4th Community Innovation Survey (CIS) and Business Register. The paper suggested novel estimation strategy for the CIS data and extended the short empirical literature of innovation impact on employment in catching-up economies.

The estimation results indicate that firm- and industry-level innovation have a positive and statistically significant effect on employment. This effect is more significant at the firm level. Distinguishing between product and process innovation reveals that process innovation tends to have a stronger positive effect on employment at the firm level and that the product innovation has a stronger positive effect at the industry level. Nevertheless the mainstream result in the empirical literature is that product innovation has positive impact on employment at the firm level, the empirical results are rather various also for the high-income countries. Our results confirm the empirical findings of the literature that have conducted the analysis at the firm and the industry level and focused on high-income countries.

The only significant divergence from the existing empirical results on high-income economies stems from the high-tech sector. Our firm-level results indicate that in the medium- and low-tech industries process innovation has significant positive effect on employment, while innovation has no impact on employment in high-tech industries. The latter conflicts the results of Greenhalgh *et al.* (2001) and Yang and Lin (2008) who found that technological change has the largest effect on employment in high-tech sector (on UK and Taiwan data respectively). This may be the result of little R&D endowment behind the innovations in Estonia. The Eastern Europe catching-up countries spend much less on R&D compared to Western Europe. They make use of the R&D of their trade partners or mother enterprises and often implement incremental innovations.

Hence, while the overall results of innovation impact on employment are similar in our exercise on catching-up country and in other studies on high-income countries; unlike in high-income countries our firm-level positive effect of innovation on employment stems mostly from the process innovation of medium and low-tech industries. Unfortunately this positive effect from process innovation does not internalise to the industry-level employment growth due to market stealing effect. The policy implication is that for the whole economy and at the industry level, only the product innovation is essential for facilitating the employment growth.

This chapter is also showing support for our proposed new estimation strategy for the Community Innovation Survey (CIS) data. In addition to the cross section estimation strategy proposed by Jaumandreu (2003), CIS data can be used also for panel estimations. But one has to rule out the direct interdependence of CIS innovation variable with employment by lagging it at least by three years.

4. THE IMPACT OF INNOVATION ON SKILL UPGRADING: INTERACTION WITH THE FDI AND THE EXPORT DESTINATION

4.1. Introduction

Most of the world economies have witnessed increased relative demand for skilled workers since 1970s. The share of non-manual labour and relative wages of skilled workers has increased regardless of the sometimes simultaneous increase in the supply of skilled labour.

There have been many explanations for this development. The main explanation is the hypothesis of skill biased technological change (SBTC). The SBTC has affected the labour markets of high-income countries and spread also to low-income countries (Berman *et al.* 1998, Berman and Machin 2000). And it has been often related to development of information and communication technologies (ICT) (Autor *et al.* 1998, Machin and Van Reenen 1998). O'Mahony *et al.* (2008) find, however, that the role of ICT on relative demand for skills started to decrease in technology leading US from around 1990s.

The second most popular explanation has been the increased trade activity and lower trade barriers. It has been estimated that increased trade activity with low-income countries has reduced the demand for low-skilled workers in high-income countries. The trade effect is generally estimated to be much weaker than the SBTC effect (Feenstra and Hanson 1999, Paul and Siegel 2001). Trade is also estimated to have interaction effects with SBTC, as trade diffuses technologies across countries (Paul and Siegel 2001). Third, organizational reorganisation together with ICT investments has been estimated to magnify the demand for skills (Bresnahan *et al.* 2002) or stand as an individual component behind increased demand for skills (Caroli and Van Reenen 2001).

The literature discusses amply the implications of technological change on skill upgrading on the data from high-income economies with a high level of technological development (see the survey paper by Chusseau *et al.* 2008). The same phenomenon is, however, not much researched on the group of Central and Eastern European (CEE) formerly planned economies. Some studies suggest that the same factors have shaped the development of skill demand in transition CEE countries as in the high-income countries. The SBTC has been estimated to have had an important effect on skill upgrading (Tarjáni 2007 on Hungarian data; Commander and Kollo (1998) on Hungarian, Romanian and Russian data). And the same effect has been found on another Communist background transition country China (Xu and Li 2008). Expectedly, the trade interaction effect with SBTC also has an important role to play. Keller (2004) generalizes that existing empirical literature indicates that foreign sources of technology have major impact on local firms' productivity and that this effect is especially important for small countries. He also generalizes that there is more evidence on technology diffusion through import and FDI than through export (Keller 2004, pp. 776–777).

For example in China the direct effect of export on local firms' skill demand has been estimated to be negative, while the indirect effect through technology adoption has been positive as exporting firms witnessed SBTC and not exporting did not. The technological change has been more skill-biased in companies with majority of foreign ownership and with private ownership (Xu and Li 2008).

Based on the Heckschler-Ohlin framework of the foreign trade a country should export goods in which production factors it is abundant. Countries abundant in low-skill labour should export labour intensive products, and countries abundant in high-skill labour should export skill intensive products. It is difficult to choose to which category one should place the CEE countries. On the one hand these countries are characterised by quite a high share of tertiary educated workers, but on the other hand their labour costs are considerably lower than in their Western European neighbours. Generally the CEE countries are positioned somewhere between the technologically leading Western countries and technologically less developed low income-countries.

The aim of this Chapter is to estimate on the data of a CEE country, Estonia, the effect of technological change on skill use. The main research question is whether technological change is skill biased or not. The chapter also seeks to uncover whether the skill bias of technological change has been magnified by trade activities or by FDI. In terms of trade activities we go deeper to see whether technological change has different effects on skills depending on the level of technological development of export destination market.

The chapter is structured as follows: next subsection presents the estimation methodology, Section 4.3 describes the data, Section 4.4 presents the results and the last section summarizes.

4.2. Methodology

The formal presentation of the SBTC usually proceeds from the cost-minimization problem of a representative firm; see the presentation by Berman *et al.* (1994) and Machin and Van Reenen (1998) as the first influential papers in this literature. As the goal is to test the substitution between skilled and unskilled labour, the list of production factors includes additionally to capital skilled and unskilled labour. The firm minimizes the cost of skilled and unskilled labour to produce a given amount of output, while capital is kept fixed (e.g. based on short-run or fixed-time cost function). Hence, a firm minimizes the function of labour costs or total variable costs. The most popular functional form in this empirical literature is the translog function. The labour cost function is presented as follows:

$$
\begin{aligned}
\ln(VC) &= a_0 + a_Y \ln Y + a_K \ln K + \sum_i a_i \ln w_i + a_Z Z \\
&+ \frac{1}{2}\gamma_{YY}(\ln Y)^2 + \frac{1}{2}\gamma_{KK}(\ln K)^2 + \frac{1}{2}\gamma_{ZZ}(Z)^2 + \frac{1}{2}\sum_i\sum_j \gamma_{ij} \ln w_i \ln w_j \\
&+ \gamma_{YK} \ln Y \ln K + \gamma_{YZ} Z \ln Y + \gamma_{KZ} Z \ln K + \sum_i \gamma_{iY} \ln w_i \ln Y \\
&+ \sum_i \gamma_{iK} \ln w_i \ln K + \sum_i \gamma_{iZ} Z \ln w_i
\end{aligned} \tag{4.1}
$$

The variable VC indicates total variable costs (labour costs), Y output, K capital, w_i wages and Z a measure of the stock of technology; the subscripts i and j can take the values S and U, where S denotes skilled and U unskilled labour. According to Shephard's lemma the optimal factor demand (for a given output) can be found taking the derivatives with respect to prices from the expenditure function. Hence, in our case:

$$
\begin{aligned}
s_i &= w_i L_i / VC = d \ln VC / d \ln w_i \\
&= a_{w^i} + \sum_j \gamma_{ij} \ln w_j + \gamma_{w^i Y} \ln Y + \gamma_{w^i K} \ln K + \gamma_{w^i Z} Z
\end{aligned} \tag{4.2}
$$

where s_i is the i^{th} input cost share and L_{i} is the corresponding cost-minimizing amount of labour. The two cost share functions, in terms of skilled and unskilled workforce, sum up to one. Hence, one cost share equation can be derived from the other, and the estimation of both of them is redundant.

One of the problems of specification (4.2) is a built-in endogeneity of the wage term as the dependent variable contains also the wage terms. This concerns the estimations that proceed from the wage-bill share of skilled workers on total wage-bill share. Hence, the wage term is often dropped from the estimations (Berman *et al.* 1994). Although this omission is mostly motivated by the before-mentioned endogeneity problem, for us data limitations have also played a role. We have information only on the average wage costs, and the introduction of industry or region average wages by skills is essentially the same as introduction of industry or region dummies (we have a cross-section data). We control for the wage dynamics by using industry and regional dummies, assuming that wages are the same within an industry and region. The specification in could still suffer under possible endogeneity of explanatory variables; we use instrumentation to alleviate this problem.

The biggest problem with our estimation is that we do not have a time series data for all of the variables to sweep out firm specific fixed effects by differencing over time[12]. Hence, we introduce differences only to these variables we

[12] This means that the estimation of equation (4.3) does not derive exactly from the cost-minimising derivation described by (4.1) and (4.2). The equation (4.3) is grounded on the assumption that $\Delta s_{S,i}$ is a function of $s_{S,i}$. This assumption is definitely problematic, but is applicable in the short-run.

have data for, i.e. for explanatory variables. The stochastic form of this equation is as follows:

$$s_{S,i} = a_{w^S,i} + \gamma_{w^S Y}\Delta \ln Y_i + \gamma_{w^S K}\Delta \ln K_i + \gamma_{w^S Z}\Delta Z_i + D^R + D^S + u_i \quad (4.3)$$

The variables D^R and D^S indicate, respectively, regional and sectoral dummies. The subscript i denotes here a firm. The dependent variable, s_i, is proxied by employment data, e.g. using the share of workers with higher education in total employment. The ΔZ denotes the change in the stock of technology or the technological change. The technological change is proxied by innovation.

The specification in terms of employment shares does not allow a direct test for SBTC, but it gives the direct relation between technological change and relative labour demand. The papers testing SBTC use usually the wage bill shares. In the rest of the chapter we use the high education employment share as the dependent variable. The most common division of employment in the literature of SBTC is the division by occupational characteristics, i.e. distinguishing between non-production and production workers or white-collar and blue-collar workers. We use the division by education due to data limitations, but there is no reason to believe that it is a poorer proxy for skills. As discussed in Chapter 1, the share of high-skilled white-collar workers and tertiary educated workers is at least at the country-level correlated. Sometimes the estimation of skill upgrading is undertaken on various proxies simultaneously. Berman and Machin (1998) use the non-production wage-bill share as the main proxy for skills, but their estimation of skill upgrading give similar results also in terms of high-skilled employment shares and high-education employment shares.

Winchester *et al.* (2006) discuss the advantages and disadvantages of either of the measures of skills, by occupation or education. They bring out that the skill classification by education is exogenous, because account for the academic qualifications. The skill classification by occupation often misclassifies jobs, the clerks and sales workers are taken to be non-production workers, while some non-production jobs entail problem-solving tasks. Wincester *et al.* (2006) derive their own skill categories by clustering occupations based on occupations' average educational attainment and wages. However their results on the impact of imports on wage inequality did not provide any different result from the mainstream in the literature that trade has had a modest role on relative wage increase in the developed world.

4.3. Data

The empirical analysis is based on data from two data sources, namely the Estonian Community Innovation Survey from year 2000 (CIS3) and the Estonian Business Register. The former is employed to obtain information on the innovativeness of firms (proxy for technological change), the share of workers with higher education, sales, foreign ownership and export. The information on capital stock and other business accounts data is obtained from the latter.

Unlike the latest surveys the 2000 CIS survey collected information on the number of tertiary educated workers in the enterprise. Firm level data on education (or occupation) of the workforce is generally very difficult to find, and the CIS survey is the only accessible source for Estonia. Information on workers education has not been collected in CIS surveys since 2000, which limits the introduction of dynamics to the empirical estimations. The rest of the variables are differentiated over two-year period whenever data limitations enabled it. Hence, partly dynamic but essentially cross-sectional data will be used. The estimation results enable to investigate the impact of recent developments in explanatory variables to the level of the dependent variable. Therefore we interpret the estimators as the impact of explanatory variables on the skill use (level) in enterprises and not skill upgrading (change).

The CIS3 survey includes 3161 enterprises from the year 2000. This year the survey covers uniquely also very small firms that employ less than 10 employees (Kurik *et al.* 2002). The CIS survey is not a whole population survey, the primary sector, some of services, including public services, are not covered by the survey. For the coverage of CIS3 survey, 1998–2000, see Table 3.1 from the previous chapter.

Table 4.1 describes the calculation of variables used in the empirical analysis of this chapter. The variable names presented in Table 4.1 are used throughout the chapter. Our innovation variables presented in Table 4.1 are self-reported by enterprises. The main characteristic of the innovation variables is that they capture the innovation activity within a longer period of time. In the CIS3 case this period is from 1998 to 2000. Hence, our technological change proxies take into account that there have been a technological switch within this period, but we cannot control for when the innovation was exactly put into practice and how large was the technological switch. The latter problem, the measurement of the magnitude of technological change, can be proxied by the innovation expenditures variable, but this variable is presented in the data set only for the year 2000. This all means that these variables may suffer under measurement problems.

Table 4.1. Description of the introduced variables.

Name of the variable	Description of the variable and source
Skill	Share of tertiary educated workers in firm's workforce, share of workers with higher or secondary professional education, ISCED97 categories 5 and 6 (UNESCO 2006), 2000, data source: CIS3
Dlrsales	Differenced logarithmic sales, deflated by GDP deflator at one-digit NACE level, difference between 1998 and 2000, data source: CIS3
Dlrcap	Differenced logarithmic capital stock (= tangible assets + intangible assets – goodwill), deflated by GDP deflator at one-digit NACE level, difference between 1998 and 2000, data source: Business Register
Inno	Innovative firm, "1" firm has introduced product or process innovation between 1998–2000, "0" no product or process innovation between 1998–2000, excluding firms that were established in this period, data source: CIS3
Innod	Product innovative firm, "1" firm has introduced any new or significantly improved products onto the market or for itself between 1998–2000, "0" no product innovation between 1998–2000, excluding firms that were established in this period, data source: CIS3
Innoc	Process innovative firm, "1" firm has introduced any new or significantly improved production professes in the market or for itself between 1998–2000, "0" no process innovation between 1998–2000, data source: CIS3
Innoexp	Expenditure on innovation activities divided by sales, 2000; excluding firms that were established between 1998–2000; CIS3
Foreign	Foreign equity in firm, "1" firm has foreign equity, "0" firm has no foreign equity, 2000, data source: CIS3
Drexpsales	Difference in the share of export volume in sales, export deflated by export deflator, sales deflated by GDP deflator at one-digit NACE level, difference between 1998 and 2000, data source: CIS3
Expeast	"1" export orientation to Eastern market bigger than to Western market (incl. EU cand. countries), "0" otherwise, data source: CIS3
Expwest	"1" export orientation to Western market (incl. EU candidate countries) bigger than to Eastern market, "0" otherwise, data source: CIS3

Our innovation variables vary somewhat from the definitions provided by the Oslo Manual (European Commission 1997). The Oslo Manual is the Eurostat guideline for the data collection of innovation indicators in the OECD countries (European Commission 1997, p. 5). The Estonian CIS surveys have been undertaken in light of this manual. The first variation originates from the different treatment of newly established firms; our definition of innovative firm is narrower as we exclude all the recently established enterprises. The establishment of a firm involves higher investments with often non-existent or small sales and the measurement of innovation is unclear as all the products and production is new for the firm. It is important to control for these developments to reduce the noisiness of the data. According to the Oslo Manual the firms established within the reference period are treated as innovators if they introduce product or process innovation that are new to their market or new to the firm later during the period (Oslo Manual 1997, p. 43). However, our data set only contains data on the new to the market product innovation and the year of the establishment of a firm. Hence, we have no criterion to select for firms which innovation activity might have been influenced by their establishment process and we, therefore, exclude the firms that were established within 1998–2000.

Second deviation from the Oslo Manual concerns the treatment of innovation activity variable. The traditional innovation activity variable defined by the Oslo Manual includes innovative activities that have led "up to the implementation of a technologically new or improved product or process"; and also not yet completed or abandoned innovation (European Commission 1997, pp. 39–40). We use only the narrower concept of innovative firm and not innovation activity as such. The introduction into practice is an important property of technological change and we employ innovation variables as a proxy for technological change

The descriptive statistics of main variables used in analysis are presented in Table 4.2. It is apparent that innovative firms use on average more tertiary educated labour, but the difference from non-innovative firms is not large. Innovative firms possess on average higher growth of capital stock, higher growth of sales, higher growth of export; and are more frequently foreign owned. Interestingly, innovative firms are more often oriented towards Western markets, but there is no difference in orientation towards Eastern markets by innovation activity.

Table 4.2. Descriptive statistics by innovativeness of firm (Inno).

	Innovative firms		Non-innovative firms		Difference between innovative and non-innovative firms
	Mean	Std. Dev	Mean	Std. Dev	t-test p-value
Skill	0.513	0.307	0.490	0.309	0.257
Dlrsales	0.220	0.665	0.071	0.692	0.000
Dlrcap	0.127	0.933	0.037	0.901	0.010
Innoexp	0.082	0.402	0.001	0.014	0.025
Foreign	0.312	0.464	0.197	0.398	0.000
Drexpsales	0.028	0.158	0.015	0.162	0.025
Expeast	0.040	0.196	0.037	0.189	0.587
Expwest	0.304	0.460	0.251	0.434	0.001

Source: Estonian Business Register, CIS3, author's calculations.

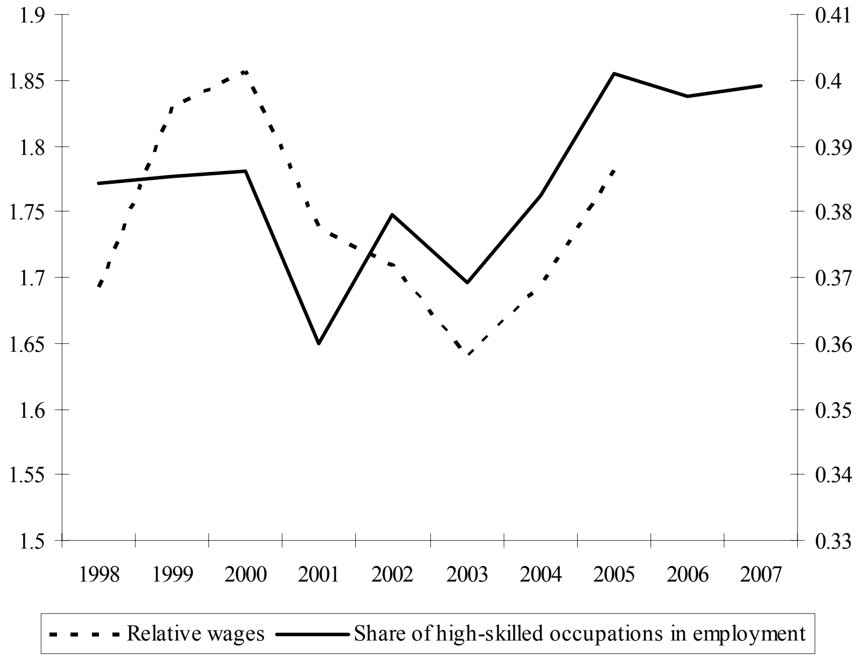

Figure 4.1. The share of high-skilled occupations in employment and the relative wages of high- and low-skilled occupations.

Source: Labour Force Surveys (Statistics Estonia 2009 for wages and Eurostat 2009a for employment shares), author's calculations.
Note: The high-skilled occupations' employment includes the workers from upper three groups of ISCO-88 classification (see Appendix A).

The comparisons above of means by innovativeness of firm are also confirmed by *t*-tests. The *t*-test indicates that the skill use is not significantly different between innovative and non-innovative firms (p = 0.257). While innovative firms have higher growth of sales (p = 0.000), capital stock (p = 0.010), export (p = 0.025) and higher probability to be foreign owned (p = 0.000). The *t*-test could not reject that the mean of export orientation to Western market is larger for innovative firms (p = 0.001), but rejected that there is any difference in export orientation to Eastern market between innovative and non-innovative firms (p = 0.587). The firms that are specialized towards markets of higher technological level, i.e. the Western markets, are characterized by more frequent innovating activity. While the firms that specialize in markets with low technological level, like Eastern market, are less active with their technological renewal.

Last, we discuss the interaction of skill use and relative wages. As we do not control directly (control only by region and industry dummies) for relative wages in our estimation, it may be that the higher/lower skill use is just a result of decrease/increase of relative wages of skilled workers. Figure 4.1 presents the relation between share of employed skilled workers and their relative wages. There is evidence that the skill use has moved cyclically together with relative wages of skilled in Estonia. Hence, at least in aggregate terms there must be other factors engaged altering the relative demand for skills.

4.4. Empirical estimation results

Our estimation begins with ordinary least squares on the relation between innovation and skills, continues with the tests for suitability of the technological change proxy and endogeneity problem. Last we discuss the impact of interaction of technological change and trade on skills.

The OLS estimators of Equation (4.3) are presented in Table 4.3. We account for possible heteroskedasticity by using robust standard errors throughout this chapter. Our preliminary estimations indicate that sales, capital and innovativeness of the firm have itself a very low explanatory power for skill use. The strongest improvement of explanatory power comes with the inclusion of industry dummies. This indicates that there are very strong industry specific effects that explain differences in skill usage. This result is logical as we do not control for firm specific effects and there are strong differences in skill composition across industries. Another group of dummies used to control for firm specific effects are region dummies. It is clear that region dummies are much weaker controls compared to industry dummies, but these still add some explanatory power to the equation.

Table 4.3. Tertiary educated workers employment share relation to innovativeness of the firm, OLS estimation.

	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Dlrsales	0.007	0.011	0.018^{**}	0.009	0.006	0.010
Dlrcap	-0.035^{***}	0.007	-0.023^{***}	0.007	-0.030^{***}	0.007
Inno	0.025^{*}	0.013	0.013	0.012	0.019	0.013
Constant	0.488^{***}	0.008	0.542^{***}	0.147	0.559^{***}	0.011
Industry dummies [a)]	No		Yes		No	
Region dummies [b)]	No		No		Yes	
Number of observations	2595		2595		2595	
R^2	0.011		0.213		0.060	

[a)] See Appendix G for the list of industry dummies used as controls.
[b)] The list of regions includes all the 15 counties of Estonia plus the capital Tallinn and cities Tartu and Pärnu.
***, **, * denote that the coefficient estimate is significantly different from 0 at, respectively, the 1%, 5%, and 10% level.

Overall it seems that the estimator for the growth of real capital stock is the most robust one to the inclusion of controls. The negative sign of this estimator may indicate that skills and capital are substitutes in our case. This negative relation is maintained even if we introduce capital by dividing it by sales. This result is inconsistent with mainstream empirical literature on developed world and also on CEE country (Tarjáni 2007 on Hungarian data). But this result is not an unknown one in the literature as Machin and Van Reenen (1998) find the same result for Japan and Germany, while skills and capital were found to be complements for other selected OECD countries (including US and UK). O'Mahony *et al.* (2008) find that capital and skills are complements for the highest skill categories, Bachelor degree and more; but not for the intermediate skill categories, from associate degree to high-school graduates. Our definition of skilled workers includes also workers with less academic and more practical or technical specific higher education (ISCED-97 category 5B). Hence, this inconsistency could also be a result of our wider definition of skilled workers.

Yet the causal relationship between skills and capital is not clear. The causality testing presumes a longer panel data. It may be that firms with lower skill endowment have invested more to capital stock. Although the result that skills and capital are substitutes is an interesting one, due to methodological limitations it should be interpreted cautiously.

The real sales growth and innovation variable are quite sensitive to the inclusion of controls. Controlling for industries reduces the innovation effect and magnifies the impact of sales while controlling for regions reduces only the impact of innovation. These findings can be considered reasonable, as in terms of regions the whole Estonian market behaves dynamically the same and there is no region-specific market expansion/shrinking dynamics (at least not over the two-year period). We include the industry and region dummies in all the estimations hereafter. We proceed by testing for the suitability of OLS for the analysis.

4.4.1. Endogeneity

The potential problem of our OLS estimators is that the explanatory variable "innovativeness of firm" could be endogenous, resulting in biased estimators. The intuition behind the possible emergence of this endogeneity problem is simple. Theoretically, the unexplained part of skill endowments of enterprise is correlated with innovating activity. Alternatively, we have an omitted variable that is correlated with innovation, but uncorrelated with other explanatory variables (Wooldridge 2002, p. 83).

In our case this means that the innovativeness of firm could also capture other factors of the firm and not only technological change. Innovative firms could include more "intelligent" firms that are inclined towards the use of higher skills. This means that our OLS estimator for innovativeness may underestimate the role of innovativeness or technological change itself. We address this issue by instrumenting the innovation variable and use 2 stage least squares (2SLS) estimators instead of OLS.

The choice of instruments that determine the innovativeness of firm, but not their skill use is of course a difficult one. The already existing skills in the enterprise are also found to be an important innovation production factor (Leiponen 2005), which raises the question of causality and shines the light on the main problem of our data set, namely the lack of dynamics. The literature explain innovativeness usually by variables like demand prospects, competition conditions, factors governing the production of knowledge, financing conditions and firm size (Arvanitis 2008).

In 2SLS, the first stage is usually taken to be the instrumentation; while the second stage is the estimation using the instrumented variables. The firm size can be proxied by sales and is therefore also used as one of the explanatory variables already included to the first stage of the 2SLS estimation (all the exogenous variables of the second stage are also included to the first stage). We limit our choice of instruments among above listed innovation production factors by (Arvanitis 2008) to the financing conditions, the stock of knowledge and knowledge production factors. Our data set does not enable to count for the demand prospects and competition conditions.

The choice of instruments concerns also the discussion on possible endogeneity of innovation in Chapter 1. The theoretical innovation endogenisation mechanisms discussed in Section 1.2.1 were the supply of skills and technology adaption costs. Theoretically the increase in the relative supply of skills should give incentives to develop relatively skill-intensive technologies (Acemoglu 1998). The introduction of this mechanism involves dynamic adjustment; as we have essentially the cross sectional data, we do not investigate the impact of the supply of skills. According to technology adoption theory (Caselli 1999) the introduction of skill-biased technologies increases the demand for skills as the new technology adaption costs are lower for skilled workers. If the existing potential for knowledge creation in the firm is high, there is less obstacles for the adoption of skill-biased technologies. Hence, we somewhat account for the adaption costs in our knowledge creation variable.

Table 4.4 presents the list of the instruments. The introduced variables on cooperation and affiliation to business group capture the potential for knowledge transfer between the firm and its partners. These variables should capture the potential for knowledge creation and also the network of knowledge used to lower the new technology adoption costs. The existence of patents in 2000 captures the accumulated codified knowledge in the firm. The cumulated profits of the firm reflect the capability to finance innovative activity irrespective of the borrowing constraints. This variable may also account for the accumulated knowledge of profit making or experience in the market.

Table 4.5 presents correlations between the initial variables used in the skill demand regression and proposed instruments. The choice of instruments seems reasonable in the sense that all the instruments are more strongly correlated with the innovation variable than the dependent variable skills. Accumulated business profits and affiliation to business group are correlated only with the innovation and/or with other instruments and not with other explanatory variables. Patents and cooperation variable are also significantly correlated with the dependent variable skills, but the correlation with innovation variable is much stronger. Among the financial variables, the business profit suited much better for instrumentation compared to net profits after taxes and financial costs and profits (this exercise is not reported in Table 4.5).

Table 4.4. Description of the instruments for innovativeness.

Name of the variable	Description and source
Business group	"1" Enterprise belongs to business group, "0" otherwise, data source: CIS3
Cooperation	Cooperation arrangements, "1" Enterprise had co-operation arrangements on innovation activities with other institutions between 1998 and 2000, "0" otherwise, data source: CIS3
Patent	Patents, "1" Enterprise had active patents in 2000, "0" otherwise, data source: CIS3
Rbusprofitcum	Cumulated business profits of enterprise (i.e. before financial deductions and taxation), from 1995 to 2000 or from the establishment year to 2000 (if established later than 1995), deflated by GDP deflator at one-digit NACE level (see the Appendix B), in billions of EEK (1EEK=0.065EUR), data source: Business Register

Table 4.5. Pearson correlation coefficients between dependent and explanatory variables and instruments.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill (1)	1							
Dlrsales (2)	-0.015 (0.438)	1						
Dlrcap (3)	-0.097 (0.000)	0.333 (0.000)	1					
Inno (4)	0.036 (0.069)	0.115 (0.000)	0.047 (0.017)	1				
Business group (5)	0.007 (0.708)	0.013 (0.506)	-0.028 (0.150)	0.177 (0.000)	1			
Cooperation (6)	0.055 (0.005)	0.059 (0.002)	0.042 (0.032)	0.473 (0.000)	0.179 (0.000)	1		
Patent (7)	0.043 (0.027)	0.021 (0.279)	-0.002 (0.934)	0.158 (0.000)	0.190 (0.000)	0.143 (0.000)	1	
Rbusprofit-cum (8)	-0.011 (0.575)	0.002 (0.919)	0.011 (0.587)	0.050 (0.011)	0.041 (0.036)	0.028 (0.158)	0.026 (0.180)	1

Note: The number of observation is 2595; the same sample is used for the regressions. The significance of correlation coefficients is reported in parenthesis.

We start with the Hausman test for endogeneity (see Wooldridge 2002, pp. 118–122). In the first stage we regress the innovativeness with its instruments and all other explanatory variables introduced to the main, skill use, equation. In the second stage we regress the residuals obtained from the first stage as an addition to our skill use equation. If these residuals are statistically significant in our skill use equation, this indicates the endogeneity of innovation variable. Yet, we should remind that this test is based on the assumption that our choice of instruments is correct.

Table 4.6. Tertiary educated workers employment share relation to innovativeness of the firm, 2SLS estimation.

	1st stage of 2SLS/Hausman		2nd stage of Hausman test		2nd stage: 2SLS	
	Dependent: Inno		Dependent: Skill		Dependent: Skill	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Dlrsales	0.063***	0.013	0.014	0.009	0.014	0.009
Dlrcap	-0.003	0.009	-0.021***	0.007	-0.021***	0.007
Inno			0.042	0.027	0.042	0.026
Business group	0.092***	0.021				
Cooperation	0.607***	0.019				
Patent	0.134***	0.043				
Rbusprofitcum	0.179**	0.080				
Residuals from stage 1			-0.039	0.029		
Constant	0.039***	0.026	0.573	0.137	0.573***	0.137
Industry dummies a)	Yes		Yes		Yes	
Region dummies b)	Yes		Yes		Yes	
Sargan test c) (p-value)					0.532	
Basmann test c) (p-value)					0.540	
List of instruments					Business group, cooperation, patent, rbusprofitcum	
Number of observations	2595		2595		2595	
R^2	0.291		0.226		0.223	

a) See Appendix G for the list of industry dummies used as controls.
b) The list of regions includes all the 15 counties of Estonia plus the capital Tallinn and cities Tartu and Pärnu.
c) Tests of overidentifying restrictions are based on the estimation with ordinary (non-robust) standard errors.
***, **, * denote that the coefficient estimate is significantly different from 0 at, respectively, the 1%, 5%, and 10% level.

We present the estimation results of individual steps in Table 4.6. The coefficients of the first stage of the Hausman test indicate that all the instruments have expected signs. The instruments or innovation inputs influence innovativeness positively and the strongest effect comes from the innovation cooperation[13]. The second stage of the Hausman test indicates that the innovation variable is not endogenous in the skill use equation (t = -1.37). Thus under conventional significance levels we cannot reject the exogeneity of the innovation variable (p = 0.172).

The 2SLS estimators with all of our instruments are reported in the last columns of Table 4.6. The second stage of Hausman test and 2SLS estimators are essentially the same. The 2SLS estimators are reported because the OLS estimators from the second stage have incorrect standard errors. But this discrepancy is negligible in our case. We test for the correctness of our instrument choice by tests of overidentifying restrictions, Sargan's and Basmann's tests. Neither of the tests can reject the null of joint validity of the instruments.

In sum, we seem to have chosen a set of appropriate instruments, but the direct tests do not indicate the endogeneity of the innovation variable. The coefficient on innovation changes quite a lot after instrumentation (Table 4.3 vs Table 4.6). The impact of innovativeness on skill use is by 2SLS much larger and the estimator is much closer of being statistically significant. The standard errors of the OLS coefficient on innovation (0.011 ± 0.012 for the OLS with industry and region controls) and 2SLS are so large and we cannot say that these coefficients differ statistically. We may generalise from the point estimates of innovation coefficients that innovating firms have around 1–4 percentage point higher share of workers with tertiary education. Nevertheless, statistical significance of this coefficient is low.

The Community Innovation Survey data allows us to use also other proxies for the innovativeness of firm. We go further by distinguishing between product and process innovativeness and introduce innovation expenditure variable. For example 20% of firms that self-reported the introduction of new or significantly improved products or production methods did not report any innovation expenditures. The expenditure variable captures potentially also the importance of innovation. See the descriptive statistics of various innovation variables in Table 3.4 in Section 3.5. Tables 4.7 and 4.8 present the results on OLS and 2SLS estimation on alternative innovation proxies. The results of the direct tests on exogeneity are discussed in the text. We go through the same estimation procedure as previously and use the same instruments as listed in Table 4.4.

[13] This instrument may be itself endogenous to the innovation variable. Nevertheless, the innovation cooperation variable includes also innovation cooperation that does not end up in the application of innovation. Some firms have the network of innovation partners without innovations put into practice. The Hausman test gives the same result when we exclude this instrument.

Table 4.7. Tertiary educated workers employment share relation to firm's innovation expenditures, OLS vs. 2SLS estimation.

	OLS		2SLS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Dlrsales	0.017*	0.009	0.018**	0.009
Dlrcap	-0.022***	0.007	-0.025***	0.007
Innoexp	0.100***	0.038	0.329	0.228
Constant	0.576***	0.136	0.575***	0.136
Industry dummies [a)]	Yes		Yes	
Region dummies [b)]	Yes		Yes	
Sargan test (p-value) [c)]			0.459	
Basmann test (p-value) [c)]			0.466	
List of instruments	–		Business group, cooperation, patent, rbusprofitcum	
Number of observations	2595		2595	
R^2	0.227		0.215	

[a)] See Appendix G for the list of industry dummies used as controls.
[b)] The list of regions includes all the 15 counties of Estonia plus the capital Tallinn and cities Tartu and Pärnu.
[c)] Tests of overidentifying restrictions are based on the estimation with ordinary (non-robust) standard errors.
***, **, * denote that the coefficient estimate is significantly different from 0 at, respectively, the 1%, 5%, and 10% level.

Similarly to overall innovativeness the exogeneity of innovation expenditures was not rejected (t = –1.09) and the instrument choice was "justified" by the Sargan and Basmann tests. The OLS estimator is again smaller and the difference between OLS and 2SLS estimators is large. As standard errors of the coefficient on innovation expenditures are large, it is may not be generalised that these coefficients statistically differ across OLS and 2SLS.

We test also for the endogeneity of product and process innovation. The Hausman test indicates weak endogeneity for product innovation (t = –1.70) and exogeneity for process innovation (t = –1.13). The tests for instruments show again the validity of the instruments. The product and process innovation variables are hardly significant in our specification, irrespective of the endogenous treatment. Again the standard errors are too large to state anything on product and process innovation coefficients difference over OLS and 2SLS.

This subsection showed that innovation proxies have no statistically significant impact on skill use. Nevertheless, overall innovation activity, product or process; and innovation expenditures were weakly related to the skill use. We tested also for the possible endogeneity of innovation and found support for the exogeneity of innovation under our choice of instruments.

Table 4.8. Tertiary educated workers employment share relation to firm's product and process innovation, OLS vs. 2SLS estimation.

	OLS		2SLS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Dlrsales	0.016*	0.009	0.013	0.011
Dlrcap	-0.022***	0.007	0.018**	0.008
Innod	-0.003	0.015	0.307	0.233
Innoc	0.019	0.015	-0.269	0.243
Constant	0.575***	0.137	0.565	0.141
Industry dummies [a)]	Yes		Yes	
Region dummies [b)]	Yes		Yes	
Sargan test (p-value) [c)]			0.746	
Basmann test (p-value) [c)]			0.749	
List of instruments	–		Business group, cooperation, patent, rbusprofitcum	
Number of observations	2595		2595	
R^2	0.226		0.047	

[a)] See Appendix G for the list of industry dummies used as controls.
[b)] The list of regions includes all the 15 counties of Estonia plus the capital Tallinn and cities Tartu and Pärnu.
[c)] Tests of overidentifying restrictions are based on the estimation with ordinary (non-robust) standard errors.
***, **, * denote that the coefficient estimate is significantly different from 0 at, respectively, the 1%, 5%, and 10% level.

We use hereafter the innovation variable "inno" for the proxy of technological change. The innovation expenditures are a more precise measure of innovativeness and may be also considered as a good proxy for technological change. We prefer innovativeness due to its' better dynamic measurement in the CIS survey. The innovation expenditures are measured for the year 2000 only and our skill variable is also measured only for the year 2000. Hence by innovation expenditures variable we would unintentionally capture some temporary effects of innovation. The innovativeness variable is measured over longer time span, 1998–2000.

4.4.2. Interaction of innovation with FDI and export

Theoretical and empirical findings from the existing literature suggest that foreign trade and outsourcing are important source of technology diffusion and that both of these factors intensify the effect of skill biased technological change (Chusseau *et al.* (2008), see Sections 1.2 and 4.1). We test for this extension by adding foreign ownership, export growth and their interaction terms with technological change to our tertiary educated employment share equation.

The existing empirical literature shows that high-income countries' skilled workers have benefited from outsourcing to low-income countries and that direct effects from trade with low-income countries are relatively weak compared to technological change (Chusseau *et al.* 2008). Foreign direct investments (FDI) and export/import of intermediate goods are the most common proxies for outsourcing. We approximate the FDI by foreign ownership equity in the firm. The impact of trade is captured by the share of export in firm's sales.

The export variable captures also part of the effect from outsourcing. The existing empirical evidence on CEECs find that export of intermediate goods has stronger positive effect on relative wages of unskilled workers than the import of intermediate goods (Egger and Stehrer 2003). Hence, the export may be taken as a good proxy for investigate the impact of trade and outsourcing on skill demand. As we do not distinguish between the export of final and intermediate goods, we cannot claim that export captures fully the effect of outsourcing.

Although our export data does not allow distinguishing between the final or intermediate goods, we have information on the export destination market. If the firm is exporting to Western countries from Estonia, it reflects the South-North type of trade or even possible outsourcing of some labour-intensive part of production from the Western countries. If the firm is exporting to Eastern markets, it reflects the South-South type of trade. Dahi and Demir (2008) show on the industry level analysis that the South-South type of trade is more capital and skill-intensive than the South-North type of trade. This indicates that the South-South type of trades should increase the demand for skills. Nevertheless, the direct micro level estimation of these types of trade on skill upgrading is absent from the empirical literature.

Table 4.9 shows that foreign owned firms possess higher share of tertiary educated workers, while our foreign ownership and innovation interaction term is negative. The foreign owned firms that are innovating are changing their technology rather to the favour of unskilled labour. Contrarily, Xu and Li (2008) found that foreign owned firms implemented skill-biased technical changes in China.

The export growth variable has significant negative effect on skill use. These results are consistent with the Heckscher-Ohlin framework and empirical investigations on the high-income countries (generalised by Chusseau *et al.* 2008) and CEECs (Egger and Stehrer 2003). Our results predict that countries abundant with cheap low-skilled labour (like Estonia compared to the Western Europe) should produce and export unskilled labour abundant products. However the export and innovation interaction term is insignificant indicating no technology diffusion through export.

Table 4.9. Tertiary educated workers employment share relation to innovativeness, foreign ownership and export growth; OLS estimation.

	OLS		OLS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Dlrsales	0.019^{**}	0.009	0.017^{*}	0.009
Dlrcap	-0.021^{***}	0.007	-0.021^{***}	0.007
Inno	0.022	0.014	0.019	0.014
Foreign	0.038^{**}	0.018	0.037^{**}	0.018
Foreign*Inno	-0.049^{*}	0.027	-0.047^{*}	0.027
Drexpsales	-0.071^{*}	0.040		
Drexpsales*Inno	0.049	0.069		
Expeast			0.036	0.126
Drexpsales*Expeast*Inno			-0.408	0.305
Expwest			-0.092^{*}	0.053
Drexpsales*Expwest*Inno			0.149^{*}	0.087
Constant	0.575^{***}	0.137	0.576^{***}	0.137
Industry dummies [a)]	Yes		Yes	
Region dummies [b)]	Yes		Yes	
Number of observations	2595		2595	
R^2	0.228		0.228	

[a)] See Appendix G for the list of industry dummies used as controls.
[b)] The list of regions includes all the 15 counties of Estonia plus the capital Tallinn and cities Tartu and Pärnu.
***, **, * denote that the coefficient estimate is significantly different from 0 at, respectively, the 1%, 5%, and 10% level.

These results might, however, depend on the origin of the foreign equity and on the destination of the export market. Presumably, if the origin and destination are a high tech economy we may experience technology diffusion and observe positive interaction terms with innovation. Our data set enables us to track the export destination market, but not the origin of foreign equity. The Western market is compared to Estonia a market with more advanced level of technology, while the Eastern market is endowed with less developed technology.

The last columns of Table 4.9 present the results where export is divided based on export destination market. These firms that are specialized in exporting to more advanced technology Western market do innovations that demand more skill use. The skill upgrading effect of technological change has characterised also the developed economies. While the firms that are specialized in technologically less developed Eastern markets have no statistically significant innovation impact on skill use. In sum, the results indicate that when we control for the destination market the export performs as technology diffusion channel and there is evidence of the impact of South-North type of trade on lower demand for skills and no evidence of South-South[14] type of trade on skill demand.

4.5. Summary

The purpose of this chapter was to estimate the impact of technological change on skill upgrading and the interaction effect of trade and FDI with technological change. The analysis is undertaken on a data of middle-developed CEE country Estonia. We use cross-sectional data and proxy the technological change by innovativeness.

The results indicate that unlike innovativeness the foreign trade has a significant effect on skill use in CEEC like Estonia. And expectedly, as predicted by Heckscher-Ohlin framework, this effect is negative. We go further from the investigation of Xu and Li (2008) and distinguish also the destination of the export market. Then we find evidence of skill-biased technological change, but interestingly this effect grounds from the interaction of innovation and foreign trade with technologically more developed economies. Hence, the foreign trade from one hand directly reduces the skill demand and from other hand acts as technology diffusion channel and increases the skill demand.

Unlike to export foreign ownership does not seem to perform as technology diffusion channel in a middle developed country. The foreign ownership weakens the innovation impact on skills, which is a surprising result. Firms with foreign ownership employ a higher share of workers with tertiary education, but they implement innovations that reduce the use of skills. This result might also depend on the origin of foreign equity in the firm, unfortunately our data set does not enable to control for that. Of course all these results may suffer under causality problem, but our data set limits the introduction of a panel data.

[14] Our variable of export destination market to the North contains also the markets of the EU new candidate countries. Hence, part of the South-South type of trade is also captured in the North-South trade variable.

FINAL CONCLUSIONS

The main findings

The aim of this thesis was to investigate the impact of technological change on labour and skill demand. We have undertaken the analysis at country, industry and firm level. The focus was set on the Central and Eastern European countries (CEEC) with Post-Soviet background. This group of countries has undergone extensive changes in their labour-markets. As the labour reallocation has taken place mostly between industries, the main focus of the analysis on these countries has been on the structural changes and the role of technological change has receded into the background. We purpose to fill this gap in the literature.

The second chapter of the thesis investigated the differences in skill structure across Western and Eastern European countries and investigated the role of technological change in skill structure shifts. The analysis was undertaken on EU25 labour-force surveys data from 2000–2004 and the skill structure was approximated by occupational structure. The results indicate that the main difference between these high and middle income countries skill endowment in 2004 derives from the different industry structure. The technology inducement within the industries is not much different across countries. More specifically, there are many CEE countries such as Czech Republic, Slovenia or Estonia, which have similar skill structure than that of the developed Europe. These country groups are rather characterised by similar technology within industries and differ in terms of their industry structure.

The dynamic analysis over the period 2000–2004 shows that over time, most of the changes in skill structure have been driven by changed skill demand within the industries. Hence, unlike to static pattern the over time changes are mostly attributable to technological change. There is also an evidence of technology diffusion across EU countries, as the changes in skill structure within industries are relatively similar across countries. This is especially true for the EU12 group of countries. The policy implication from this chapter is that some of the CEE countries, including Estonia, use similar technology within industries. The differences in skill demand across Western and Eastern Europe is mostly attributable to different industry structure. The CEECs have larger share of non-skill-intensive industries and lower share of skill-intensive industries.

The third and fourth chapter of the thesis investigated the impact of technological innovation on employment at the firm and industry level. We made use of Estonian firm-level data. The third chapter of the thesis proceeded from the dynamic panel data from 1996–2006 and the fourth chapter from the cross-section of data from 1998–2000.

The results of the third chapter of the thesis indicate that overall innovation activity has positive and statistically significant employment effect at the firm and industry level. This effect seems to be stronger at the firm level. These results are significant after the control for real labour costs; real capital stock; controls on industry and economic cycle; and endogeneity of real labour costs and real capital stock.

Process innovation has a significant positive effect on employment at the firm level and product innovation at the industry level. These results confirm the firm- and industry-level results from high-income countries. The firm-level positive impact of process innovation on employment derives from the medium- and low-tech industries and is probably reflecting the competition over prices and elastic demand. Insignificant effect from firm-level product innovation reflects probably the low novelty of new products or only little improvements in product quality due to product innovation.

The only significant divergence of our results from the existing empirical literature stems from the high-tech sector. Our firm-level results indicate that in the medium- and low-tech industries process innovation has significant positive effect on employment, while innovation has no impact on employment in high-tech industries. Latter conflicts the results on high-income economies. This may be the result of little R&D endowment behind the innovations in Estonia. The Eastern European catching-up countries spend much less on R&D compared to Western Europe. They make use of the R&D of their trade partners or mother enterprises and often implement incremental innovations.

Hence, while the overall results of innovation impact on employment are similar in catching-up and high-income countries; unlike in high-income countries the firm-level positive effect of innovation on employment stems mostly from the medium and high-tech industries in catching-up countries. The industry-level analysis indicates that industries oriented on product innovation experience higher employment growth. The policy implication of this is that product innovation has the most important role in facilitating the industry and country level employment.

The fourth chapter of the thesis indicates on Estonian data that innovativeness has positive, but insignificant effect on employment. This result is robust on the treatment of innovation as exogenous or endogenous. We implement the cross-sectional analysis and test for the endogeneity of innovation. Innovation is instrumented by knowledge stock (patents), potential for knowledge creation (affiliation to business group and innovation cooperation) and accumulated business profits. The formal tests support our choice of instruments, but cannot reject the exogeneity of innovation under this choice of instruments.

Unlike innovativeness the foreign trade has a significant effect on skill use in CEEC like Estonia. And expectedly, as predicted by Heckscher-Ohlin framework, this effect is negative. We go further from the investigation of Xu and Li (2008) and distinguish also the destination of the export market. Then we find evidence of skill-biased technological change, but interestingly this effect grounds from the interaction of innovation and foreign trade with technologically more developed economies. This indicates that foreign trade from one hand directly reduces the skill demand and from other hand acts as technology diffusion channel and increases the skill demand.

Contrarily the foreign ownership directly increases the skill use, while the interaction effect of foreign ownership and innovation is negative. Or using other words; firms with foreign equity use more tertiary workers in the production, but implement innovations that reduce the demand for skills. The policy implication of this is that unlike to export the foreign ownership does not seem to perform as technology diffusion channel in a middle-developed country. This result might also depend on the origin of foreign equity in the firm, unfortunately our data set does not enable to control for that. Our results indicate that the main factor behind skill diffusion and skill upgrading is the learning by exporting to markets with more developed technology.

This thesis proposes also two novel estimation strategies for the set of problems purposed. First, we undertake the skill structure decomposition analysis at the static framework. The so called static shift-share analysis is often implemented for regional studies, like for regional income level convergence analysis (Esteban 2000). We are not aware of any other empirical exercise employed for the similar skill structure analysis. This tool for static analysis is easy to implement and enables informative graphical presentation on simple scatter graphs.

The third chapter proposes a new estimation strategy of the innovation impact on employment on the CIS (Community Innovation Survey) data. We demonstrate that in addition to the cross-section estimation strategy proposed by Jaumandreu (2003), the CIS data can be used also for panel estimations. The estimation strategy by Jaumandreu (2003) estimates the impact of innovation on employment over a three-year time-span. The impact of innovation on employment may take effect after quite a long adjustment period. Van Reenen (1997) finds that the peak effect of innovation on employment takes place after six years. Hence, the short time-series in this kind of analysis may cause underestimation of the total impact of innovation on employment.

We overcome the limitations of CIS survey by merging consecutive waves of CIS surveys to a panel. Most of the firms surveyed in consecutive Estonian CIS surveys overlap in different waves. This enables us to obtain quite representative unbalanced panel. This estimation strategy may be suitable for smaller countries where the firms covered by different surveys often overlap and where it is expensive to undertake alternative longitudinal innovation survey suitable for the dynamic panel analysis.

The bottleneck of CIS data in a dynamic framework is to accommodate the innovation variable from CIS data for the dynamic analysis. The CIS data measures innovation as a binary choice variable over the surveyed three years. We suggest two alternative accommodation schemes to rule out the direct interdependence of CIS innovation variable with the current employment. First, by lagging the innovation variable at least by three years; or second, by first-differencing the whole data set over the two years for which the innovation is collected.

Suggestions for future research

This thesis set a focus on the effect of technological change on labour demand in CEECs. One of the future extensions of this topic would be to investigate also the wage adjustments due to technological changes. As brought out by the literature review the latest technological changes associated with Information and Communication Technologies (ICT) have increased the demand for high-skilled jobs and reduced the demand for jobs related to routine tasks (Autor, Levy and Murnane 2003). This increase in relative demand for skilled workers have increased the college wage gap in US and induced unemployment of the low-skilled in Europe (Freeman and Soete 1997).

There is a vast literature on the contribution of technological change on inequality, see Chusseau *et al.* (2008) for the literature review. It may be generalised, that the focus of theoretical and empirical literature has been rather on the impact of technological change on inequality than on the resulting relative demand for skills. As the inequality is a vital topic in any of the countries under transition, it would be interesting to investigate how much have technological changes contributed to inequality in transition. There is a scarce empirical literature on that topic on CEECs. Esposito and Stehrer (2008) focus on the impact of sector biased technological change and find that this explains some part of the skill premium in CEECs.

Another set of extensions could be to investigate further the technology diffusion across countries. We have employed the data at industry levels and compared the industry developments across countries for the proxy of technology diffusion. The industry or a firm level data from a single country is a common strategy in this kind of estimations. The further methodological challenge of these studies could be to merge firm-level data over several countries. For example, to facilitate the investigation of the effect of traded (intermediate) goods simultaneously in host and home country.

Last but not least. The data limitations have restricted our analysis towards a more sophisticated variables or methods. In this thesis a lot of effort has been dedicated to find the best estimation strategy under ample data problems. Yet, another extension would be to undertake the same analysis on the data with a more sophisticated innovation variable or to perform the firm-level analysis of skill-biased technological change on panel data.

APPENDICES

Appendix A. ISCO-88 classification at one-digit level ('major groups')

High-skilled non-production occupations	
Isco 1	Legislators, senior officials and managers
isco 2	Professionals
isco 3	Technicians and associate professionals
Low-skilled non-production occupations	
Isco 4	Clerks
Isco 5	Service workers and shop and market sales workers
Skilled production occupations	
Isco 6	Skilled agricultural and fishery workers
Isco 7	Craft and related trades workers
Isco 8	Plant and machine operators and assemblers
Unskilled production occupations	
Isco 9	Elementary occupations
Remaining occupations	
isco 0	Armed forces
iscoun	Occupational group unknown

Appendix B. NACE classification at one-digit level

A	Agriculture, hunting and forestry
B	Fishing
C	Mining and quarrying
D	Manufacturing
E	Electricity, gas and water supply
F	Construction
G	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods
H	Hotels and restaurants
I	Transport, storage and communication
J	Financial intermediation
K	Real estate, renting and business activities
L	Public administration and defence; compulsory social security
M	Education
N	Health and social work
O	Other community, social and personal service activities
P	Private households with employed persons
Q	Extra-territorial organizations and bodies
Un	Sector unknown

Appendix C. Total differences in occupational shares between countries and EU averages

Table C.1. Differences between member country's and EU average occupational structures in 2004.

	isco1	isco2	isco3	isco4	isco5	isco6	isco7	isco8	isco9	isco0	iscoun
Belgium	0.025	0.0608	-0.0426	0.0517	-0.0259	-0.0197	-0.037	-0.0128	-0.0005	0.0017	-0.0007
Austria	-0.0253	-0.0447	0.0773	0.026	0.0067	0.0045	-0.0067	-0.0323	-0.0006	-0.0027	-0.0022
Denmark	-0.0161	0.0073	0.0558	-0.0047	0.0159	-0.0165	-0.0261	-0.0294	0.0174	-0.0018	-0.0017
Finland	0.0048	0.0313	0.0106	-0.0288	0.0231	0.0044	-0.0236	-0.0072	-0.0113	-0.0023	-0.001
France	-0.0115	-0.0164	0.0284	0.0267	-0.012	-0.0008	-0.0165	0.0023	-0.0051	0.0059	-0.0011
Germany	-0.0282	0.0016	0.0617	0.0238	-0.0157	-0.0241	0.0144	-0.0238	-0.0191	0	0.0093
Greece	0.0172	-0.0006	-0.0731	0.0114	0.0029	0.0775	0.0113	-0.0192	-0.0328	0.0079	-0.0024
Ireland	0.0882	0.0313	-0.0869	0.025	0.02	-0.0364	-0.009	-0.0166	-0.0109	-0.0022	-0.0024
Italy	0.0054	-0.0404	0.0478	0.0162	-0.0297	-0.0174	0.024	-0.0037	-0.005	0.0052	-0.0024
Luxembourg	-0.0157	0.0551	0.0352	0.0498	-0.0575	-0.0238	-0.0442	-0.0205	0.0272	-0.0038	-0.0018
Netherlands	0.0179	0.049	0.0337	0.0194	-0.001	-0.028	-0.0531	-0.0334	-0.0101	-0.0016	0.0071
Portugal	0.0032	-0.0553	-0.0663	-0.0032	-0.0032	0.0663	0.0464	-0.0124	0.0264	0.0004	-0.0024
Spain	-0.0135	-0.0126	-0.0447	-0.0133	0.0127	-0.0089	0.0286	0.0009	0.0542	-0.001	-0.0024
Sweden	-0.0344	0.0418	0.0532	-0.0069	0.0528	-0.0186	-0.0478	0.0048	-0.0404	-0.0038	-0.0008
UK	0.0582	-0.0054	-0.0272	0.0394	0.0344	-0.0322	-0.0479	-0.0274	0.0109	-0.0029	-0.0001
Czech Republic	-0.023	-0.0359	0.0543	-0.0225	-0.0111	-0.0257	0.0524	0.0566	-0.0399	-0.0032	-0.002
Cyprus	-0.0626	-0.013	-0.022	0.0263	0.035	-0.0109	0.009	-0.0403	0.0751	0.0057	-0.0024
Estonia	0.0455	-0.0233	-0.018	-0.0595	-0.0043	-0.0222	0.0053	0.0543	0.0256	-0.0011	-0.0024
Hungary	-0.0137	-0.0071	-0.0195	-0.0138	0.0053	-0.0124	0.0447	0.0291	-0.015	-0.0019	0.0043
Latvia	0.0145	-0.0257	-0.0342	-0.0383	0.0075	0.0397	0.0046	0.008	0.0302	-0.0039	-0.0024

Table C.1 continued.

	isco1	isco2	isco3	isco4	isco5	isco6	isco7	isco8	isco9	isco0	iscoun
Lithuania	-0.0126	0.0191	-0.0626	-0.063	-0.0214	0.0895	0.044	-0.0014	0.0137	-0.0029	-0.0024
Malta	0.0032	-0.0391	-0.0116	0.0121	0.0182	-0.0245	-0.0006	0.0121	0.0247	0.0079	-0.0024
Poland	-0.0254	-0.0159	-0.0218	-0.0317	-0.0171	0.1187	0.0181	-0.0004	-0.0226	0.0003	-0.0022
Slovakia	-0.021	-0.0369	0.0308	-0.0393	0.0049	-0.0305	0.0521	0.0495	-0.0077	0.0005	-0.0024
Slovenia	-0.0254	-0.0059	0.0063	-0.0125	-0.0219	0.041	-0.0125	0.0637	-0.0429	-0.0016	0.0117
EU25 cross-country average	0.0871	0.1412	0.1499	0.1018	0.1341	0.0432	0.1423	0.0952	0.0967	0.0061	0.0024

Source: Labour Force Surveys from 25 EU countries, authors' calculations.

Appendix D. The industrial, within and interaction effects

Table D.1. Between effects of the EU-25 countries' occupational structures in 2004.

	isco1	isco2	isco3	isco4	isco5	isco6	isco7	isco8	isco9	isco0	iscoun
Belgium	-0.0039	0.0235	0.0177	0.0079	0.0022	-0.0257	-0.0141	-0.0043	-0.0053	0.0026	-0.0007
Austria	0.005	-0.0061	0.0023	0.0041	0.0135	-0.0083	-0.0048	-0.0024	-0.0025	-0.0004	-0.0004
Denmark	-0.0053	0.0198	0.0222	0.0014	0.0114	-0.0193	-0.0151	-0.0084	-0.0055	-0.0011	-0.0002
Finland	-0.0046	0.0147	0.0142	-0.0015	0.0014	-0.0082	-0.0124	-0.0008	-0.0011	-0.0018	0.0001
France	-0.0043	0.0106	0.0112	0.0019	0.0057	-0.0136	-0.0138	-0.0076	0.0085	0.0016	-0.0005
Germany	-0.0015	0.0024	0.0128	0.0044	0.0009	-0.0247	0.0051	0.0049	-0.004	0.0005	-0.0007
Greece	0.006	-0.0165	-0.0169	-0.0052	0.0124	0.0407	-0.0135	-0.0125	0.0055	0.0008	-0.0009
Ireland	0.0029	-0.0054	-0.0002	0.0003	0.0065	0.0006	0.0073	-0.0082	-0.001	-0.0019	-0.0008
Italy	0.0025	0.0002	-0.0026	-0.0006	0.0012	-0.0129	0.0092	0.0025	0.002	-0.0006	-0.0009
Luxembourg	-0.0006	0.0165	0.0243	0.0304	-0.008	-0.0258	-0.0225	-0.019	-0.0001	0.0046	0.0002
Netherlands	0.0023	0.0168	0.0201	0.0052	0.0125	-0.02	-0.03	-0.017	-0.0033	0.0011	0.0124
Portugal	0.0014	-0.0262	-0.0217	-0.0145	-0.0006	0.0378	0.0168	-0.0041	0.013	-0.0007	-0.001
Spain	0.0036	-0.0197	-0.0152	-0.0066	0.0125	-0.0041	0.0213	-0.0051	0.0151	-0.0009	-0.001
Sweden	-0.0062	0.0449	0.0225	-0.0006	0.0058	-0.0243	-0.025	-0.0126	-0.0028	-0.0011	-0.0006
UK	0.0005	0.0249	0.0171	0.0073	0.0149	-0.0317	-0.0165	-0.0143	-0.0019	-0.0002	-0.0001
Czech Republic	-0.0009	-0.0167	-0.0075	-0.0012	-0.0156	-0.0118	0.0341	0.0268	-0.0059	-0.0005	-0.0008
Cyprus	0.008	-0.0186	-0.0139	0.0004	0.0344	-0.0059	-0.001	-0.0213	0.0191	-0.0001	-0.001
Estonia	-0.0022	-0.0037	-0.0071	0.0001	-0.0179	-0.0054	0.0168	0.0238	-0.0035	-0.0001	-0.0008
Hungary	-0.0009	0.001	-0.0041	-0.0006	-0.0095	-0.0065	0.0133	0.013	-0.0051	0.0002	-0.0008
Latvia	-0.0011	-0.0138	-0.017	-0.0033	-0.0176	0.0449	0.0019	0.0095	-0.0022	-0.0004	-0.0009
Lithuania	-0.0017	-0.0086	-0.0195	-0.015	-0.017	0.064	0.0017	0.0007	-0.0017	-0.0019	-0.001

Table D.1 continued.

	isco1	isco2	isco3	isco4	isco5	isco6	isco7	isco8	isco9	isco0	iscoun
Malta	0.0035	-0.0005	-0.0008	0.0057	0.0172	-0.0259	-0.0001	0.006	-0.0059	0.0016	-0.0007
Poland	-0.0005	-0.0146	-0.0167	-0.0099	-0.0276	0.0722	-0.006	0.0082	-0.0036	-0.0005	-0.0009
Slovenia	0.001	-0.0157	-0.0141	-0.0061	-0.0203	0.0216	0.0141	0.0219	-0.0036	-0.0008	0.0021

Source: Labour Force Surveys from 25 EU countries, authors’ calculations.

Table D.2. Within effect of the EU25 countries' occupational structures in 2004.

	isco1	isco2	isco3	isco4	isco5	isco6	isco7	isco8	isco9	isco0	iscoun
Belgium	0.0279	0.0285	-0.0474	0.0372	-0.0279	0.0164	-0.0244	-0.0093	-0.0023	-0.0007	-0.0011
Austria	-0.0291	-0.0406	0.0766	0.0214	-0.0036	0.0146	-0.0028	-0.0317	-0.0003	-0.0024	-0.0021
Denmark	-0.0141	-0.0018	0.0306	-0.0037	-0.0073	0.0050	-0.0119	-0.0223	0.0278	-0.0009	-0.0015
Finland	0.0093	0.0217	-0.0007	-0.0237	0.0140	0.0141	-0.0093	-0.0057	-0.0180	-0.0006	-0.0011
France	-0.0080	-0.0200	0.0196	0.0234	-0.0195	0.0179	-0.0057	0.0109	-0.0210	0.0034	-0.0010
Germany	-0.0279	0.0002	0.0444	0.0190	-0.0161	0.0015	0.0082	-0.0254	-0.0153	-0.0006	0.0089
Greece	0.0053	0.0227	-0.0549	0.0206	-0.0103	0.0171	0.0347	-0.0055	-0.0365	0.0060	-0.0024
Ireland	0.0857	0.0382	-0.0867	0.0283	0.0164	-0.0366	-0.0197	-0.0086	-0.0142	-0.0006	-0.0024
Italy	0.0029	-0.0395	0.0503	0.0161	-0.0313	-0.0068	0.0118	-0.0067	-0.0036	0.0062	-0.0024
Luxembourg	-0.0044	0.0291	0.0022	0.0307	-0.0475	0.0015	-0.0342	0.0123	0.0166	-0.0047	-0.0016
Netherlands	0.0302	0.0318	0.0057	0.0175	-0.0122	-0.0179	-0.0316	-0.0195	-0.0097	-0.0014	0.0071
Portugal	0.0029	-0.0316	-0.0482	0.0170	0.0059	0.0153	0.0291	-0.0066	0.0144	0.0012	-0.0024
Spain	-0.0193	0.0152	-0.0366	-0.0050	0.0060	-0.0047	0.0067	0.0070	0.0303	-0.0002	-0.0024
Sweden	-0.0311	0.0061	0.0421	-0.0060	0.0187	0.0101	-0.0242	0.0229	-0.0356	-0.0034	0.0004
UK	0.0570	-0.0213	-0.0387	0.0297	0.0157	-0.0064	-0.0365	-0.0156	0.0182	-0.0025	0.0002
Czech Republic	-0.0221	-0.0185	0.0685	-0.0215	0.0041	-0.0192	0.0142	0.0269	-0.0297	-0.0030	0.0004
Cyprus	-0.0618	0.0190	-0.0168	0.0244	0.0062	-0.0050	0.0094	-0.0265	0.0447	0.0058	-0.0024
Estonia	0.0450	-0.0190	-0.0058	-0.0603	0.0171	-0.0194	-0.0099	0.0246	0.0251	-0.0010	-0.0024
Hungary	-0.0128	-0.0083	-0.0078	-0.0143	0.0123	-0.0075	0.0276	0.0152	-0.0093	-0.0021	0.0040
Latvia	0.0158	-0.0047	-0.0170	-0.0423	0.0280	-0.0006	0.0039	-0.0041	0.0243	-0.0038	-0.0024
Lithuania	-0.0023	0.0392	-0.0415	-0.0572	-0.0055	0.0097	0.0451	0.0017	0.0117	-0.0015	-0.0024
Malta	-0.0021	-0.0370	-0.0119	0.0071	0.0006	0.0033	0.0015	0.0052	0.0278	0.0047	-0.0024
Poland	-0.0138	0.0020	0.0016	-0.0233	0.0098	0.0142	0.0191	-0.0005	-0.0079	0.0008	-0.0021
Slovakia	-0.0184	-0.0280	0.0418	-0.0344	0.0318	-0.0278	0.0159	0.0287	-0.0081	0.0008	-0.0024
Slovenia	-0.0206	0.0127	0.0263	-0.0054	-0.0069	0.0112	-0.0197	0.0292	-0.0342	-0.0007	0.0052

Source: Labour Force Surveys from 25 EU countries, authors' calculations.

Table D.3. Interaction effect of the EU25 countries' occupational structures in 2004.

	isco1	isco2	isco3	isco4	isco5	isco6	isco7	isco8	isco9	isco0	iscoun
Belgium	0.001	0.0088	-0.0129	0.0066	-0.0003	-0.0104	0.0015	0.0008	0.0071	-0.0002	0.0011
Austria	-0.0012	0.0019	-0.0016	0.0004	-0.0031	-0.0019	0.001	0.0018	0.0022	0.0001	0.0003
Denmark	0.0032	-0.0108	0.0031	-0.0024	0.0117	-0.0023	0.0009	0.0013	-0.0049	0.0001	0
Finland	0.0001	-0.0051	-0.0029	-0.0037	0.0077	-0.0015	-0.0018	-0.0007	0.0078	0.0001	0
France	0.0007	-0.007	-0.0024	0.0014	0.0018	-0.0051	0.0029	-0.001	0.0074	0.0009	0.0004
Germany	0.0012	-0.001	0.0045	0.0004	-0.0004	-0.0008	0.0011	-0.0033	0.0002	0.0001	0.0012
Greece	0.0059	-0.0068	-0.0014	-0.004	0.0008	0.0196	-0.01	-0.0012	-0.0018	0.001	0.0009
Ireland	-0.0003	-0.0016	0	-0.0037	-0.0029	-0.0004	0.0033	0.0002	0.0043	0.0003	0.0008
Italy	0	-0.0011	0.0001	0.0007	0.0004	0.0023	0.003	0.0005	-0.0034	-0.0004	0.0009
Luxembourg	-0.0107	0.0095	0.0087	-0.0112	-0.0019	0.0005	0.0124	-0.0138	0.0107	-0.0036	-0.0004
Netherlands	-0.0147	0.0005	0.0079	-0.0033	-0.0012	0.0099	0.0085	0.0032	0.0029	-0.0012	-0.0125
Portugal	-0.0011	0.0026	0.0036	-0.0056	-0.0084	0.0133	0.0005	-0.0017	-0.001	0	0.001
Spain	0.0022	-0.0081	0.0071	-0.0018	-0.0058	-0.0001	0.0006	-0.001	0.0088	0.0001	0.001
Sweden	0.0029	-0.0092	-0.0114	-0.0003	0.0283	-0.0044	0.0015	-0.0055	-0.002	0.0007	-0.0006
UK	0.0007	-0.009	-0.0056	0.0023	0.0038	0.0059	0.0051	0.0025	-0.0054	-0.0002	-0.0002
Czech Republic	-0.0001	-0.0007	-0.0067	0.0002	0.0004	0.0053	0.0042	0.0029	-0.0042	0.0003	-0.0016
Cyprus	-0.0089	-0.0133	0.0088	0.0015	-0.0056	0	0.0006	0.0076	0.0114	0	0.001
Estonia	0.0028	-0.0006	-0.0051	0.0007	-0.0035	0.0026	-0.0015	0.0059	0.0039	0.0001	0.0008
Hungary	0	0.0002	-0.0076	0.0012	0.0025	0.0016	0.0038	0.0009	-0.0006	0	0.0011
Latvia	-0.0002	-0.0072	-0.0001	0.0073	-0.0029	-0.0046	-0.0012	0.0026	0.0081	0.0003	0.0009
Lithuania	-0.0086	-0.0114	-0.0016	0.0092	0.0011	0.0159	-0.0028	-0.0039	0.0037	0.0005	0.001
Malta	0.0017	-0.0016	0.001	-0.0007	0.0004	-0.0019	-0.0021	0.0009	0.0028	0.0016	0.0007
Poland	-0.0111	-0.0033	-0.0067	0.0015	0.0007	0.0323	0.005	-0.0081	-0.0111	0	0.0008
Slovakia	0.0002	0.0002	-0.004	-0.0009	-0.0085	0.005	0.0032	0.0005	0.0045	-0.0004	0.0002
Slovenia	-0.0058	-0.0029	-0.0059	-0.001	0.0054	0.0082	-0.0068	0.0125	-0.0051	-0.0001	0.0045

Source: Labour Force Surveys from 25 EU countries, authors' calculations.

Appendix E. Selection of firm-level studies on technological change and employment

Authors, date	Data	Countries	Industries	Innovation variables	Employment variables	Estimation method	Results
Harrison, Jaumandreu, Mairesse, Peters, 2008	CIS3 micro data, 1998–2000	France, Germany, Spain and the UK	Manufacturing and services	Process innovation, sales growth due to new products	Firm-level employment	Combined labour demand function from the cost functions of production of new and old products (IV)	Positive relation between employment growth and product innovation, negative insignificant relation between employment growth and process innovation
Fung, 2006	1992–2003, 79 (out of 100) banking holding companies, US Securities and Exchange Commission, US Patent and Trademark Office	Top 100 banking holding companies	Banking	Process innovation: patented process innovations per firm and per industry, ICT expenditures	Full-time equivalent employees in firm	CES production function, estimated dynamic differenced labour demand function (OLS, IV)	Process innovation and employment positively related, whole industry's employment benefits from patented process innovations (yearly effects)
Piva, Vivarelli, 2005	1992–97, 575 firms, investment bank Mediocredito Centrale questionnaire survey	Italy	Manufactu-ring	Innovative investments	Firm-level employment	CES production function, estimated dynamic differenced labour demand function (GMM-SYS)	Innovativeness and employment positively related, effect small in size (yearly effects)

Rennings, Ziegler, Zwick, 2004	2000, 1040 environmentally innovating establishments from IMPRESS project telephone interviews	Germany, UK, Italy, the Netherlands, Switzerland	Manufacturing, services	Discrete variables of environmental product (service) or process innovation	Increasing, decreasing or unchanged employment due to environmental innovation in establishment	Not structural models, various discrete choice models	Product innovation has positive effect on employment, process innovation has no significant effect (cross-section effects)
Evangelista, Savona, 2003	1993–95, cross-section of 943 innovative firms from National Statistical Office innovation survey	Italy	Services	Discrete variables of service or process innovation, total innovation expenditures per employee	Increasing, decreasing or unchanged employment due to innovation in firm	Not structural models, logit models for high- and low-skilled and total employment	Product innovation and innovation expenditures per employee have positive effect on employment and on highly-skilled employment, process innovation has no significant effect (effect within 3 years)
Greenan, Guellec, 2001	1986–90, 15186 firms from French annual business survey and survey of technological innovation	France	Manufacturing	Discrete variables of product or process innovativeness during 1986–90	Annual mean of the 5-year change in full-time equivalent employees in firm	Structural model of supply (Cobb-Douglas production function) and demand, estimate labour demand with 2SLS	Process and product innovation have positive effect on employment, process innovation effect is stronger (medium-term effect of 5 years)
Van Reenen, 1997	1976–82, 598 firms listed on London Stock Exchange merged with SPRU innovation count data	UK	Manufacturing	"Successful commercial introduction of new or improved products and processes" specified by experts. Major technological shifts.	Firm employment in UK	CES production function, estimated dynamic differenced labour demand function	Innovation has positive effect on employment. Product innovation has positive effect, process innovation has insignificant effect.

Appendix F. Selection of sectoral-level studies on technological change and employment.

Authors, date	Data	Country	Industries	Level of disaggregation	Employment and innovation measure	Estimation method	Results
Evangelista, Savona, 2003	1993–95, cross-section of 943 innovative firms from National Statistical Office innovation survey	Italy	Services	22 sub-industries at 2- and 3-digit NACE level	Qualitative employment variable (increase, no change or decrease of employment due to firm's innovation activity)	For every sub-industry of services the index of impact of innovation has been calculated (weighted by the number of employees)	Innovation activity has replaced low-skilled jobs with high-skilled jobs, overall effect of innovation on employment in services is negative (effect within 3 years)
Antonucci, Pianta, 2002	1994–96, 10 industries, CISII cross-section	Germany, France, Italy, Denmark, the Netherlands, the UK, Sweden, Finland	Manufacturing	10 sub-industries	Change in sub-industry employment, total innovation expenditures in sales, new or changed product share in sales, process innovations in sales (sales includes all the sales in sub-industry)	Cross-country regression between change in employment (1994–99), innovation variables (1994–96), change in demand (1994–96), change in labour compensation (1994–96)	Innovation has negative impact on employment; process innovation has a negative effect, product innovation has a positive, but insignificant effect
Greenan, Guellec, 2001	1986–90, 15186 firms from French annual business survey and survey of technological innovation	France	Manufacturing	37 manufacturing industries in 7 size categories (255 categories in total)	Net growth employment rate calculated as job creation rate minus job destruction rate, discrete variable of innovation activities between 1986–90	Net growth employment rate regressed with the share of innovative firms across industries (weighted by the number of employees)	Innovativeness and product innovation are positively related to employment, process innovation has no significant effect (yearly effects)

Appendix G. The list of industries used as controls in regression analysis

	Industry	Code by Estonian classification of economic activities 2003 (NACE Rev. 1.1)
1	Agriculture, forestry and fishing	A, B
2	Mining and quarrying	C
3	Manufacture of food products, beverages	DA
4	Manufacture of textiles and textile products; leather and leather products	DB, DC
5	Manufacture of wood and wood products	DD
6	Manufacture of pulp, paper and paper products; publishing and printing	DE
7	Manufacture of coke, refined petroleum products and nuclear fuel; chemicals, chemical products and man-made fibres	DF, DG
8	Manufacture of rubber and plastic products; other non-metallic mineral products	DH, DI
9	Manufacture of basic metals and fabricated metal products	DJ
10	Manufacture of machinery and equipment n.e.c.	DK
11	Manufacture of electrical and optical equipment	DL
12	Manufacture of transport equipment	DM
13	Manufacture of furniture; manufacturing n.e.c.; recycling	DN
14	Electricity, gas and water supply	E
15	Construction	F
16	Wholesale trade and commission trade, hotels	G; H
17	Transport, storage	60–63 within I
18	Post and telecommunications	64 within I
19	Financial intermediation	J
20	Real estate activities; other business activities	70, 71 and 74 within K
21	Computer and related activities; Research and development	72 and 73 within K
22	Public services	75–93

Source: Statistics Estonia (2008), Estonian classification of economic activities 2003.

Appendix H. The OECD/Eurostat classification of industries based on technology

Industry	Code by Estonian classification of economic activities 2003 (NACE Rev. 1.1)
High-technology industries	
Manufacturing	
Pharmaceuticals	244
Office, accounting and computing machinery	30
Radio, TV and communication equipment	32
Medical, precision and optical instruments	33
Aircraft and spacecraft	353
Knowledge-intensive high-technology services	
Post and telecommunication	64
Computer and related activities	72
Research and development	73
Medium-technology industries	
Medium high-technology manufacturing	
Chemicals excluding pharmaceuticals	24 excl. 244
Machinery and equipment, n.e.c.	29
Electrical machinery and apparatus, n.e.c.	31
Motor vehicles, trailers and semi-trailers	34
Railroad equipment and transport equipment, n.e.c.	35 excl. 351,353
Medium low-technology manufacturing	
Coke, refined petroleum products and nuclear fuel	23
Rubber and plastics products	25
Other non-metallic mineral products	26
Basic metals and fabricated metal products	27–28
Building and repairing of ships and boats	351
Knowledge-intensive services	
Water transport	61
Air transport	62
Financial intermediation, insurance and its' auxiliary activities	65–67
Real estate activities, renting of machinery, other business activities	70, 71. 74
Other knowledge-intensive services (education, health, recreation)	80, 85, 92
Low-technology industries	
Manufacturing	
Food products, beverages and tobacco	15–16

Textile, textile products, leather and footwear	17–18, 19
Wood and wood products	20
Pulp, paper and paper products; publishing and printing	21–22
Furniture	361
Manufacturing n.e.c., recycling	36 excl. 361, 37
Less-knowledge-intensive services	
Wholesale and retail trade, hotels and restaurants	50–52, 55
Land transport; auxiliary transport activities; travel agencies	60, 63
Other less-knowledge-intensive services	75, 90, 91, 93, 95–97, 99

Source: OECD 2007, Eurostat 2008c.

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SUMMARY IN ESTONIAN – KOKKUVÕTE

TEHNOLOOGILISED MUUTUSED JA TÖÖJÕU NÕUDLUS

Töö aktuaalsus

Tehnoloogilised muutused on läbi ajaloo mõjutanud inimeste tööd ja töövõtteid. Näiteks aurumasin vähendas sama hulga toodangu tootmiseks vajalikku tööjõu hulka ning asendas väljaõppinud käsitöölised tsunftides lihttöölistega tehases (Chin, Juhn ja Thompson 2006). Seega vähendas tööstusrevolutsiooni esimene faas nõudlust oskustööliste järele ning suurendas nõudlust lihttööliste järele (*de-skilling*). Alates elektrienergia rakendamisest tööstuses on tehnoloogilised muutused olnud oskuste suunas nihkega (*scill-biased*). Goldin ja Katz (1998) toovad välja, et aurumasina asendamine elektrienergiaga muutis mittevajalikuks lihttööliste tööjõu, kes olid seotud söe ladustamise ja ahjude kütmisega. Acemoglu (2002b) toob välja, et viimase 150 aasta jooksul on arenenud riikides kapitali hind olnud pea muutumatu, aga tööjõu hind on kasvanud; mis viitab, et tehnoloogilised muutused sel perioodil on olnud pigem tööjõu nõudlust suurendavad (*labour augmenting*).

Kunagi varem pole tehnoloogilised uuendused muutnud suhtelist nõudlust oskuste järele nii palju kui seda on teinud arengud informatsiooni- ja kommunikatsioonitehnoloogiates (IKT) alates 1970ndatest. Autor, Levy ja Murnane (2003) näitavad, et IKT areng on suurendanud nõudlust mitterutiinsete töövõtete järele ning et arvutid on asendanud nn rutiinseid töövõtteid. Vähenenud nõudlus nn rutiinsete töövõtete järele on kaasa toonud vähenenud nõudluse madala kvalifikatsiooniga tööjõu järele. Hüppeline nõudluse kasv kõrge kvalifikatsiooniga tööjõu järele on suurendanud palgaerinevust kõrge ja madala kvalifikatsiooniga tööjõu vahel USAs ning suurendanud tööpuudust madala kvalifikatsiooniga tööjõu hulgas Euroopas (Freeman ja Soete 1997). IKT arengu ajastu on toonud kaasa ka tehnoloogiate globaalselt oluliselt laiema ning kiirema leviku. See on seotud nii suurenenud väliskaubandusvoogude ja kapitali mobiilsusega kui selle grupi tehnoloogiate omapäraga, *informatsiooni* edastamise ja *kommunikatsiooni*vahendite arenguga. (Bruland ja Movery 2005) Sarnaseid muutusi tootmisharude hõive struktuuris on täheldatud nii arenenud kui arenevates riikides (Berman, Bound ja Machin 1998, Berman ja Machin 2000).

Post-kommunistlike Kesk- ja Ida-Euroopa riikide tööturud on läbi teinud suuri muutusi turumajanduse suunas liikudes. Ulatuslik tootmisharude ja tootmise ümberstruktureerimine on suurendanud töökohtade kadumist ja struktuurse tööpuuduse tekkimist. Sarnaselt arenenud maailmaga on ka nendes riikides täheldatud suhtelist nõudluse suurenemist kõrgema kvalifikatsiooniga tööjõu järele (Kézdi 2002, Tarjáni 2007, Commander ja Kollo 2008). Siiski on selliste muutuste põhjustele ning just tehnoloogiliste muutuste mõjule tööhõivele ja hõive struktuurile nendes riikides vähe tähelepanu pööratud. Antud doktoritöö on pühendatud selle tühimiku täitmisele kirjanduses.

Uurimuse eesmärk ja ülesanded

Käesoleva töö eesmärgiks on hinnata tehnoloogiliste muutuste mõju tööjõu nõudlusele Kesk- ja Ida-Euroopa üleminekumaade näitel. Mõju tööjõu nõudlusele käsitletakse nii kogumõjuna hõivele kui hõive struktuurile tööjõu kvalifikatsiooni lõikes. Uuring viiakse läbi nii riigi, tootmisharu kui ettevõtte tasandil. Uurimuse eesmärgi täitmiseks püstitatakse neli uurimisülesannet.

Esimese ülesandena antakse ülevaade teoreetilistest seostest tehnoloogiliste muutuste ja tööjõu nõudluse vahel. See osa illustreerib kohandumisprotsesse, mis tekkivad peale tehnoloogiliste muutuste toimumist ettevõtte, haru või riigi tasandil. Lisaks antakse ülevaade kuidas ajalooliselt tööstusrevolutsiooni jooksul on erinevad tehnoloogiad mõjutanud tööjõu nõudlust ning nõudlust erinevate oskustega tööjõu järele.

Teiseks uurimisülesandeks on hinnata tehnoloogiliste muutuste rolli tööjõu struktuuri kujunemisel ELi riikide võrdluses. Rõhuasetus on riikide gruppide võrdlusel: rikkad Lääne-Euroopa riigid *vs.* vaesemad Kesk- ja Ida-Euroopa (KIE) üleminekuriigid. Võrreldakse riikide hõive struktuuri 2004.aastal ning analüüsitakse millised tegurid on mõjutanud muutusi riikide hõive struktuuris.

Kolmandaks ja neljandaks uurimisülesandeks on hinnata tehnoloogiliste muutuste mõju tööjõu nõudlusele ettevõtte tasandil. Nende uurimisülesannete täitmiseks kasutatakse valimit Eesti ettevõtete andmetest. Kolmandaks uurimisülesandeks on hinnata tehnoloogiliste muutuste mõju kogu tööjõu nõudlusele Eesti ettevõtete paneeli näitel. Lisaks hinnatakse kas siinkohal on erineva tehnoloogiamahukusega sektoritel erinev roll, st analüüs viiakse läbi eraldi kõrg-, kesk- ja madaltehnoloogia harudes. Ettevõtte tasandi analüüsile sarnaselt teostatakse analüüs ka tootmisharu tasandil.

Neljandaks uurimisülesandeks on hinnata tehnoloogiliste muutuste mõju ettevõtte nõudlusele kõrge kvalifikatsiooniga tööjõu järele. Hinnatakse kas Eesti ettevõtetes on toimunud oskuste suunas nihkega tehnoloogiline muutus ning kas eksport või välisinvesteeringud on kiirendanud tehnoloogiliste muutuste jõudmist Eesti ettevõtetesse. Igale uurimisülesandele pühendatakse töös üks peatükk.

Teoreetiline ja empiiriline taust

Käesolev töö haakub kahe erineva majandusteoreetilise koolkonna töödega. Ühelt poolt kasutatakse käesolevas töös tehnoloogiliste muutuste mõju analüüsil neoklassikalise majandusteooria raamistikku. Teisalt kasutatakse empiiriliste tulemuste tõlgendamisel ja analüüsi laiendamisel tõekspidamisi majanduse evolutsiooniteooriast (*evolutionary economics*). Vähemalt majanduskasvu seletavate teoreetiliste mudelite osas on nende kahe koolkonna mudelid ajas teineteisele lähenenud (Verspagen 2005).

Neoklassikalisest raamistikust lähtuvad mudelid võimaldavad hästi illustreerida tehnoloogiliste muutuste tõttu toimuvaid kohandumisprotsesse ettevõttes. Seda Walras üldise tasakaalu mudeli omadust kohanduda tasakaalu suunas tunnustas ka majanduse evolutsiooniteooria suurnimi Schumpeter. Kuid erinevalt neoklassikalisest koolkonnast ei uskunud Schumpeter püsiva tasakaalu eksisteerimisse majanduses ning tunnustas Walras mudelit vaid kui illustreerivat näidet kuidas kohandumisprotsessid majanduses toimuvad. Schumpeteri järgi on majandus pidevas muutumises ning selle dünaamika aluseks on ettevõtete innovaatilisus. Nimelt uskus Schumpeter, et erinevalt neoklassikalisest koolkonnast, kus ettevõtted konkureerivad madalama hinna pärast, konkureerivad ettevõtted tehnoloogia pärast. Parem tootmistehnoloogia, parem toode, uus turunduskanal, parem organisatoorne ülesehitus on need näitajad, mis annavad ettevõttele turul konkurentide ees eelise. Ning kui ettevõte suudab edukalt ellu viia ühe neist innovatsioonidest, saavutab ta turul parema positsiooni ning võib kasumit teenida. Ettevõte ei saa aga pikalt nautida saavutatud positsiooni turul, kuna ühe ettevõtte innovatsioon turul stimuleerib ka teiste ettevõtete imiteerimist ning uute innovatsioonide loomist. Seega on Schumpeteri järgi majandus pidevas muutumises ning ettevõtted konkureerivad pidevalt omavahel parema/efektiivsema tehnoloogia pärast. (Fagerberg 2003)

Käesolevas töös on kesksel kohal tehnoloogiliste muutuste ehk tehnoloogiliste innovatsioonide roll tööjõu nõudluse kujunemisel. Kuna innovatsioon on keskne mõiste majanduse evolutsiooniteoorias, siis selles osas lähtutakse oluliselt majanduse evolutsiooniteooriast. Siiski, innovatsiooni "nimetus" neoklassikalise koolkonna varasemates töödes, tehnoloogiline muutus, leiab rohket käsitlemist ka neoklassikalise koolkonna poolt. Majanduse evolutsiooniteooria ambitsioonikaim, kuid teoorias mitte just väga suurt tuge leidnud väide on (Fagerberg 2003, Verspagen 2005), et innovatsioon on ka pikemaajaliste majandustsüklite ja majanduskasvu allikas. Tulenevalt innovatsiooni kesksest kohast majanduse evolutsiooniteoorias on sellelt koolkonnalt tulnud mitmeid täiendusi innovatsiooni leviku ja süsteemsuse osas. Käesolevas uuringus kasutatakse lisaks innovatsiooni mõistele majanduse evolutsiooniteooriast ka teisi mõisted nagu: innovatsioonide levik (*diffusion*), majandusharude liigitus tehnoloogiamahukuse järgi ning innovatsioonide koostoime väliskaubandusindikaatorite ja välisinvesteeringutega. Neid mõisteid kasutatakse töös aga eelkõige empiiriliste tulemuste laiendamisel.

Teoreetilised mudelid modelleerivad tehnoloogiliste muutuste või innovatsioonide mõju hõivele üldise tasakaalu mudelite raamistikus. Me tutvustame esmalt teoreetilist ja empiirilist kirjandust tehnoloogiliste muutuste mõjust tööjõu struktuurile ning seejärel tehnoloogiliste muutuste mõjust kogu hõivele.

Tehnoloogiliste muutuste mõju hõivele võib tuleneda kas muutunud ühe tootmisteguri tootlikkusest või mingi majandusharu tegurite kogutootlikkuse (*total factor productivity*) muutusest. Esimesel juhul nimetatakse toimunud tehnoloogilist muutust tootmisteguri suunas (*factor-biased*) nihkega tehnoloogiliseks muutuseks ning teisel juhul majandusharu suunas nihkega (*sector-biased*) tehnoloogiliseks muutuseks.

Empiiriline kirjandus on kasutanud tootmisteguri või majandusharu suunas nihkega tehnoloogiliste muutuste eristamiseks hõive struktuuri muutuste dekomponeerimist. Hõive struktuuris toimunud muutused on dekomponeeritud majandusharu sisesteks ja majandussharude vahelisteks muutusteks. Majandusharusisesed muutused on seostatud tootmisteguri suunas ning majandusharude vahelised muutused majandusharu suunas nihkega tehnoloogiliste muutustega. Selle metoodika kasutajad on leidnud, et alates 1970ndatest kõrge ja keskmise sissetulekutasemega riikides toimunud nõudluse kasv kõrgema kvalifikatsiooniga tööjõu järele on seletuv peamiselt majandusharu siseste muutustega ehk tootmisteguri suunas nihkega tehnoloogiliste muutustega. Enim tsiteeritud artiklid ses vallas on Berman, Bound ja Machin (1998) ning Berman ja Machin (2000). Majandusharude vahel toimunud muutused, mida seostati majandusharu suunas nihkega tehnoloogiliste muutustega, seletasid oluliselt väiksema osa kasvanud suhtelisest nõudlustest kõrgelt kvalifitseeritud tööjõu järele. Majandusharu suunas nihkega tehnoloogiliste muutuste põhjustajana on nähtud elavnenud rahvusvahelist kaubandust nn rikkama Põhja ja vaesema Lõuna vahel, mis Heckschler-Ohlin mudeli raamistikus on nihutanud tööjõumahukate kaupade tootmise madala kvalifikatsiooniga tööjõu poolest rikastesse nn Lõuna riikidesse.

Hõive struktuuri dekomponeerimise põhjal tehtud analüüsidel on mitmeid puudusi. Chusseau, Dumont ja Hellier (2008) üldistavad, et majandusharu siseste muutuste tõlgendamine tootmisteguri suunas nihkega tehnoloogilise muutusena ülehindab selle teguri tegelikku rolli rikastes riikides. Selle metoodika peamiseks puuduseks peetakse, et arvesse ei ole võimalik võtta nn väljasttellimise (*outsourcing*) mõju. Väljasttellimise puhul jagatakse toote tootmine etappideks ning toote erinevad tootmisfaasid ei pruugi aset leida ühes majandusharus ega ühes riigis. Seega arenenud riikide suurenenud suhteline nõudlus kõrgelt kvalifitseeritud tööjõu järele võib olla seotud tööjõumahukate tootmisetappide tellimisega tööjõumahukatest keskmise ja madala sissetulekuga riikidest. Lisaks ei võta see metoodika arvesse teiste tootmistegurite hindade muutust. (Chusseau *et al.* 2008) Seega täpsema pildi saamiseks tehnoloogiliste muutuste rollist suhtelise tööjõu nõudluse kujunemisel peaks kasutama detailsemalt spetsifitseeritud mikroandmetel analüüsi.

Chusseau *et al.* (2008) üldistavad, et mõlemat tüüpi tehnoloogilised muutused, tootmisteguri suunas nihkega ning majandusharu suunas nihkega on olnud olulised suhtelise tööjõu nõudluse kujunemisel ning et Heckschler-Ohlin raamistikust lähtuvate kaubandusvoogude roll on olnud väiksem. Samas rahvusvahelise väljasttellimise roll on olnud oluline suhtelise tööjõu nõudluse kujunemisel. Ning, et lisaks peab arvestama ka nende tegurite koostoime efektiga, kuna väliskaubandus toimib tehnoloogia leviku kanalina

Viimaste kümnendite nn võtmetehnoloogia, mis on mõjutanud kõiki majandusharusid, on olnud seotud IKTga. Selliseid tehnoloogilisi muutusi, mille mõju ulatub kõigisse majandusharudesse nimetatakse ka üldise kasutusega tehnoloogiateks (*general purpose technologies*). IKT arenguga seotud tehnoloogilised muutused on valdavalt olnud oskuste suunas nihkega. Seda seost on rohkelt uuritud ning on leitud, et viimastel kümnenditel kogetud suhtelise nõudluse kasv kõrgema kvalifikatsiooniga tööjõu järele seletub kui mitte peamiselt siis suures osas IKT arenguga (Berman, Bound, Griliches 1994; Autor, Katz, Krueger 1998; Autor, Levy, Murnane 2003).

Sarnaselt on ka KIE riigid kogenud suhtelise nõudluse kasvu kõrgema kvalifikatsiooniga tööjõu järele (Kézdi 2002, Tarjáni 2007, Commander ja Kollo 2008). Kuigi eeldatavalt on KIE riikides tehnoloogiliste muutuste roll suhtelise nõudluse kujunemisel kõrge kvalifikatsiooniga tööjõu järele väiksem kui arenenud riikides. Peamiseks põhjuseks selles on struktuursed muutused tootmisharudes. Sotsialistlik tootmine oli kallutatud primaar- ja sekundaarsektori arengu suunas ning see mõjutab post-kommunistlikke riike veel tänase päevani. Balti riikides moodustab tootmisharude vaheline töökohtade liikumine endiselt peamise osa kogu töökohtade liikumisest (Masso, Eamets ja Philips 2006).

Järgnevalt tehnoloogiliste muutuste mõjust kogu hõivele. Tooteinnovatsiooni mõju hõivele käsitletakse ettevõtte tasandil kui nõudluse šokki ning protsessiinnovatsiooni kui pakkumise šokki (Smolny 1998, Greenan ja Guellec 2003). Tooteinnovatsioon, mis parandab toodete kvaliteeti või toob turule täiesti uue toote, toob ettevõttele kaasa nõudluse kasvu ning suurenenud nõudluse tootmistegurite, sealhulgas tööjõu järele. Mida väiksem on loodud tooteinnovatsiooni uuenduslikkus, seda väiksem on selle võime suurendada nõudlust toote järele ning seda väiksem on mõju tööjõu nõudlusele. (Greenan ja Guellec 2003) Smolny (1998) käsitleb neid teoreetilisi seoseid laiemat, nii et ettevõtte innovaatiline tegevus mõjutab ka tema konkurentide innovaatilisust. Ta näitab, et tootmisharudes, kus tehakse rohkelt tooteinnovatsioone, on konkurents madalam ning muudatusi toote hindades tehakse harvem.

Protsessiinnovatsiooni mõju ettevõtte tööjõu nõudlusele sõltub sellest kui palju paraneb tootmisprotsessi efektiivsus ja seega palju alaneb toote hind ning toote nõudluse hinnaelastsusest. Kui protsessiinnovatsiooni tulemusel kaasneb toote hinna alanemine, siis lõplik mõju ettevõtte tööjõu nõudlusest sõltub järgmise kahe efekti vahekorrast: kas hinna alanemisest tulenev toote nõudluse laienemine kompenseerib tootmisefektiivsuse kasvust tulenevat vähenenud tootmissisendite vajadust. (Greenan ja Guellec 2003) Smolny (1998) näitab, et tootmisharudes, kus tehakse sagedasti protsessiuuendusi, on tihe hinnakonkurents ning suhteliselt elastne nõudlus. Mis tähendab, et sellistes harudes muudetakse sageli hindasid.

Empiirilised hinnangud leiavad tavaliselt, et innovatsioonid ja hõive on ettevõtte tasandil positiivses seoses. Innovaatiliste ettevõtete hõive kasvab kiiremini (Pianta 2005 ja Djellal; Gallouj 2007 esitavad kirjandusülevaate) ning et tooteinnovatsioonid suurendavad hõive kasvu enam (Van Reenen 1997, Greenan ja Guellec 2001; Harrison, Jaumandreu, Mairesse, Peters 2008). Protsessiinnovatsiooni osas on tulemused vastakamad, kuigi enamus uuringuid leiab, et see seos on positiivne (Greenan ja Guellec 2001, Fung 2006 ja Harrison *et al.* 2008); on ka uuringuid mis leiavad mitteolulise (Van Reenen 1997) või negatiivse seose (Evangelista ja Savona 2003).

Ettevõtete tasandi positiivne innovatsioonide mõju hõivele ei pruugi veel tähendada üldist hõive kasvu haru tasandil, kuna pole võimalik jälgida kas suurenenud on kogu haru hõive (*market expansion effect*) või valik ettevõtteid on suurendanud oma turuosa teiste ettevõtete arvelt (*business stealing effect*) (Piva ja Vivarelli 2005). Tootmisharu tasandil uuringuid on samaaegselt ettevõtte tasandi uuringutega läbi viidud väga vähe. Evangelista ja Savona (2003) leiavad teenuste sektori näitel, et innovatsiooni positiivne mõju hõivele on suurem ettevõtte tasandil kui haru tasandil. Antonucci ja Pianta (2002) ning Greenan ja Guellec (2001) leiavad, et haru tasandil on protsessiinnovatsiooni mõju hõivele valdavalt negatiivne ning tooteinnovatsiooni mõju positiivne.

Empiirilised analüüsid näitavad, et tehnoloogiliste muutuste või innovatsioonide mõju hõivele on erinev erineva tehnoloogiamahukusega majandusharudes. Greenhalgh, Longland ja Bosworth (2001) leiavad, et tehnoloogiliste muutuste mõju hõive kasvule on tugevam kõrgtehnoloogilistes majandusharudes kui tehnoloogilised muutused on mõõdetud T&A kulutustena ning tugevam madaltehnoloogilistes harudes kui tehnoloogilised muutused on mõõdetud patentidena. Yang ja Lin (2008) leiavad, et protsessiinnovatsioonid (protsessiuuenduslikud patendid) suurendavad tööjõu nõudlust kõrgtehnoloogilistes harudes, kuid vähendavad tööjõu nõudlust madaltehnoloogilistes harudes. Seega, innovatsioonide mõju hõivele tundub olevat tugevam pigem kõrgtehnoloogilistes harudes.

Tehnoloogiliste muutuste või innovatsioonide mõju hõivele on keskmise- ja madala sissetulekuga riikide andmetel väga vähe uuritud. Eranditeks on empiirilised uuringud autoritelt Lundin, Sjöholm, Ping ja Qian (2007); Yang ja Lin (2008); ning Benavente ja Lauterbach (2008). Hiina andmetel on leitud, et investeeringud teadusesse ja tehnoloogiasse ei ole seotud suurema tööjõu nõudluse kasvuga (Lundin *et al.* 2007); Taiwani andmetel on leitud positiivne seos teadus- ja arendustegevuse (T&A) kulutuste ja patentide ning hõive kasvu vahel (Yang ja Lin 2008). Benavente ja Lauterbach (2008) leiavad Tšiili andmetel, et tooteinnovatsioonid mõjutavad hõive kasvu positiivselt ja protsessiinnovatsioonid ei oma olulist mõju hõivele.

Uuringu tulemused ja ettepanekud edasisteks uuringuteks

Käesoleva töö eesmärgiks oli hinnata tehnoloogiliste muutuste mõju hõivele ja hõive struktuurile. Analüüs viidi läbi nii riigi, tootmisharu kui ettevõtte tasandil. Riigi tasandil analüüs teostati EL25 riikide näitel, analüüsimeetodina kasutati hõive ametikohtade struktuuri dekomponeerimist.

EL10 uute riikide hõives moodustavad kõrget kvalifikatsiooni eeldavad ametikohad oluliselt väiksema osa kui EL12 liikmete hulgas. See erinevus seletus 2004. aastal peamiselt tootmisharude vaheliste erinevustega, mitte erineva ametikohtade struktuuriga tootmisharude sees. Nagu ülal välja toodud, siis seda tüüpi analüüsis kasutatakse tootmisharu sisest ametikohtade struktuuri muutust lähendina tootmistehnoloogia kirjeldamiseks (Berman *et al.* 1994 ja Berman *et al.* 1998, Berman ja Machin 2000). Seega ei seletu EL uute liikmesriikide madalam nõudlus kõrge kvalifikatsiooniga tööjõu järele mitte kehvema tehnoloogiaga neis riikides vaid erineva tootmisharude struktuuriga. Siinkohal eristuvad KIE riikidest Tšehhi Vabariik, Sloveenia ja Eesti, kus tootmisharude sisene kõrge kvalifikatsiooniga valgekraede osakaal on võrreldaval tasemel rikaste Lääne-Euroopa riikidega.

Aastate 2000–2004 dünaamilised muutused ametikohtade struktuuris seletuvad aga enamikes EL riikides tootmisharude siseste muutustega. Seega kui KIE riigid eristuvad EL12 riikidest madalama nõudlusega kõrge kvalifikatsiooniga tööjõu järele erineva tootmisharude struktuuri tõttu, siis üle aja toimuvad muutused oskuste nõudluses on nii KIE kui EL12 riikides sarnased. Need seosed annavad tunnistust tehnoloogia levikust üle EL riikide. Sarnane tootmisharusisene ametikohtade struktuuri muutus, mida tõlgendatakse tehnoloogiate levikuna, on aga tugevam EL12 riikide grupi sees. Ka harusiseste muutuste roll oskuste suhtelise nõudluse kasvu seletamisel on KIE riikides mõneti väiksem. Ülal välja toodud riikidest, kes omavad kõrgeimat harusisest nõudlust kõrge kvalifikatsiooniga valgekraede järele, on vaatlusalusel perioodil hõive struktuur kõige vähem muutunud Eestis. Nii Tšehhi Vabariigis kui Sloveenias on kasvanud kõrge kvalifikatsiooniga valgekraede osakaal hõives, kuid Eestis on see pisut vähenenud.

Töö kolmandas ja neljandas peatükis viidi läbi ettevõtte ja haru tasandi analüüs Eesti ettevõtete andmetel. Kolmas peatükk kasutas dünaamilisi paneelandmeid aastatest 1996–2006 ja neljas peatükk ristandmeid vahemikust 1998–2000. Kolmas peatükk hindas tehnoloogiliste muutuste ehk tehnoloogiliste innovatsioonide mõju hõivele ettevõtte ja haru tasandil. Uuringu tulemused näitasid, et tehnoloogilised innovatsioonid suurendavad tööjõu nõudlust nii ettevõtte kui haru tasandil. Ettevõtte tasandil suurendab tehnoloogiline innovatsioon veel kolm aastat peale innovatsiooni toimumist hõive kasvu 2–3%. Seega innovaatiliste ettevõtete hõive kasvab kiiremini kui mitte innovaatiliste ettevõtete hõive; see efekt on püsiv ka peale palkade, kapitali, tootmisharu ning majandustsükli mõju arvesse võtmist.

Ettevõtte tasandil on innovatsioonide mõju hõivele tugevam kui haru tasandil. Ning kui ettevõtte tasandil mõjutab hõive kasvu positiivselt ja statistiliselt oluliselt vaid protsessiinnovatsioon, siis haru tasandil mõjutab hõive kasvu positiivselt ja statistiliselt oluliselt tooteinnovatsioon. Tooteinnovatsiooni statistiliselt mitteoluline mõju hõivele võib ettevõtte tasandil olla seotud ellu viidud innovatsioonide vähese uudsusega. Teoreetilised mudelid näitavad, et mida suurem on toote uudsus, seda positiivsem peaks olema mõju ettevõtte tööjõu nõudlusele. Kuna ettevõtte tasandil suudavad kasvada just protsessiuuendajad, siis võib see viidata suhteliselt elastsele nõudlusele ja hindade üle konkureerimisele Eesti turul. Haru tasandi analüüsi tulemused on ootuspärased, tooteinnovatsioonid on seotud haru laienemisega ehk haru hõive kasvamisega. Seega harud, kus tehakse palju tooteinnovatsioone kasvavad ülejäänud harudest kiiremini.

Nii haru kui ettevõtte tasandi tulemused on sarnased arenenud riikide andmetel teostatud uuringute tulemustele. Ainsaks oluliseks erinevuseks on, et kui kõrgtehnoloogia sektorit peetakse majanduse kasvu mootoriks ning arenenud riikide andmed on leidnud selles harus tehnoloogiliste muutuste ja hõive vahel positiivse seose, siis Eesti andmetel vastav seos puudub. Ettevõtte tasandil tuleneb innovatsioonide positiivne mõju hõivele põhiliselt kesk- ja madaltehnoloogilisest sektorist ning protsessiinnovatsioonist. Näiteks madaltehnoloogilises sektoris on tooteinnovatsioonide mõju ettevõtte hõivele sisuliselt olematu, kuid protsessiinnovatsioonid suurendavad hõive kasvu oluliselt. Seega, ettevõtte tasandi innovatsioonide positiivne mõju hõivele tuleneb protsessiinnovatsioonide positiivsest mõjust kesk- ja madaltehnoloogilistes harudes, kuid haru tasandil suurendavad innovatsioonid hõivet vaid rohkelt tooteinnovatsioone tegevates majandusharudes.

Käesoleva töö neljas peatükk jätkas Eesti andmetel analüüsi. Ettevõtete andmetel hinnati tehnoloogiliste muutuste ehk tehnoloogiliste innovatsioonide mõju kõrgharidusega hõivatute nõudlusele ettevõtte tasandil. Analüüsi tulemused näitavad, et tehnoloogilised innovatsioonid ei ole suurendanud ettevõtete nõudlust kõrgharidusega tööjõu järele. See tulemus ei sõltu ka sellest, kas käsitleda innovatsiooni endogeense või eksogeensena kõrgharidusega töötajate osakaalu suhtes. Formaalsed testid näitasid, et kui instrumentidena kasutada teadmiste hulka (patendid), teadmiste kasvu potentsiaali ettevõttes (kuulumine kontserni, koostöökokkulepped ühiseks innovaatiliseks tegevuseks teiste institutsioonidega) ning ettevõtte akumuleeritud ärikasumit, siis ei saa ümber lükata innovatsiooni eksogeensuse eeldust.

Küll omavad aga tehnoloogilised innovatsioonid statistiliselt olulist mõju kõrgharidusega tööjõu nõudlusele koostoimes väliskaubandusnäitajate ja ettevõtte välisosalusega. Eksportimine otseselt vähendab ettevõtte nõudlust kõrgharidusega tööjõu järele, kuid ekspordi ja innovatsiooni koostoimeefekt kõrgharidusega tööjõu nõudlusele on positiivne. Need tulemused haakuvad teises peatükis teostatud dekomponeerimise analüüsiga. Selline positiivne koostoimeefekt tuleneb vaid ekspordist arenenud riikide turule, mitte aga ekspordist vähemarenenud riikide turule. Kuna arenenud riigid on kogenud just nõudluse kasvu kõrgharidusega tööjõu järele, võib seda tulemust tõlgendada kui tehnoloogia levikut läbi eksportimise.

Huvitaval kombel ei toimu sarnast õppimist läbi välisinvesteeringute, ettevõtete välisosaluse ja innovatsiooni koostoimeefekt on negatiivne. Vastupidiselt ekspordi mõjule; välisosalusega ettevõtted omavad suuremat kõrgharidusega töötajate osakaalu, kuid teevad innovatsioone, mis vähendavad suhtelist nõudlust kõrghariduse järele. Seega, laiema üldistusena võib välja tuua, et Eesti ettevõtted on kogenud sarnaseid arenguid tööjõu nõudluses ehk kogenud tehnoloogia ülekande efekte tänu eksportimisele arenenud riikide turgudele.

Käesolevas töös pakuti välja ka kaks metodoloogilist uuendust antud uurimisülesannete teostamiseks. Esiteks, teostati riikide ja haru tasandil oskuste struktuuri dekomponeerimise analüüs teadaolevalt esmakordselt ka staatilises raamistikus. Antud metoodika on leidnud käsitlemist regionaalse sissetulekute taseme konvergentsi analüüsil (Esteban 2000), kuid oskuste struktuuri dekomponeerimisel seda metoodikat teadaolevalt kasutatud ei ole. See metoodika võimaldab lihtsalt hinnata ning ülevaatlikult esitada, millistest teguritest tulenevalt mingi riik või majandusharu kasutab riikide või majandusharude grupi keskmisest vähem või rohkem kõrge kvalifikatsiooniga tööjõudu.

Teiseks, käesolevas töös pakuti CIS andmetel innovatsioonide ja hõive vahelise seose hindamiseks välja alternatiivne hindamisstrateegia. CIS (*Community Innovation Survey, CIS*) andmed on maailmas enimkasutatavad innovatsiooniuuringu andmed, mida kogutakse küll ettevõtete tasandil, kuid kasutatakse ka riikide innovaatilisuse võrdlemiseks. Kuigi CIS andmetes kogutakse informatsiooni innovaatilise tegevuse kohta üle kolmeaastase perioodi, võimaldavad CIS andmed analüüsi vaid ristandmetena. See on takistanud CIS andmete kasutamist pikemaajalist kohandumist eeldavate protsesside, nagu seda on ka innovatsioonide mõju hõivele, hindamisel.

Jaumandreu (2003) on pakkunud välja teoreetilise raamistiku ja empiirilise hindamisstrateegia CIS andmetel innovatsioonide ja tööjõu nõudluse vahelise seose hindamiseks. See strateegia on leidnud ka rohket kasutust empiirilises kirjanduses (Peters (2004) Saksamaa; Harrison, Jaumandreu, Mairesse ja Peters (2008) Prantsusmaa, Saksamaa, Hispaania ja Suurbritannia; Hall, Lotti ja Mairesse (2008) Itaalia; ning Benavente ja Lauterbach 2008 Tšiili andmetel). Samas innovatsioonide mõju hõivele avaldub suhteliselt pika viitaja vältel. Van Reenen (1997) leidis, et innovatsioonide mõju hõivele oli kõige suurem kuus aastat peale innovatsiooni teostamist. Seega võivad Jaumandreu (2003) poolt pakutud strateegiat kasutavad uuringud, mis hindavad innovatsioonide mõju hõivele kahe-aastase perioodi möödumisel, alahinnata innovatsioonide mõju hõivele.

Käesolevas töös välja pakutud alternatiivne hindamisstrateegia ühendab järjestikused CIS andmed paneeliks, mis võimaldab kasutada dünaamilist paneelandmete analüüsi. Euroopa Liidus on läbi viidud juba viis järjestikust CIS küsitlust. Eestis on läbi viidud kolm CIS uuringut ning nende ühendamine CIS paneeliks andis väga häid tulemusi, kuna enamus ettevõtteid sattus järjestikuste uuringute valimisse mitmel korral. Eeldatavalt peaks selline andmete ühendamine olema edukam just väikeste riikide andmetel, kus pole mõtet raisata ressursse mitme erineva innovatsiooniuuringu läbi viimiseks ning kus samad ettevõtted sattuvad valimisse sagedamini. Tulenevalt innovatsiooni mõõtmise eripärast CIS andmetes tuleb saadud paneelil innovatsioonide mõju hindamiseks kas diferentsida andmebaas üle kahe-aastase perioodi või lülitada innovatsiooni muutuja analüüsi vähemalt kolmeaastase viitajaga.

Edasistes uuringutes võiks keskenduda lisaks tehnoloogiliste muutuste mõjule tööjõu nõudlusele ka tehnoloogiliste muutuste mõjule palkadele. Nagu ülal välja toodud on viimaste kümnendite tehnoloogilised muutused (IKT arengud) USAs põhjustanud palgaerinevuste kasvu ning Euroopas madala kvalifikatsiooniga töötajate tööpuuduse kasvu. Üleminekuriikides suureneb üleminekuprotsessi käigus sageli ebavõrdsus, ka KIE riigid on võrreldes oma Lääne-Euroopa naabritega oluliselt suurema palga ebavõrdsusega. Üks võimalik idee edasisteks uuringuteks oleks hinnata kui suurt rolli mängivad tehnoloogilised erinevused palgavahe kujunemisel.

Teiseks edasiarenduseks võiks olla detailsem teadmiste leviku uurimine arenenud riikidest KIE riikidesse. Praegune analüüs, käesolevas töös kasutatu ning ka teiste riikide andmetel teostatu, tugineb ühe riigi haru või ettevõtte tasandi andmetel. Edasiseks väljakutseks seda tüüpi analüüsides võiks olla erineva arengutasemega, kuid majanduslikult integreeritud riikide ettevõtete tasandil andmete ühendamine.

Viimaseks, käesolevas töös on pühendatud rohkelt energiat olemasolevate andmepiirangute juures sobiva analüüsimeetodi või -võimaluse leidmisele. Suuri probleeme valmistas CIS andmete innovatsiooni näitaja lülitamine dünaamiliste paneelandmete analüüsi ning vaid ristandmete põhjal oskuste suunas nihkega tehnoloogilise muutuse mõju hindamine. Seega üks käesoleva töö edasiarendus võiks olla ka sarnane analüüs, kuid parema andmebaasi abil.

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