STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
5350 Master's thesis in economics
Academic year 2015–2016

Labor market patterns in offshoring-receiving countries: Evidence from Poland

Rosa Lauppe (40559) and Karin Lindell (40612)

Abstract

Labor markets in highly industrialized countries in Western Europe and the United States have polarized over the last decades, which means that the share of middle-income occupations has decreased relative low- and high-income occupations. Two potential explanations for this are routine-biased technological change (RBTC) and offshoring, which both are expected to reduce middle-income occupations in highly industrialized countries. This study makes a first contribution to fill a gap in this research by investigating how labor markets are affected in relatively well-developed countries that are mainly receiving offshoring, such as Poland. Offshoring should, if it is an influential factor, work against a polarization in the labor markets in offshoring-receiving countries. The results show that no job polarization is present in Poland over the time period 1997-2010. However, the employment structure appears to be relatively unaffected by offshoring and routineness. There are no signs of polarization in relative wage development. In fact, change in wages consists of two trends: prior to 2004 high-income occupations experienced the largest wage growth, but after 2004, high-income occupations had the smallest wage growth. Overall, offshoring does not have a substantial effect on the Polish labor market. Routineness does have significant impact on wages, but so does skill level. The results suggest that skill-biased technological change (SBTC) might be a key factor for the Polish labor market, rather than RBTC.

Keywords: Poland, job polarization, offshoring, routine-biased technological change, skill-biased technological change

JEL: F16, J21, J23, J24, J31, P20

Supervisor:	Jesper Roine
Date submitted:	December 15, 2015
Date examined:	January 14, 2015
Discussants:	Amanda Olsson and Caroline Nacksten
Examiner:	Kerem Cosar

Contents

Figures, tables and equations

1. Introduction

> They call the new economy an "hourglass," with a concentration of wealth at the top, low-paying service jobs at the bottom and "a spectacular loss of median-wage jobs in the middle".
> William Julius Wilson, sociologist and Harvard professor, quoted in Chozick (2015)

Over the last years, the shrinking of the middle-class and the decline of typical middle-income occupations such as office clerks, travel agents or plant operators has been observed with concern, both by scholars and the public. The question is, what is destroying the middle-class? Are robots or offshoring potential explanations? If offshoring is an influential factor, what happens in the country that receives the jobs?

Several research papers have investigated the changes in the labor market over the last decades. The findings are similar: middle-income occupations in industrialized nations have decreased disproportionally, while low- and high-skill occupations have continued to increase. As a result, the job market has gradually become more polarized (Kampelmann and Rycx 2011; Abel and Deitz 2012; Goos and Manning 2007; Goos, Manning and Salomons 2014; Adermon and Gustavsson 2015; Oldenski 2014; Dustmann, Ludsteck and Schönberg 2009). A number of the studies have also found a similar development in incomes, that is, an increased wage polarization in the labor market (Autor and Dorn 2013; Abel and Deitz 2012; Oldenski 2014; Dustmann, Ludsteck and Schönberg 2009).

Two possible explanations behind job polarization commonly discussed are technological change and offshoring (Autor and Dorn 2013; Goos, Manning and Salomons 2014; Oldenski 2014; Kampelmann and Rycx 2011; Adermon and Gustavsson 2015; Goos and Manning 2007). According to the first explanation, recent technological advancements have made it possible to substitute away workers performing routine tasks that are easily codified and replicable, and replace them with robots or computers. The routine-intense jobs are mainly found in the middle-income group, and this might be a reason for its decline. Based on the second explanation, the middle-income jobs also coincide with the most offshorable occupations. A more globalized market has enabled companies to offshore business operations to countries where labor costs are lower. Today, many of the consumption goods found in Western Europe and North America are produced in lower-wage countries, and call centers and business services are moved abroad. Middle-income occupations such as plant operators and office clerks are more easily offshored than others, and as the level of offshoring increases, the middle-income group takes the hardest hit (Goos, Manning and Salomons 2014).

As research on job polarization is a relatively new field of literature, it has so far mainly focused on industrialized nations that offshore goods and services to other countries. The purpose of this paper is to make a first contribution to fill a gap in current research by investigating how the labor market has changed over time in a developed country that mainly receives offshoring. In this context, the role of offshoring and technological change is explored as potential key factors affecting the labor market. The study focuses on Poland, as it is a major location for offshoring but also a relatively well-developed economy. A high enough level of development is important in this context, as it enables routine tasks to potentially be replaced by technology. Thus, this country provides the opportunity to study the effects of technological change and offshoring, in a setting where offshoring might create jobs, rather than destroying them.

After the fall of the centrally planned economy, Poland has become more attractive as an investment location for multinational enterprises and the inflow of offshoring has increased

(Capik and Drahokoupil 2011; Sass and Fifekova 2011). Poland is now a popular location for offshoring (Szymczak 2013:4), which is due to several factors; Polish labor is relatively cheap, but still well educated, and the close proximity to Western Europe offers a strategic location. The communication infrastructure is well functioning, political conditions are stable and the EU membership simplifies the process of offshoring (Sass and Fifekova 2011).

The paper is organized as follows. Section 2 provides a short background on Poland. In section 3, findings of previous literature, trade theory and the theoretical development from skill-biased technological change to routine-biased technological change are presented. Section 4 establishes our research focus. Information on data and methods used is found in section 5. Section 6 outlines the Polish position regarding offshoring and technology. The results of the study are presented in section 7. A discussion of the results is found in section 8, while section 9 concludes. Additional tables, figures and estimations are presented in Appendix A, B and C.

2. Background: Poland between 1997 and 2010

Poland changed from a centrally planned to a market oriented economy after the "Solidarnosc" movement had triumphed over the communist forces in the 1989 elections. Economic transformation towards a market economy was based on a “shock therapy” program and the years after the fall of the communist regime were characterized by deep economic and social restructuring, as in many neighboring countries at the time (Sachs 1995). The restructuring also affected the labor market. “Full employment” under the communist regime disguised unemployment and led to low productivity of labor. After the change of the political system, unemployment suddenly became visible (Gawrycka, Sobiechowska-Ziegert and Szymczak 2012). However, already in 1995, Poland reached its pre-1989 GDP levels as the first post-communist country and in 1997 the European Commission concluded that “Poland can be regarded a functioning market economy” (European Commission 1998:13), and that it should be able to compete with its western neighbors. Large steps were taken also in other areas, in 1997 the European Commission observed that: “Poland presents the characteristics of a democracy, with stable institutions guaranteeing the rule of law, human rights and respect for and protection of minorities” (European Commission 1998:13).

Partly due to these positive evaluations and its strong economic performance, Poland was able to join the European Union in May 2004 and has since then often been referred to as an example for successful European integration (Piatkowski 2013). The Polish economy also remained relatively unaffected by the global financial crisis, the European debt crisis and the overall financial recession in 2008-2012 (IMF 2012). Instead, the Polish economy continued to grow each year and reached an annual average of 3.4 percent over the time period 2008-2012 (World Bank 2014b).[1]

The EU membership substantially increased the flow of goods and services, capital and individuals across the Polish borders. Two important effects of the EU accession relevant to this study are an increase in FDI inflow, trade and offshoring, reflecting a stronger integration of Poland into the EU, and an unparalleled rise in migration (Belka 2013). From the year prior to the EU accession (2003) to the final year of our study (2010) the inward position of FDI increased by 281 percent, and approximately 90 percent of the FDI over the whole time period

[1] Poland’s annual GDP growth was 3.9 and 2.6 percent in 2008 and 2009, respectively. The numbers were 3.7 and 4.8 percent in 2010 and 2011, and 1.8 percent in 2012 (World Bank 2014b).

came from other European countries (OECD.Stat 2012b). The EU accession has been followed by an unprecedented outflow of individuals seeking job opportunities abroad. Since Poland became a EU member, the Poles have gradually obtained access to foreign labor markets. The United Kingdom, Ireland and Sweden implemented an open door policy in the labor market already in 2004, and other European Union countries did so gradually over the subsequent years (Fihel and Okolski 2009:186-203).[2] The precise number of permanent Polish residents working abroad is not readily available, however, the Central Statistical Office in Poland estimated that by the beginning of 2004 approximately 1 million individuals were temporarily staying in a foreign country.[3] In 2007, this number had increased to 2.3 million individuals. The number decreased slightly at the break of the financial crisis, but started to increase again in 2010 (Central Statistical Office 2011).[4]

Prior to the EU accession, the majority of the migrant workers were engaged in low-income jobs. This type of migrants continued to be a prominent migrant group after the EU accession as well (Fihel and Okolski 2009:186-203). The group primarily consisted of middle-aged and low-educated men who migrated mainly to countries that did not open up their labor markets immediately, such as Germany and Italy (Kaczmarczyk and Okolski 2008). The EU membership, and the accompanying removal of institutional restrictions, resulted in Poles gaining access to the formal labor market in other European countries. This gave rise to a second large group of migrants (Fihel and Okolski 2009:186-203). This second group consists of young and highly educated men who mainly migrate to the United Kingdom or Ireland (Kaczmarczyk and Okolski 2008).

However, even though migration is an important phenomenon in Poland, the knowledge on its effect on the labor market in Poland is limited. Increased levels of migration should, according to theory, result in decreased unemployment in the short-term and upward pressure on wages in the medium-term as labor supply is reduced (Kaczmarczyk and Okolski 2008). However, research suggests that the overall short- and medium-term impacts of the post-accession migration on the labor market have in general been modest (Kaczmarczyk and Okolski 2008; Anacka et al. 2011).

The study period of our analysis comprises the years 1997 to 2010. The starting year is suitable as it can be assumed that the economic transition had, to a large extent, been completed at this point in time: the European Commission concluded that Poland had become an established market economy in 1997 (European Commission 1998). Moreover, this time period includes approximately seven years before the EU membership and seven years as a member country. This allows us to study potential changes correlated with European integration. The study period also comprises years of economic crisis in Europe as the financial recession continued throughout the years 2008-2010. However, as mentioned before, the effect of the crisis was relatively small in Poland. In order to ensure robustness of our results relative to the chosen time period, we report regression results for periods with different start and end years in Table 18 in Appendix C.

---

[2] Finland, Greece, Iceland, Italy, Spain and Portugal implemented an open door policy in 2006, the Netherlands in 2007, France in 2008 (Fihel and Okolski 2009:188), and Germany and Austria in 2011 (Strzelecki and Wyszynski 2011).

[3] Based on permanent residents in Poland, who are above 15 years old.

[4] In this data, a temporary worker is defined as a permanent resident staying abroad for more than two months (the definition prior to 2007) or three months (definition from 2007 and onwards) (Anacka et al. 2011).

3. Theoretical framework and current knowledge

3.1. Technological change

The last decades have been characterized by an unprecedented increase in technological advancements, and as a result, researchers' interest in the effects of technological change on labor markets has grown. Technological progress can potentially benefit various groups of workers in the labor market differently. A large strand of literature argues that highly educated individuals can more easily develop an understanding of advanced technology and that, as new technology develops, the relative demand for highly educated workers will therefore increase among employers. According to this reasoning, technological progress is biased towards improving the position of the highly skilled workers; it is therefore known as skill-biased technological change (SBTC) (Katz and Autor 1999:1530-1535). As skills are almost impossible to measure on a large scale, education is mostly used to account for skill level.[5]

Several researchers have investigated the theory of SBTC, and find it to be an important explanation of increased demand for skilled workers. Industries that adopt new technology do increase the number of skilled workers (Levy and Murnane 1996; Mark 1987), and the same holds for plants that implement new technology (Doms, Dunne and Troske 1997). Bartel and Lichtenberg (1987) find similar results; as the age of a plant and its equipment increases, the relative demand for skilled workers decreases. This effect is especially pronounced in R&D-intense industries. Moreover, a positive relationship between indicators of technological progress and the growth in number of skilled workers employed has been found (Autor, Katz and Krueger 1998; Machin and Van Reenen 1998) Industries that have a high level of computer usage, rate of computer investment and computer capital per employee are also the ones that have upgraded the skill-level in its work force at the fastest pace (Autor, Katz and Krueger 1998). Machin and Van Reenen (1998) find that a higher R&D-intensity is linked to a growing demand for more skilled workers in seven different OECD countries.[6]

The actual outcome of SBTC on the labor market is not straightforward. Jan Tinbergen, the first Nobel-Prize winning economist (quoted in Goldin and Katz 2009:3-4), argued that:

> [i]nequality is the outcome of a race between education and technology. When technological advance vaults ahead of educational change, inequality generally rises. By the same token, when increases in educational attainment speed up, economic inequality often declines.

Tinbergen (1975) developed a supply-demand model for educated labor, which has lately been further elaborated on by Goldin and Katz (2008). The model analyzes how the wage premium for highly educated workers (herein referred to as skill premium) is determined by the supply and demand for skills. Figure 1 displays a graphical illustration of the model. The x-axis represents the relative number of skilled workers, that is, the ratio of skilled workers over unskilled workers (L_S/L_U). The y-axis shows the relative wage of skilled workers, which corresponds to the ratio of skilled workers' wage over unskilled workers' wage (w_S/w_U). A shift in the relative demand for skills is driven by skill-biased technology. As new technology is invented, the demand for highly skilled workers increases. The relative supply of skills is driven by changes in the number of well-educated workers (Goldin and Katz 2008:291-296) Relative supply is based on past educational

[5] Wages are also used as a measure of skills.

[6] Denmark, France, Germany, Japan, Sweden, the United Kingdom and the United States.

investments, and is thus perfectly inelastic in the short-run (Goldin and Katz 2008:96) The supply will, however, eventually adjust as a response to shifts in relative demand (Atkinson 2008:7-15).

Figure 1. Increased inequality – race won by technology

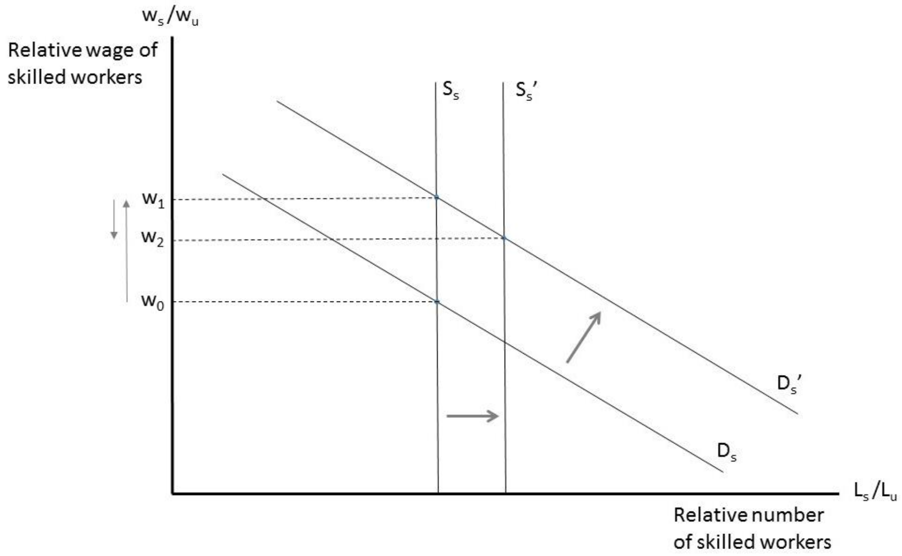
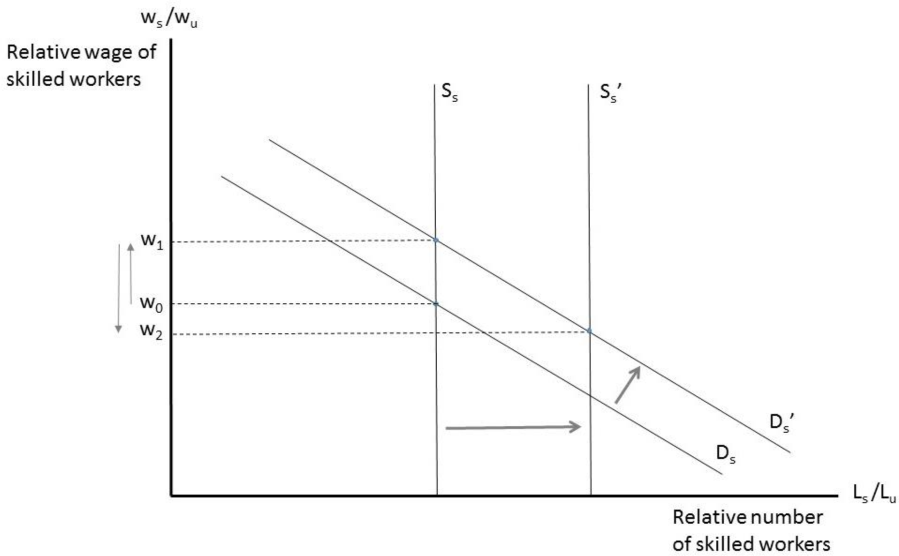


Figure 2. Decreased inequality – race won by education



The supply-demand model illustrates the theory of a race between education and technology (Goldin and Katz 2008:291-296). In both Figure 1 and Figure 2, the relative demand for skills shifts outwards from D_S to $D_S´$ as a result of SBTC. The wage premium for skilled workers increases to a temporary level at w_1. A higher skill premium will increase the attractiveness of getting an education, the number of skilled workers will thus eventually increase and the relative supply will shift outwards from S_S to $S_S´$. If the shift in relative demand exceeds that of relative supply, the skill premium increases above the start position. This case is presented in Figure 1, in which w_2 is higher than w_0. This corresponds to a race won by technology (the demand side), in which wage inequality increases. If relative supply, on the other hand, increases more than relative demand, the final skill premium will be below the starting point. This scenario is presented in Figure 2. If this is the case, education (the supply side) has won the race, and wage inequality decreases (Atkinson 2008:7-15).

In a study based on data from the United States over the time period 1940-1996, Autor, Katz and Krueger (1998) find that growth in relative demand for skilled workers has been persistently high over the whole time period. However, it accelerated further in the 1980s, and the skill premium also started to increase by the late 1970s. The most rapid growth in demand appeared in technology-intense industries, suggesting that SBTC is a main driver behind the increased relative demand, and in extension, the increased skill premium. Autor, Katz and Krueger (1998) also note that after the large acceleration in the 1980s, the growth in relative demand slowed down in the early 1990s. Katz and Murphy (1992) focus on the United States over the time period 1963 to 1987, and confirm the finding that a higher relative demand for more skilled employees has been one of the key drivers behind an increased skill premium. Goldin and Katz (2008:320-321) conclude that since the 1980s, the race in the United States has been won by technology, as displayed in Figure 2. Technological progress has resulted in a continually increasing relative demand; however, the supply of skilled workers has not managed to keep up the pace. This is mainly due to an education slowdown; a lower share of the population enrolls in college.

The literature on SBTC was the starting point for research on the effects of technological progress on the labor market (Acemoglu and Autor 2010:1044-1045). As the research presented above illustrates, the theory of SBTC does explain historical developments in the labor market well. Recently, however, a new line of research argues that SBTC fails to explain more recent developments in the labor market. Over the last decades, the middle-skill occupations have decreased in size relative low- and high-skill occupations in several countries. The theory of SBTC, in which technological progress increases the relative demand for skilled workers, does not explain the relative increase in low-skill jobs. This new line of research has therefore developed the new theory of routine-biased technological change (RBTC), which is explained in more depth later in this section (Goos, Manning and Salomons 2014).

The relative decrease in the share of middle-skill occupations, and the simultaneous relative increase in the share of low- and high skill occupations have gradually polarized the labor market. This development has therefore become known as "job polarization". As a result of job polarization, a lower share of the work force is engaged in typical middle-income occupations, such as office clerks, machine and stationary plant operators. Instead, occupations that are gaining ground are low-income occupations, such as salespersons, childcare workers, cleaners and hairdressers, as well as high-income occupations, such as corporate managers, engineers and health professionals (Goos, Manning and Salomons 2014). Goos, Manning and Salomons (2014) find job polarization in 16 Western European countries.[7] Job polarization has also been found in more specific studies of Sweden (Adermon and Gustavsson 2015) and Germany (Kampelmann and Rycx 2011; Dustmann, Ludsteck and Schönberg 2009), as well as in the United States (Autor and Dorn 2013; Abel and Deitz 2012; Oldenski 2014). This development has often, but not always, been accompanied by a similar polarization in wages (Autor and Dorn 2013; Abel and Deitz 2012; Dustmann, Ludsteck and Schönberg 2009; Oldenski 2014).

[7] The 16 Western European countries included are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden and the United Kingdom (Goos, Manning and Salomons 2014).

Several researchers have considered two important factors, routineness and offshorability, as possible explanations of the rise of job polarization (Adermon and Gustavsson 2015; Abel and Deitz 2012; Autor and Dorn 2013; Goos, Manning and Salomons 2014; Oldenski 2014). The argument regarding the first factor, routineness, is that new technological development is biased towards substituting individuals in routine occupations, which are mainly found in the middle-income group. This type of technological development is therefore named routine-biased technological change (RBTC). Routine tasks are easily codified and replicable, and can therefore be replaced by robots or computers. This mainly affects routine-intense occupations such as office clerks, plant and machine operators, that is, occupations commonly found in the middle-skill sector (Goos, Manning and Salomons 2014). Low-skill occupations are not possible to automate to the same extent, as it includes occupations such as childcare workers, salespersons and hairdressers for which personal contact is crucial. For highly skilled workers, technological advancements and a lower cost of technology implies that a complementing input in the work process has become less expensive. Scientists and managers can use the new technology to improve the efficiency within their work, and this group thus benefits from technological change (Autor and Dorn 2013). This new strand of literature represents a shift away from SBTC, in which highly skilled workers are the winners while all unskilled workers are the losers, towards RBTC, in which both low- and high-skill workers benefit relative medium skilled workers (Goos, Manning and Salomons 2014).

The second factor, offshoring of tasks, is also believed to mainly affect the middle-income group. A more globalized market has enabled companies to offshore business operations to countries where labor costs are low. A large number of call centers and business services have moved to foreign destinations, and many consumption goods are produced in lower-wage countries. Middle-skill occupations such as machine operators and office clerks are more easily offshored than others, and as the level of offshoring increases, the middle-income group takes the hardest hit (Goos, Manning and Salomons 2014; Oldenski 2014). Low-skill occupations, such as personnel security and garbage collectors, require personal proximity to the work place. Although some high-skill workers may be offshorable, such as mathematical and engineering professionals, high-skill occupations are in general less offshorable since they include jobs such as health professionals and corporate managers (Goos, Manning and Salomons 2014).

A number of researchers find that RBTC is an important factor explaining recent job polarization (Goos, Manning and Salomons 2014; Adermon and Gustavsson 2015; Autor and Dorn 2013; Kampelmann and Rycx 2011). Several findings indicate that the effect of offshoring is much smaller (Goos, Manning and Salomons 2014; Adermon and Gustavsson 2015; Autor and Dorn 2013). Ebenstein et al. (2014), however, do find a negative effect of offshoring on wages in offshoring-intense occupations, and Oldenski (2014) also find a significant effect of offshoring on polarization in wages.

3.2. Theories on trade

The fall of the communist regime and the opening up to the West in 1989, as well as the European Union membership in 2004, can be interpreted as events that resulted in increased openness to trade for Poland. Effects of the increased openness on the labor market and wage developments can be analyzed through the lens of trade theory. According to Ricardo's principle of comparative advantages, an agent will produce more of and consume less of a good for which he has a comparative advantage under free trade (Gandolfo 2014:11-29). The Heckscher–Ohlin model builds on Ricardo's theory of comparative advantages. In a setting of two countries, two factors of production and two products, the model predicts that a country will export the product that uses the factor of production that is abundant and cheap within the own country. The product that uses the scarce factor of production will be imported instead (Harrison, McLaren, and McMillan 2011; Oldenski 2014). However, the Heckscher-Ohlin model has not been successful in explaining empirical developments of inequality, both between and within countries (Harrison, McLaren, and McMillan 2011). In addition to this, both Ricardo's theory and the Heckscher–Ohlin model only consider cases in which labor and capital are immobile between countries (Friedman 2012). This is an important shortcoming of the models given the increased international mobility, especially in settings such as the European Union, as well as the increased importance of offshoring both within Europe and in the overall global arena.

Feenstra and Hanson (1996) introduce offshoring (when firms allocate single tasks to another country) in their model of international trade. The two countries in the model have a varying level of skilled and unskilled workers; one country is skill-rich while the other is skill-poor. Less skill-intense tasks are offshored from the skill-rich country to the skill-poor country. If the possibility to offshore increases due to a change in the environment, such as the EU membership, more tasks will be offshored to the skill-poor country. The newly offshored tasks had been the least skill-intense tasks still performed in the skill-rich country, but they are also more skill-intense than previously offshored tasks. In this manner the skill-rich country 'loses' its least skill-intense tasks, simultaneously as the skill-poor country receives its most skill-intense tasks. This implies that the skill-level increases in both countries as the concentration towards skills increases, which gives rise to a higher skill premium and inequality level in both economies.

However, recent research on offshoring shows that the least skill-intense jobs are usually not the ones offshored to low-wage countries since these jobs often require the physical presence of the worker (Blinder and Krueger 2013; Goos, Manning and Salomons 2014). Examples of low-skill jobs in which physical proximity is essential are cleaners, personal or elderly care personnel, garbage collectors or security personnel. Instead, as previously mentioned, it is mainly the middle-income occupations that are offshored (Goos, Manning and Salomons 2014; Harrison, McLaren, and McMillan 2011). For this reason, although the model presents a good first approach to incorporate offshoring into trade models it might not fully reflect reality. Moreover, this model represents the stylized case of a highly developed country offshoring to a country at the lowest end of the development scale. Poland, however, is not among the least developed countries and is, from a global perspective, relatively well developed. This implies that the jobs created as a result of received offshoring in Poland are unlikely to represent the most skill-intense jobs in the Polish economy. Instead, they are more likely to be found in the middle of the skill- and income-scale. Thus, the model may be useful as it provides some theoretical intuition on offshoring, but it needs certain adjustments when considering offshoring to relatively well-developed countries.

4. Research focus

As the literature overview illustrates, research on job polarization to date has focused on 'Western' industrialized countries with the typical characteristics of high labor costs and high levels of technology and computerization. In these environments, job polarization has occurred over the last decades; evidence is accumulating from countries such as the United States (Autor and Dorn 2013; Abel and Deitz 2012; Oldenski 2014), Germany (Dustmann, Ludsteck and Schönberg 2009; Kampelmann and Rycx 2011), Sweden (Adermon and Gustavsson 2015), United Kingdom (Goos and Manning 2007), and other Western European countries (Goos, Manning and Salomons 2014).

The reasons behind the phenomenon of job polarization are less clear. Technological change has been identified as an essential driver behind the relative decrease of middle-income jobs, as these jobs can be substituted most effectively by technology. Another potential factor is offshoring of middle-income jobs to other countries in order to save on labor costs. Offshoring and technological change are closely interlinked in fully industrialized countries, and many jobs are prone to both offshoring and substitution by technology. As both factors work in the same direction, namely by reducing the middle-income jobs, it is a current challenge in the literature to separate the two channels.

Research on labor market polarization is a fairly new field and so far, researchers have primarily focused on highly industrialized countries, in which certain jobs are often offshored to foreign destinations. The development in labor markets in countries receiving offshoring has, to the best of our knowledge, not been investigated yet. The case of Poland provides the opportunity to study the development of labor market patterns in a transition economy, which also is a main receiver of offshoring (Szymczak 2013:4). Moreover, Poland is developed in terms of technology to a level high enough for substitution of jobs by machines or computers to be possible. In theory, offshoring and RBTC should work in opposite directions in Poland if both affect labor market patterns. The intention of our thesis is therefore to study the Polish labor market in order to gain first insights into the developments in employment and wages in countries, which are relatively well developed but still a main receiver of offshoring.

Generally, changes in the labor market are driven by demand and supply of labor.[8] Both technological change and offshoring are factors affecting the demand for labor while leaving the supply side relatively untouched. Shocks on the demand or supply side of the labor market do not necessarily affect the number of employed individuals, and if they do, the effect might not be immediate. Instead, the shocks might be reflected by changes in wage development in the short-term, or medium-term when assuming the existence of rigidities in the market. We therefore regard the development of wages, in particular the impact of technological change and offshoring on the relative change in wages over time, an important factor to investigate in our research.

Our research questions are:

As a developed country and main receiver of offshoring, which patterns appear in the Polish labor market?

Which conclusion can be drawn about the importance of RBTC and offshoring for the Polish labor market?

If offshoring that Poland receives from other countries does have a significant impact on the labor market, we would expect an increase in the share of middle-income jobs relative low- and high-income jobs. As demand rises for middle-income workers, their wages would also be expected to rise. As previously explained in section 3.2., we would expect medium-skill occupations to benefit most from offshoring into Poland due to the relatively high level of development of the country. However, RBTC would simultaneously cause a downward pressure

[8] Labor supply is the total hours that workers wish to work at a given real wage rate. Factors affecting labor supply can, for instance, be an increase in the total number of workers due to immigration. The demand side represents employers, i.e. how many hours they wish to employ workers for; it can be affected, for example, by shifts in product demand.

on the most routine-intense jobs, i.e. the middle-income jobs. Offshoring and routineness should therefore, in the context of relatively high developed offshoring-receiving countries, work in opposite directions. The aggregate effect, and the patterns over time in the Polish labor market, should thus depend on which of the factors that is most prominent. We hypothesize that we find polarization in the labor market if offshoring is substantially less influential than RBTC, that we do not find polarization if both factors are about equally important and that we find the opposite of polarization if the effect of offshoring is stronger than that of RBTC. These hypotheses are certainly very stylized, and they ignore that there might be other factors influencing labor market patterns. They should be understood more as guidance throughout the paper than real expectations for the results. The importance of offshoring and RBTC relative to other factors is tested separately and we do not draw a direct conclusion on the importance of offshoring and RBTC from our findings on polarization.

5. Data and methodology

5.1. Data

5.1.1. The Polish Household Budgets Survey

The main data source is a Polish household survey, the Polish Household Budgets Survey (BBGD), which covers the years 1997 to 2013.[9] This independently pooled cross-sectional survey captures variables such as income, occupation and education of the survey respondent, the industry within which the individual works, as well as several other demographic variables. The data set is not publically available and access is provided by the Centrum Analiz Ekonomicznych, CenEA, the institute for economic analysis in Szczecin, Poland. The analysis covers the years 1997-2010 and includes approximately 393,402 individual observations.[10] The years 2011-2013 are excluded from the analysis due to a shift in occupational coding between 2010 and 2011.

The occupations of the respondents are based on the International Standard Classification of Occupations (ISCO) from the International Labour Organization (ILO n.d.).[11] The type of occupation in ISCO is defined at a four-digit level, while the occupation variable in the Polish data set is provided at a two-digit precision. For the years 1997-2010, the occupation is coded based on ISCO-88. For 2011-2013, occupational coding is based on the newer revision, ISCO-08. As the occupation variable in the data set is specified at a two-digit precision, it is not possible to overcome the switch from ISCO-88 to ISCO-08 by recoding, and it is thus not appropriate to compare the observations in years 1997-2010 with those in 2011-2013. The analysis is therefore restricted to the years 1997-2010, when ISCO-88 was used. In the following parts of the thesis the occupational coding will always refer to ISCO-88 unless otherwise specified. The classification of occupations in ISCO-88 is displayed in Table 7 in Appendix A.

[9] The Polish Household Budgets Survey has been harmonized into the CenEA-PHBS database, which is the one used in this study.

[10] This is approximately 27 percent of all observations included in the survey. Section 5.1.1. presents a more detailed description on observations excluded from the analysis.

[11] More specifically, the occupation variable in the data set is based on the Polish classification system for occupations, Klasyfikacja zawodów i specjalnosci (KZiS). KZiS is based on ISCO, and the versions of KZiS correspond to ISCO with only a few exceptions.

The variable that indicates in which industry the respondent works is based on the Statistical Classification of Economic Activities in the European Community (NACE), which is a framework for industry classification used within the European Union.[12] NACE classifies industries at a four-digit level and the industry variable available in the Polish data set is specified at a two-digit level. Industry coding is not consistent over the whole time period in the data set. For the years 1997-2007, the occupational coding in the data is based on NACE Rev. 1 and NACE Rev. 1.1. The two versions are very similar, only minor changes were made in the update and it is therefore highly unlikely to influence the result. However, a larger shift in the data occurred in 2008 when the coding shifted from NACE Rev. 1.1 to NACE Rev. 2. Conversion tables between NACE Rev. 1.1 and NACE Rev. 2 have been used to recode the later years to NACE Rev. 1.1 in order to have a consistent industry classification throughout the whole time period.[13] As the industry variable in the data set is at a two-digit level, this method contains some mistakes since a four-digit level would be needed to perform an exact recoding. In order to minimize the impact of such errors, industry coding in the analysis is used only at the one-digit level (letter codes). This increases the group size and minimizes the effect of potential errors. Table 8 in Appendix A provides an overview of the letter codes in NACE Rev. 1.1.

Dependent variables in the regressions are employment and income. Employment is measured in persons and not in hours due to data limitations described in section 5.2.4. The gross income variable is originally measured in current złoty (Polish currency) and is transformed into real gross income with base year 1997 using the World Bank inflation measure, which is based on the annual change in consumer price index (World Bank 2014c). Other variables, such as age, education and gender, are also available in the data set and included as controls in the regressions. Education is used to account for the effect of skills on employment and wages. The level of education is measured by the highest degree a person has accomplished and is divided into the different types of educational establishments in the Polish education system. We recode education creating five levels of education ordered from "no education" to "university education".

5.1.2. Measures of routineness and offshorability

In the analysis, measures of routineness and offshorability are used to capture the impact of the level of routine and the possibility to offshore within different occupations. Goos, Manning and Salomons (2014) use the two measures of routineness and offshorability in their research and we are thankful to the authors for providing us with the measures.

The Routine Task Intensity (RTI) index is used to measure the level of routine tasks in different occupations, and has previously been used by Autor and Dorn (2013) and Autor, Dorn and Hanson (2015) in research focused on the labor market in the United States. The index is constructed by three different task measures, namely abstract, routine and manual tasks, which measure the intensity of the different task contents in specific occupations. The categories are based on US data on job task requirements from the Dictionary of Occupational Titles (DOT) (Autor, Levy and Murnane 2003). The RTI index is then calculated as follows:

Equation 1. RTI index

$$RTI_i = \ln\left(T_{i,t}^r\right) - \left(ln\left(T_{i,t}^a\right) + ln\left(T_{i,t}^m\right) \right)$$

[12] To be more specific, the industry variable is based on the polish classification system of occupational activities, Polska Klasyfikacja Dzialalnosci (PKD), which in turn is based on NACE. Up to the fourth digit, PKD-2004 is fully comparable to NACE Rev. 1.1 and the same holds for PKD-2007 relative NACE Rev. 2.

[13] Conversion tables provided by Eurostat (n.d.).

where RTI_i is the Routine Task Intensity for occupation i, while $T^r_{i,t}$, $T^a_{i,t}$ and $T^m_{i,t}$ are the routine, abstract and manual task contents of occupation i in the base year t (Autor and Dorn 2013). Goos, Manning and Salomons (2014) match the RTI index to the two-digit occupational codes in ISCO-88 and standardize the index. This is the measure used in our study. A high value on the RTI index indicates that occupation i is mainly composed of routine tasks, while a low value corresponds to manual or abstract tasks being the main component in the occupation (Autor and Dorn 2013).

A routine task-intense occupation can require both non-cognitive and cognitive skills, but is also easily routinized and substituted by a computer. Machine operators and office clerks are two examples of occupations with a high level of routine tasks. Occupations with abstract tasks usually require high education, such as degrees in engineering or management. Instead of substituting labor, technological advancements are expected to complement and increase the efficiency in abstract-intense occupations (Adermon and Gustavsson 2015). Occupations such as hairdressers and childcare workers require personal contact, and involve mainly manual tasks, and are therefore less easily replaced by technology (Goos, Manning and Salomons 2014).

The index used to measure the offshorability of an occupation was developed by Blinder and Krueger (2013), and is also used by Goos, Manning and Salomons (2014). Blinder and Krueger (2013) define offshorability as the feasibility to perform and move a specific job abroad, while the goods and services produced are still sold in the home country market. The movement of a job abroad can either take place within the company, for example if a German company has its call center located at its office in Warsaw, or to another company, a local Polish actor. Blinder and Krueger (2013) develop several different measures, but find the most accurate one to be based on estimates of professional coders of the ease with which specific job tasks can be moved abroad, that is, how offshorable a specific job is (Blinder and Krueger 2013). A high value on the offshorability measure means that an occupation is offshorable, while a lower value implies that the job is less likely to be offshored (Goos, Manning and Salomons 2014). Highly offshorable and medium offshorable occupations include, for example, phone-based customer service where workers do not have to be physically present to perform their work duties or occupations where the whole work place (factory or production plant) can be moved abroad. This is less possible for non-offshorable occupations such as managerial teams, cleaners and garbage collectors (Adermon and Gustavsson 2015). Goos, Manning and Salomons (2014) match the offshorability index to the two-digit codes in ISCO-88 and standardize it, and this is the measure used in our study.

The Blinder and Krueger (2013) offshorability measure for occupations is mainly used throughout the analysis. At a few occasions, we use a very similar measure by Blinder and Krueger (2013) in which offshorability is coded for industries instead of occupations. The measure assesses how easily jobs within a certain industry can be offshored.[14]

The offshorability measure is originally developed for the United States labor market. We still believe it to be an appropriate measure for this study since, in the context of our analysis, the offshorability measure has to fit those countries offshoring to Poland, not Poland itself. Offshoring into Poland, to a large extent, originates from Western European countries, which are at a similar state of development as the United States. The offshorability measure is therefore likely to well reflect the offshorability of Western European occupations and industries.

[14] Blinder and Krueger (2013) use the North American Industry Classification System (NAICS) to specify the industries. We have matched the NAICS-codes to the two-digit level NACE Rev 1.1, which is the classification system we use. A conversion table for 2002 NAICS to NACE Rev. 1.1 was used (United States Census Bureau n.d.). The matching is approximate and does have its limitations, but it is still suitable for our purpose.

Moreover, Goos, Manning and Salomons (2014) use this offshorability measure in their study of 16 Western European countries implicitly assuming its suitability.

5.1.3. Other data sources

Data on inward positions of foreign direct investments (FDI) by industry and partner country is retrieved from OECD.Stat online database, and is reported in USD millions (OECD.Stat 2012a; OECD.Stat 2012b).[15] Data on exports by product is collected from WTO Statistics Database, and is measured in USD. The products are classified according to the third revision of the Standard International Trade Classification (SITC Rev. 3) (WTO Statistics Database 2014). Data on high-technology exports (USD) is retrieved from the World Bank (2013b), and so is the data on GDP (USD) (World Bank 2014a). The inflation measure is retrieved from the World Bank (World Bank 2014c). Data on the percentage share of the labor force with tertiary education is collected from the World Bank (World Bank 2012), and so is the Gini index (World Bank 2013a).

5.2. Descriptive statistics

In order to provide a general impression of the data set and developments of certain variables over time, we present selected descriptive statistics on the data in Table 10 to 12 in Appendix A. Table 10 shows descriptive statistics for variables used in our estimations. The mean level of routineness (RTI) in 2010 is reduced to a quarter of its initial level in 1997. This implies that the individuals in the data set, on average, have less routine-intense occupations in 2010 than in 1997. The average level of offshorability in the whole data set decreases slightly between 1997 and 2010, from 0.01 to -0.04. This might be due to the fact that many of the largest growing industries are those with a low level of offshorability, such as health professionals or sales personnel (see Table 11). This seems natural, as the Polish economy has grown rapidly. The mean level of education increases over the years, and the overall education level is higher in 2010 than in 1997. The standard deviation increases slightly between 1997 and 2010, which hints at an increasing spread from low to high levels of schooling among the population. The mean age of workers increases slightly with about one year. The standard deviation indicates on an increase in the age-spread in the labor force in 2010, compared to in both 2004 and 1997. The share of females grows during the time period 1997-2004, but is reduced to its original value in 2010. The female share in the labor market, 47 percent, is relatively high. This might be an overestimation, as we are unable to account for hours worked. Since females, to a larger extent than men, often have a part-time work, they might be over-represented here.

Table 11 presents the five job types that are increasing most in relative size and the five job types that experience the largest decreases in their share of total employment. The strongest growing job type, building workers in construction, grew by 2.5 percentage points during the time period 1997-2010. Craft workers in the manufacturing industry, on the other hand, lost 3.4 percentage points in size. Table 12 shows job types in a similar manner but based on highest and lowest wage growth instead. Three of the five jobs with highest wage growth are found within the communication industry; their wages more than doubled from 1997 to 2010. The job types

[15] The industry coding used corresponds to NACE Rev 1.1, but the data does not cover the following industries: "Armed forces" (01), "Public administration and defence; compulsory social security" (L), "Education" (M), "Health and social work" (N), "Other community, social and personal service activities" (O), "Activities of households" (P) and "Extra-territorial organizations and bodies" (Q). This is unlikely to have a large effect on the results since the excluded industries are not the typical industries in which foreign entities invest. Furthermore, the two industries "Agriculture, hunting and forestry" (A) and "Fishing" (B) have been grouped together.

experiencing the lowest wage growth are, for example, general managers in hotels and restaurants and customer service clerks in the retail trade industry.

5.3. Methodology

The first part of the analysis concentrates on the developments in the Polish labor market and assesses if the labor market has polarized over time. The second part examines the potential role of routineness and offshorability for the developments in the Polish labor market. The methodology for both parts is commonly used in the literature on job polarization, for example by Autor and Dorn (2013), Adermon and Gustavsson (2015), Goos, Manning and Salomons (2014) and Kampelmann and Rycx (2011).

5.3.1. Preparation for analysis

In a similar manner as Adermon and Gustavsson (2015), we define a specific job type as a certain occupation in a certain industry. Job types are produced through the construction of an industry/occupation matrix, in which 14 industry letter codes (NACE Rev. 1.1) and 27 two-digit occupation codes (ISCO-88) are used.[16] The matrix generates 378 different job types (27 occupation codes multiplied with 14 industries). The names of the different job types are constructed by using industry letter and occupation code, such that job type F_41, for instance, represents office clerks (41) in the construction industry (F). Job types with less than ten observations are omitted, which implies that approximately 200 job types are used in the study.

The analysis is restricted to adults aged 18-65 with part-time or full-time employment, and for whom occupation and industry codes are available in the data. Self-employed individuals are generally excluded. Individuals with income from both employment and self-employment are included only if employment is their primary income source. This implies that an individual who is, for example, mainly working as a teacher but who also sells farm products on the side is still included in the analysis. Self-employed individuals are excluded since they might distort the results of our analysis as it is unclear how self-employed individuals classify their occupation in a survey situation. For example, an individual who owns a small carpentry company with two employees might assign himself the occupation code "precision, handicraft, printing and related trades workers" (73), however, the occupation "general manager" (13) is also applicable since the individual manages an enterprise. The analysis will therefore focus on employees, for whom it is more clear which occupation code is suitable.

The study analyzes changes in the labor market in 1997-2010, as well as in 1997-2004 and 2004-2010. On May 1, 2004, Poland became a member of the European Union, and the division of the longer time period into two parts aims to compare the labor market prior to and after the entrance into the union. The division also makes it possible to compare two time periods of approximately equal length.

5.3.2. Polarization in the labor market

In order to visualize labor market patterns over time, we rank the job types based on their mean wage in the first year of the data, 1997. Based on this wage rank, the different job types are then

[16] For the occupation codes, one occupation is excluded, namely "Armed forces" (01), and the total number of occupations used in the analysis is therefore 27. The industry coding is based on letters from A to Q. Two industries are excluded from the analysis, "Activities of households" (P) and "Extra-territorial organizations and bodies" (Q). Industries "Agriculture, hunting and related service activities" (A) and "Fishing" (B) have been grouped together due to the small size of the fishing industry. The total number of industries used in the industry/occupation matrix is hence 14.

grouped into quintiles.[17] The lowest quintile represents the 20 percent of the individuals who work in a job type with the lowest mean wages in 1997. On the opposite side of the spectrum, the highest quintile contains the 20 percent of the individuals working in the job types with the highest mean wages in 1997. In the literature on job polarization the use of median or mean wages varies; Adermon and Gustavsson (2015) and Kampelmann and Rycx (2011) use median wages, while Autor and Dorn (2013) and Goos, Manning and Salomons (2014) use mean wages. Adermon and Gustavsson (2015) confirm that their results are robust to a shift from median wages to mean wages. We use mean wages because of the technicality that quintiles vary stronger in size when median wages are used, since job types are not split between quintiles. The use of median wage would therefore distort the graphical analysis. For reasons of consistency we use mean wages throughout the analysis but also report regression results using median wages in Table 14 in Appendix C. The minor changes in results are described later in the paper (section 7.2.2.).

To investigate if employment in low-, medium- and high-income job types, respectively, has increased or decreased, we compare the number of individuals in the job types in a certain quintile in 1997 (approximately 20 percent in each quintile) with the share of total employment the job types in this quintile represent in year 2010. More specifically, we calculate the percentage point change in employment of each 1997 quintile (as share of total employment) from 1997 to 2010. This means that the employment share of a group of specific job types in 1997 is compared to the corresponding number in 2010; the observations for the years 1998-2009 are not included. The same comparison is performed for 1997-2004 and 2004-2010. The number of individuals is 27 501 in 1997, 24 996 in 2004 and 31 920 in 2010, which is also shown in Table 10 in Appendix A.

In addition to a visual examination of the data, several studies use a more formal test for polarization (Adermon and Gustavsson 2015; Goos and Manning 2007; Kampelmann and Rycx 2011). We also perform a formal test for both job and wage polarization over the whole time period 1997-2010, as well as for the sub-periods of 1997-2004 and 2004-2010, based on the following regressions:

Equation 2. Formal test of polarization in employment

$$\Delta\,\text{Employment share}_{i,j,t} = \beta_0 + \beta_1 \log(mean\ wage)_{i,j,t-1} + \beta_2 \log(mean\ wage)^2_{i,j,t-1} + \varepsilon_{i,j,t}$$

The formal test for wage polarization over the three different time periods is as follows:

Equation 3. Formal test of polarization in wages

$$\Delta\,\log(\text{mean wage})_{i,j,t} = \beta_0 + \beta_1 \log(mean\ wage)_{i,j,t-1} + \beta_2 \log(mean\ wage)^2_{i,j,t-1} + \varepsilon_{i,j,t}$$

The linear and quadratic variables are the log mean wages in 1997, which the ranking of job types is based on. Change in employment share, as well as in mean wage, is calculated per job

[17] Specific job types are not split up when quintiles are created, which means that each quintile will not cover exactly 20 percent of the individuals in the data. In our study, the size of the quintiles are very close to 20 percent, the exact percentages are as follows: quintile 1 – 20.5 percent, quintile 2 – 19.5 percent, quintile 3 – 20.3 percent, quintile 4 – 19.8 percent and quintile 5 – 20.0 percent.

type i,j (per occupation i in industry j). If the regression generates a negative coefficient for the linear variable combined with a positive coefficient for the quadratic variable, the regression line is U-shaped. This implies that polarization is present in the employment or wage structure, as both ends of the wage ranking grow comparatively more than the middle (Kampelmann and Rycx 2011).

5.3.3. The effect of routineness and offshorability

After formally testing for job polarization, the next step is to investigate if routineness and offshorability have an effect on the changes in the Polish labor market, more specifically, on changes in employment shares and mean wages. The RTI and offshorability measures are to some extent correlated with each other, as presented in Table 13 in Appendix C. However, there are also essential differences between the two measures. For instance, the tasks in occupation groups such as "models, salespersons and demonstrator" (52) are highly routine-based, but the possibility to offshore these tasks is still low. For "physical, mathematical and engineering science professionals" (21), on the other hand, the routine level is low but the jobs are highly offshorable.

The first of our two fully specified models is presented in Equation 4, and the dependent variable is the change in the share of the specific job type i,j (occupation i in industry j) in total employment over time, between t and t-1. The central independent variables are the Routine Task Intensity (RTI) index and offshorability of occupation i.[18] If routine-intense jobs are indeed replaced by technology, an increase in the RTI index (increased level of routine tasks) for occupation i, will result in a decrease in the employment share in job types within this occupation. Offshorability in the case of Poland as an offshoring-receiving country might work in the other direction. The more offshorable a specific occupation i is, the more jobs within this occupation might be offshored to Poland and employment shares in this job type would thus increase.

Shifts in both supply and demand can affect the labor composition, and the size of different occupations. On the supply side, factors such as an aging labor force, increased female labor force participation and educational levels may positively or negatively affect the relative size of a job type over time. Influences on labor demand can stem from, for example, shifts in product demand, increased technological change and offshoring (Kampelmann and Rycx 2011). Therefore, a set of controls has been included to control for factors that might cause changes in job-specific employment shares through shifts in demand and supply. The controls include change in education, age and share of females between t and t-1, as well as industry dummies to control for shifts in product demand.

Equation 4. Regression model for change in employment

$$\Delta\, Employment\ share_{i,j,t} = \beta_0 + \beta_1 RTI_i + \beta_2 Offshorability_i + \beta_3 \Delta\, Education_{i,j,t} + \beta_3 \Delta\, Age_{i,j,t} + \beta_5 \Delta\, Female_{i,j,t} + \beta_6 Industry_{j,t} + \varepsilon_{i,j,t}$$

In order to investigate how routineness and offshorability affect wages, we estimate the model specified in Equation 5. The independent variables remain the same, but the dependent variable is now the change in the logarithm of the mean wage. For both models, the time periods examined are 1997-2010, 1997-2004 and 2004-2010.

[18] RTI and offshoring indeces are independent of time t.

Equation 5. Regression model for change in wage

$$\Delta \log mean\ wage_{i,j,t} = \beta_0 + \beta_1 RTI_i + \beta_2 Offshorability_i + \beta_3 \Delta\ Education_{i,j,t} + \beta_4 \Delta\ Age_{i,j,t} + \beta_5 \Delta\ Female_{i,j,t} + \beta_6 Industry_{j,t} + \varepsilon_{i,j,t}$$

In the estimations of the models, the job types are weighted by the initial employment share of that specific job type in 1997. The opinions on the use of weights vary in the literature. Both Kampelmann and Rycx (2011) and Goos and Manning (2007) prefer to use weights, and the argument is that it prevents biased results due to changes in small job types.[19] Adermon and Gustavsson (2015), on the other hand, choose not to use weights. Their argument is based on the notion that, for example, routine-intense jobs can be the largest in the base year, while abstract-intense jobs can be the smallest. If this has switched by the final year so that routine-intense jobs are now the smallest job group and abstract-intense jobs the largest, the use of weights will result in an overestimation of the impact of routine-intense jobs and an underestimation of the effect from abstract-intense jobs. However, Adermon and Gustavsson's (2015) study covers the time period 1975-2005, while the time period in our study is substantially shorter, 1997-2010. It is less likely that structural changes, on which the argument of Adermon and Gustavsson (2015) is based on, will occur during a shorter time period. To investigate if this is true, we plot the size of job types in 2010 (based on share of total employment) against their size in 1997 (see Figure 11 in Appendix B). The positive relationship shows that, in our data, job types that were large in the base year tend to be among the larger ones in the final year and thus the argument against weights is less fitting in our case. Based on this, we believe that using size weights is appropriate in the context of our study.

5.3.4. Limitations arising from the data

As previously mentioned, employment is measured in the number of individuals employed and is not adjusted for how many hours single individuals work. This is due to the fact that our data set does not cover hours worked. This could potentially lead to some mismeasurement since both a part-time and a full-time worker are each counted as one employed individual. However, Goos, Manning and Salomons (2014) and Kampelmann and Rycx (2011), estimate their model using both number of hours and number of individuals employed without finding any relevant changes in the results. One additional measure available in our data set is a binary variable for part-time and full-time employment. However, the variable is only available for the years 2003-2010, and not for 1997-2002. In order to better account for part-time workers, we use average shares of part time workers (2003-2010) by job type and create additional weights for the regressions.

[19] For example, a small job type, containing 10 individuals might increase in employment share by 2 percentage points while a large job type containing 1000 individuals might increase by 1 percentage point. If weights are not used, equal emphasis will be put on both job types (independent of the large difference in absolute numbers of additional employees), which will bias the results.

Table 1. Part-time employment and regression weights for the eight largest jobs (largest employment share in 1997)

Job type (certain occupation in certain industry)	Share in total employment in 1997	Avg. share of part-time employees (2003-2010)	Standard deviation (variation over time)	$W_{part-time}$
Craft workers in manufacturing industry	7.9%	5.5%	0.01	0.97
Teachers in education industry	5.3%	6.2%	0.01	0.97
Salespersons in wholesale and retail trade industry	4.7%	12.0%	0.02	0.94
Metal and machinery workers in manufacturing industry	4.4%	2.3%	0.01	0.99
Health professionals in health industry	3.2%	5.2%	0.02	0.97
Building workers in construction industry	3.2%	7.2%	0.02	0.96
Drivers in transport industry	2.4%	2.6%	0.00	0.99
Extraction workers in mining industry	2.1%	0.5%	0.00	1.00

Notes: The titles of job types often contain abbreviations of occupations and industries. For full names see Table 7 and Table 8 in Appendix A.
Source: Calculations done by the authors using the main data set BBGD.

Table 1 shows the average share of part-time employees over the time period 2003-2010 in the eight largest job types (based on their size in 1997), as well as the corresponding standard deviation of the share of part-time workers over time. While there are differences in the share of part-time workers between jobs, the standard deviations are generally low, which shows that the share of part-time employees in the different jobs is relatively stable over time.[20]

The method we apply for creating the weights is based on two assumptions:

1) While we know that part-time employment shares are stable from 2003 to 2010 we assume that the part- and full-time relationship from 1997 until 2003 is also relatively stable. Thus, we assume that the average percentage of part time workers over the period 2003-2010 is representative for the whole time period of the analysis.
2) We assume that part-time employees work on average 50 percent, thus every person employed part-time is counted as half an individual employed full-time.

The weight adjusting for part-time employment $W_{part-time}$, thus accounts for part-time workers by counting them as 'half a worker':

[20] Since the total number of job types is approximately 200, we cannot show results for all job types here. For all job types only five have a std. dev. larger than 0.1. The average std. dev. over all job types is 0.035 with in turn a std. dev. of 0.028. Generally, a higher std. dev. in a certain job type is mainly due to smaller number of total employees. Since smaller groups also account for smaller share of total in employment in the year 1997 the jobs with higher standard deviation are also the ones less influential in regressions and graphical representations.

Equation 6. Part-time weights

$$W_{part-time} = 1 - \frac{1}{2} Avg.share\ part\ time\ workers_{2003-2010}$$

In order to adjust for part-time workers in the regressions, we multiply the weight $W_{part-time}$ with the original weight (share of total employment in 1997) and use this combined weight in all regressions.

However, it is important to notice that this method does not give us estimates for full-time equivalents in the traditional sense. We do adjust the weights in the regressions but it is not possible to change the way calculations are made. For example, when calculating the mean level of education per job type, we still count both a part-time and a full-time worker as one employed individual. Accounting for part time workers in the calculations preceding the regressions is not possible since the data is cross-sectional and the measure of part-time/full-time is not available for all years. Thus, this data limitation might still affect the results even though the effect is reduced by the use of part-time adjusted weights.

5.3.5. Robustness checks of regression results

It might be possible that results are influenced by certain assumptions or decisions underlying the preparation of the data or the main models (Equation 4 and Equation 5). The robustness of the results is therefore tested by estimating the main models while changing certain factors such as the reference period, or by including an interaction variable. In addition, the regressions are also estimated on sub-samples of the data in which the effect of offshorability might be more pronounced than in the full data set. This is done to ensure that the impact of offshoring is not 'overlooked' in the regressions based on the full sample. The sub-samples include areas more prone to offshoring (geographical regions with higher investment attractiveness and urban regions and industries) and also specific industries. In the following, the methodology used for all robustness checks is presented shortly.

Median wage as dependent variable
For our main analysis, mean wage per job type is used as opposed to median wage, for reasons previously explained in section 5.2.2. In order to ascertain that the use of mean wages does not alter the results, the regressions are also estimated using the median.

Threshold for exclusion of job types
The amount of ten employees per job type is used as a cut-off point and all job types that do not reach this threshold are excluded. However, since this cut-off value seems adequate yet rather arbitrary, the main models are estimated using thresholds of both five and thirty employees per job type.

Regression weights adjusted for part-time employees
Following the argumentation in section 5.2.4., all regression observations (job types) are weighted based on their relative size in 1997 and their average share of part-time workers. As a test for robustness, the main model is also estimated without the use of part-time weights using only the weights based on a job type's employment share.

Interaction between RTI and offshorability
RTI and offshorability are correlated to a certain degree since several occupations are both routine-intense and highly offshorable. An interaction variable is included in the estimations to control for interactive effects between the two measures.

Reference periods
With the applied method, results are potentially highly dependent on the selection of the start and the final year. If one year represents values that can be classified as outliers, this might distort the results. In order to control for this in our analysis, the main regressions are estimated over different time periods. In the reported regressions, the start year varies between 1997 and 1998 and the end year between 2010, 2009 and 2008. Using 2008 as a final year allows us to study effects not yet influenced by the financial crisis and the European debt crisis. Moreover, results for the time period 2005-2010 are reported in order to address the issue that changes due to EU membership might take some time to manifest itself. In addition to this, it also tests the robustness of the period 2004-2010 used in most regressions in this study.

Regional differences
In order to account for regional differences in Poland, we examine the effect of RTI and offshorability in geographical areas that are more attractive to foreign investors. The Gdansk Institute for Market Economics, in collaboration with the Konrad-Adenauer-Stiftung, publishes a yearly report on the investment attractiveness of the different Polish regions. The voivodships (provinces) are valuated based on their characteristics within seven different fields, and are ranked based on that valuation. The seven factors are the following: access to labor and labor costs, investment-enhancing activities, access to transport, the market's absorption capacity, level of economic and social infrastructure, and the level of public safety (The Gdansk Institute for Market Economics and Konrad-Adenauer-Stiftung 2011). The ranking does not vary much over the years for which previous reports have been published (The Gdansk Institute for Market Economics and Konrad-Adenauer-Stiftung 2009, 2010), which implies that there has not been any substantial change in the relative investment attractiveness of different regions.[21] The ranking for 2010, as presented in Table 9 in Appendix A, is used in our study.

Prior to 1999, Poland was divided into 49 different voivodships. Following the enforcement of an administrative reform in January 1999, the former provinces were replaced by the 16 current voivodships (Büttner 2012:109). In order to perform an analysis over the whole time period of 1997-2010, we match the 49 voivodships from prior to 1999 with the 16 current ones, and recode them in the dataset. The borders of the current provinces do not fully correspond to previous borders, and the matching is therefore an approximation. However, we do not believe that this will have any substantial effect on the results since the ranking of voivodships is mainly based on factors that change gradually over space (such as, for example, access to transport) as opposed to factors that change suddenly at the border of a province. Thus, slightly changed borders in the first two years of the analysis period should not have a considerable effect on investment attractiveness. We estimate the fully specified models (Equation 4 and Equation 5) for the sub-sample of the more attractive half of the voivodships, that is, the eight voivodships in the upper part of the investment attractiveness ranking. They represent those regions most likely to attract offshoring from abroad.

Urban and rural areas
Poland is still a relatively rural nation with more than a third of the population living in the countryside.[22] It seems plausible that developments in the labor market due to factors such as RBTC and offshoring might be less pronounced in rural areas than in urban areas, such as Warsaw or Krakow. In the data set, the size of the town in which an individual lives is reported. This is used as a proxy for the size of the town in which the individual is working. The sample is

[21] Yearly rankings from 2005 until 2010 are correlated with each other by 95.9% or higher (Spearman rank correlation).
[22] 39 percent of the Polish population lived in rural areas in 2010, compared to 15 and 19 percent in Sweden and the United Kingdom, respectively, as well as 26 percent in Germany (World Bank 2014d).

then divided into rural and urban population based on the definition of an urban area as all towns with 100,000 inhabitants or more. The fully specified models are estimated for the urban sub-sample in order to evaluate if RTI or offshorability have different or more pronounced effects in highly urbanized areas.

Industries prone to offshoring
Some industries are more prone to offshoring than others and to account for this, Blinder and Krueger (2013) rank industries according to their potential offshorability, details on this measure are described in section 5.1.2. The fully specified models (Equation 4 and
Equation 5) are estimated on a sub-sample of the theoretically most offshorable industries, in order to investigate if the effects of RTI or offshorability are more pronounced among industries prone to offshoring. Industries included in the sub-sample are "business activities" (K), "manufacturing" (D), "financial intermediation" (J), "transport and communication" (I) and "construction" (F).

6. Offshoring and technology in Poland

6.1. Offshoring

The rationale of our research and the use of measures of offshorability and routineness are implicitly based on two assumptions. First, that Poland is, in fact, receiving offshoring from other countries within those jobs defined as "offshorable" and, second, that Poland has a technology level high enough for routine-intense jobs to be replaced by technology.

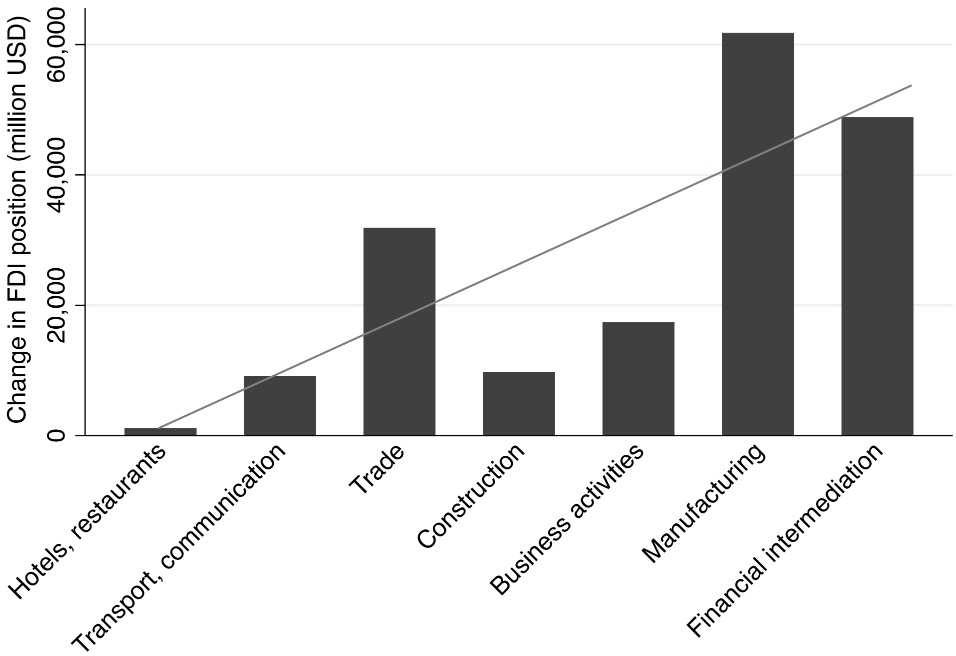
Since data on offshoring is not available, proxies for offshoring are used to show that Poland has received substantial amounts of offshoring over the period of interest. One such proxy is FDI. FDI and offshoring overlap to a large extent but the two concepts also have some differences.[23] On the one hand, FDI includes investments made without the direct intention to substitute labor in the home country, for example, investments to enter a new market, while offshoring entails the movement of jobs from the home country to another country. On the other hand, FDI does not include inter-firm offshoring, that is, goods and services offshored to a Polish company.[24] Because of these shortcomings, we also study exports from Poland as offshored goods and services have to be bought back by the offshoring country and are thus registered as exports in Poland.

Poland receives substantially larger amounts of FDI than it invests abroad; in 2010, the outward position of FDI corresponded to 21 percent of the inward position (OECD.Stat 2012b). Figure 3 shows changes in Poland's inward FDI position for certain industries. It illustrates that the industries that industrialized countries are most likely to offshore are also the ones that receive most FDI; this relationship is significant at a 5 percent level and has a Spearman rank correlation coefficient of 0.86. The graph displays the absolute change in the inward FDI position (million USD) over the time period 1997-2010, based on data from OECD.Stat (2012a).[25] A theoretical

[23] Offshoring, in this study, is defined in line with Blinder and Krueger's (2013) definition: as the movement of jobs abroad, independent of whether the job stays in the original company or is moved to a Polish company.
[24] An example of inter-firm offshoring is when a German company, that formally produced entire cars in the home country, buys car components produced by a Polish company.
[25] OECD defines FDI as a long-term investment of an entity in one country into an entity in another country (OECD 2008). The inward position of FDI is the stock of investments in Poland held by a foreign entity (OECD iLibrary n.d.)

measure of offshorability by industry reported by Blinder and Krueger (2013) is used for ranking the different industries by their possibility to be offshored. The industries to the left in the graph are the least offshorable while the industries to the right are the most offshorable. Offshoring (proxied for by FDI) is high in the industries that are the most offshorable in Western Europe, a pattern that is expected for an offshoring-receiving country such as Poland. The most offshorable industries "manufacturing" (D) and "financial intermediation" (J) had the largest absolute changes in FDI. Industry K, which includes, among other business activities, computer related activities such as data processing and database activities, also attracted relatively large amounts of FDI.[26] [27]

Figure 3. Change in inward FDI position per industry, over the time period 1997-2010



Notes: Industries on the x-axis are ranked based on offshorability. Industries to the left are least offshorable, and industries to the right most offshorable. The labels on the x-axis are abbreviations for the following industries: "Manufacturing" (D), "Construction" (F), "Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods" (G), "Hotels and restaurants" (H), "Transport, storage and communication" (I), "Financial Intermediation" (J) and "Real estate, renting and business activities" (K).
Source: Data on inward FDI position from OECD.Stat (2012a) and offshorability by industry from Blinder and Krueger (2013), calculations done by the authors.

---

[26] The relatively high level of FDI in the low-offshorable industry "wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods" (G) is likely due to the limitations of using FDI as a proxy for offshoring. For example, Swedish companies that open stores in Poland with the aim of entering a new market do invest in the country, but this does not count as offshoring.

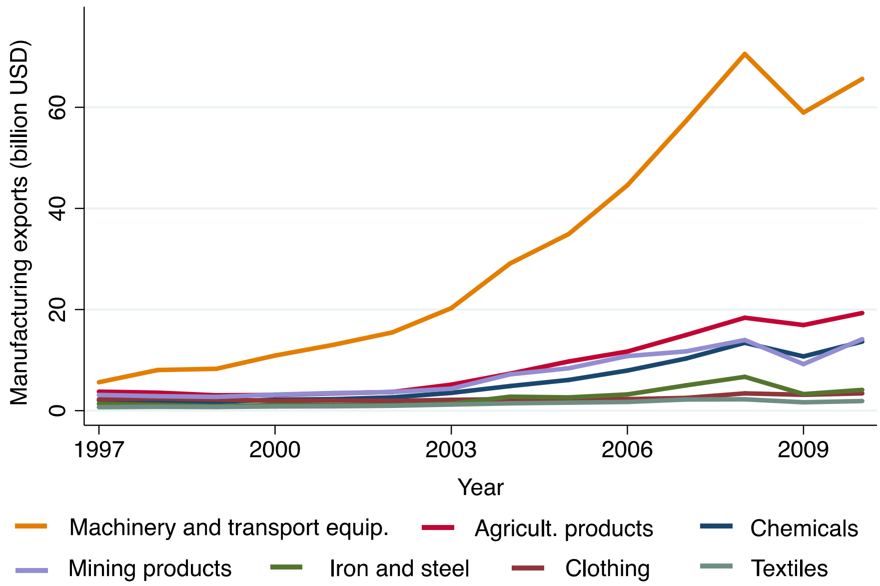
[27] Industries for which OECD does not report data on FDI or for which Blinder and Krueger (2013) do not provide an offshorability estimation are not included in the graph. This is, however, unlikely to have any significant impact since the omitted industries are those less prone to receive FDI or to be offshored. This implies that the industries included in the graph are those for which offshoring and FDI are primarily relevant.

Industries not covered by the data on FDI are: "Armed forces" (01), "Public administration and defence; compulsory social security" (L), "Education" (M), "Health and social work" (N), "Other community, social and personal service activities" (O), "Activities of households" (P) and "Extra-territorial organizations and bodies" (Q). Furthermore, the two industries "Agriculture, hunting and forestry" (A) and "Fishing" (B) have been grouped together.

Industries for which no offshorability measure is reported are: "Agriculture, hunting and forestry" (A), "Fishing" (B), "Mining and quarrying" (C) and "Electricity, gas and water supply" (E).

Since the use of FDI as a proxy for offshoring is suitable but not without limitations, we complement the picture by examining how exports have changed over time. An increased level of offshoring should be reflected in the data on exports of goods and services as the offshored goods and services have to be, to a large extent, re-imported into the offshoring country. The availability of export data per industry is limited, and we therefore use data on exports per product (WTO Statistics Database 2014). Figure 4 illustrates the development over time for the Polish manufacturing exports in millions USD. Machinery and transport equipment exports in particular has experienced a significant growth. This includes, for example, the exported cars produced at FIAT's Polish manufacturing plant, which is one of the largest production plants in Europe (EY 2015).

Figure 4. Manufactures exports

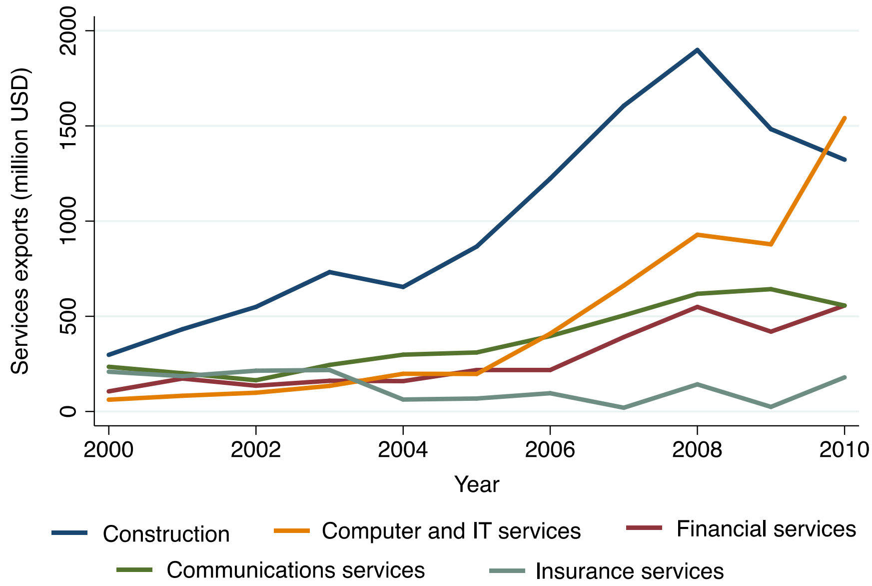


Source: WTO Statistics Database (2014)

Figure 5 displays the export of services.[28] Exports are highest in construction, as well as in computer and information services, but communication services and financial services have also experienced an increase over time. Several of these services experienced a substantial increase between 2004 and 2006, that is, within two years after the accession to EU. The growth in exports of computer and information services indicates that Poland has reached a level of technology high enough for its exports to be attractive to other countries.

[28] The time periods vary between the graphs, as data on exports of services is not available prior to year 2000. Note also that the scale on the y-axis in Figure 4 is different from the scale in Figure 5.

Figure 5. Services exports



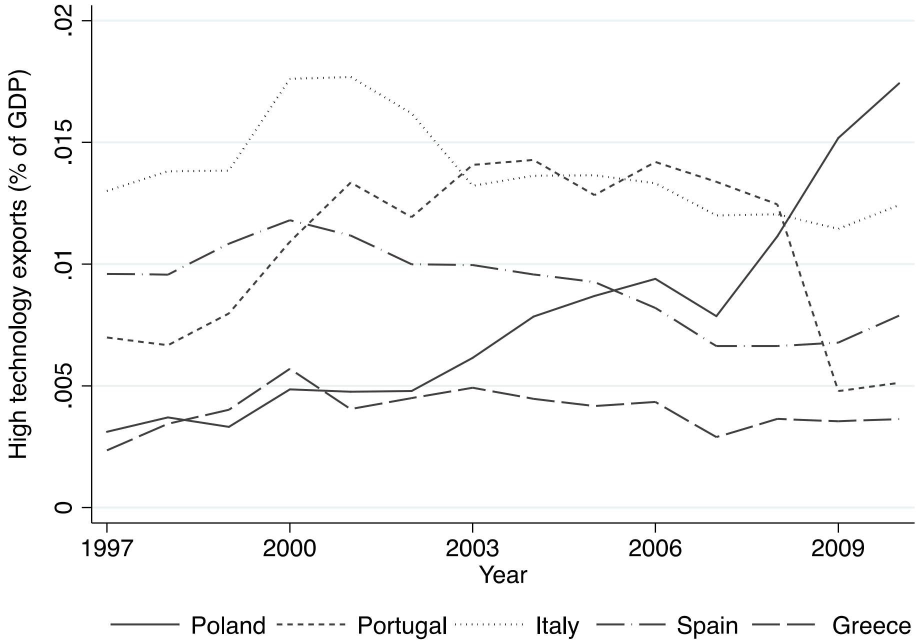
Source: WTO Statistics Database (2014)

6.2. Technology

There is no straightforward method to show that Poland has a technology level high enough for routine-intense jobs to be replaced by technology. It is, however, possible to compare Poland to other countries. In their study on job polarization in Western Europe, Goos, Manning and Salomons (2014) also include Southern European countries such as Greece, Italy, Portugal and Spain. When including a dummy for these Southern countries, they find that the negative and significant effect of RTI on the change in employment persists in these countries. These countries are therefore good candidates for comparison.

It is important to note that replacement of labor does not require a high level of technology per se. For example, plant workers might be replaced by machines, which are not necessarily machines of high technology. However, since the level of technology necessary for routine jobs to be replaced is not easily defined, and the technological level in different countries is not readily available, high technology exports can be used as a rough proxy for the overall level of technology. Figure 6 displays high technology exports (products) in percentage of GDP over the time period 1997-2010 in Greece, Italy, Portugal, Spain and Poland. As for Poland, the country started at a lower level in 1997, but high-technology exports have increased substantially over time. This is a sign that the general technology level has increased in Poland, and that the possibility to replace labor by technology has increased. More importantly, all countries in the graph have a similar level of high-technology exports. Since Goos, Manning and Salomons (2014) successfully apply the RTI index on Greece, Italy, Portugal and Spain, it seems suitable to do so for Poland as well.

Figure 6. High technology exports from Poland and the Southern European states



Source: Data on high-technology exports from the World Bank (2013b); GDP (USD) data from the World Bank (2014a), calculations done by the authors.

7. Results

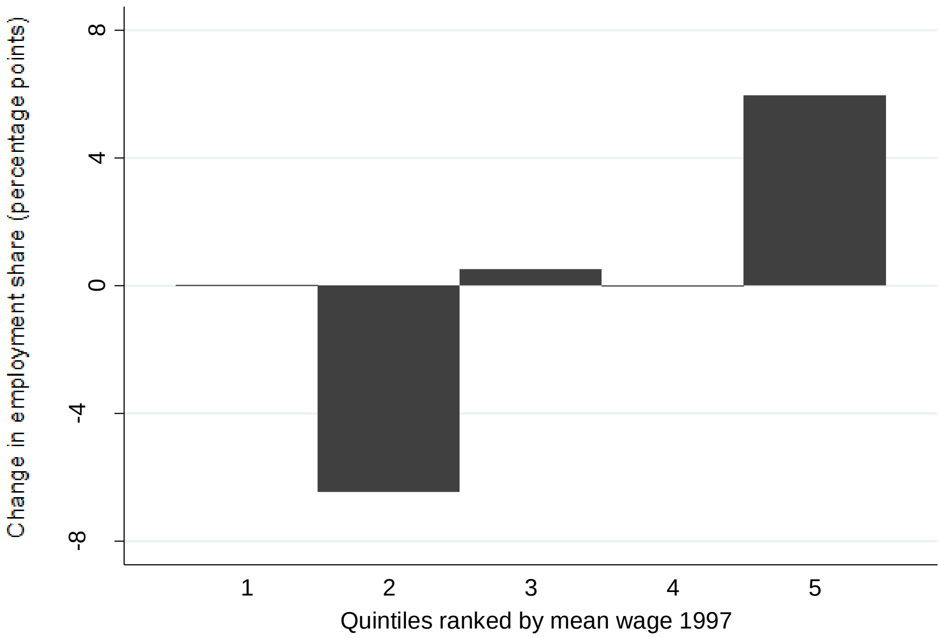
7.1. The existence of polarization

7.1.1. Job polarization

The existence of job polarization is investigated through visual analysis of the data, as well as a formal regression test. Figure 7 shows the change in the relative number of employees within different jobs (i.e. the change in employment share) over the time period 1997-2010, grouped into quintiles and ranked according to the average mean wage of a specific job type in 1997. Noticeably, the highest wage quintile (quintile 5) gains in relative size while the second lowest wage quintile (quintile 2) shrinks. The remaining quintiles do not display any change of considerable size in the relative number of employees. The presence of job polarization would imply an increase in the outer quintiles, that is, the lowest- and highest income groups, and a decrease in the middle quintiles, the middle-income groups. Over the period of 1997-2010, the overall picture does not show a complete pattern of job polarization, since only small changes in the employment share occur in the lowest quintile, as well as in the third and fourth quintile. Figure 14 in Appendix B shows the same measures but with job types divided into three groups instead of five.[29] This graph displays the following pattern: a decrease in the size of the lowest wage tertile, an increase in the highest wage tertile, and an unchanged middle wage tertile, which does not support the theory of job polarization. This implies that a change in the number of groups from five to three does not affect the visual interpretation.

[29] Goos, Manning and Salomons (2014) show figures with three groups. Since the authors find job polarization in their study, we want to make sure that the patterns in the figures are not distorted due to our choice of five groups rather than three.

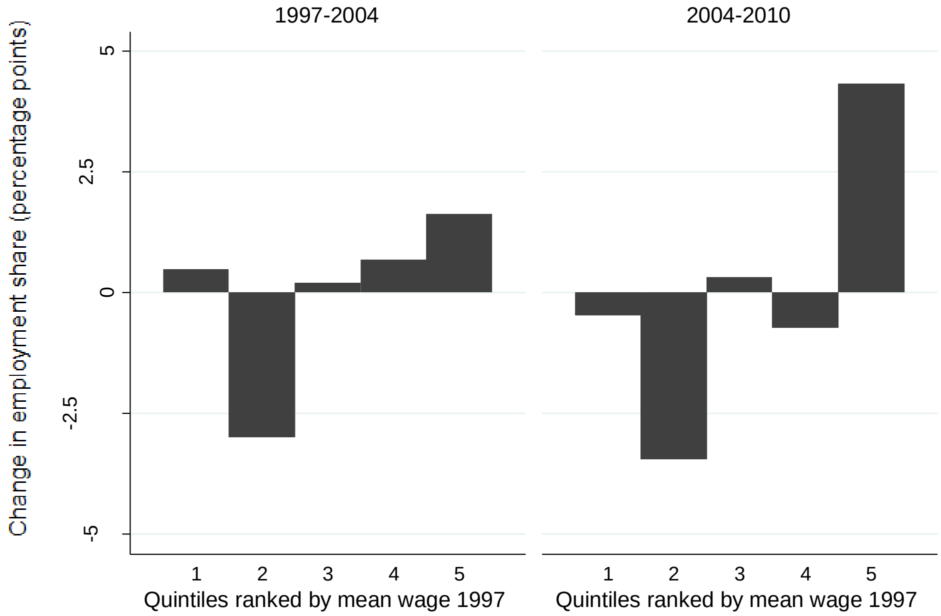
Figure 7. Change in employment share of different job types, 1997-2010



Source: Calculations done by the authors using the main data set BBGD.

The division of the time period into two sub-periods, 1997-2004 and 2004-2010, reveals the different patterns of development during the two time periods. The developments in the second and fifth quintiles are consistent over the two sub-periods; the second quintile decreases while the fifth quintile increases. The first and fourth quintiles, however, display opposite developments. In 1997-2004 the share of lowest paying jobs (quintile 1) increases while it falls during the period thereafter. The fourth quintile shows a similar development but more distinctively. The two sub-periods also do not display any patterns of job polarization. In Figure 15 in Appendix B, the job types are divided into three groups instead of five, and job polarization is not present.

Figure 8. Change in employment share of different job types, 1997-2004 and 2004-2010



Source: Calculations done by the authors using the main data set BBGD.

Figure 7 and Figure 8 above provide a visual illustration of the development of employment in Poland and suggest that employment might not have polarized to the same extent as in other countries previously researched. In order to establish this with more certainty, a formal test for the presence of job polarization is performed, based on Equation 2. Results of the test are reported in Table 2. The dependent variable in the regression represents the change in employment share, that is, the y-axis in the figures above. The independent variable is the logged initial mean wage per job type, which is the same variable that the ranking of quintiles in the figures is based on. By including squared initial wage, we account for the U-shaped relationship we would expect in the case of job polarization. The regression results in Table 2 consolidate the picture in the figures. The initial mean wage is not a significant predictor of growth in employment share, that is, low- and high-income jobs did not grow significantly more than medium-income jobs in any of the time periods.

Table 2. Formal test for job polarization - OLS regressions: change in job-specific employment share

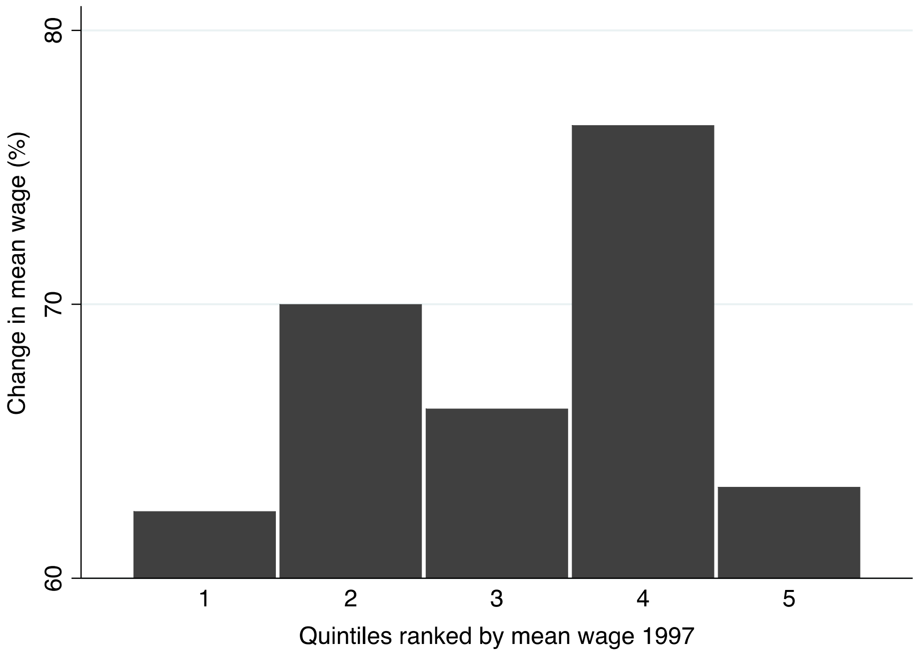
	(1) 1997 - 2010	(2) 1997 - 2004	(3) 2004 - 2010
Log initial mean wage	0.909	0.298	0.611
(1997)	(0.713)	(0.832)	(0.691)
Squared log initial mean	-0.054	-0.018	-0.037
wage (1997)	(0.757)	(0.859)	(0.739)
Constant	-3.672	-1.206	-2.466
	(0.671)	(0.805)	(0.647)
N	214	214	214

p-values in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

7.1.2. Wage polarization

As a transition economy, Poland is in the phase of catching up with its richer neighbors in the west and a general growth in wages is therefore expected. In fact, this is represented in our data; as shown in Figure 9, all quintiles have experienced a positive growth of more than 60 percent in mean wages during the time period 1997-2010. It is, however, of more interest to study the relative change in wages between groups. The middle-income groups have had the highest percentage growth over the whole time period, while the low- and high income groups exhibit the lowest. As Figure 9 illustrates, no clear pattern of wage polarization is present; in fact, the pattern appears to be the opposite of a U-shaped relationship with the middle-income groups demonstrating the largest percentage increases in income.

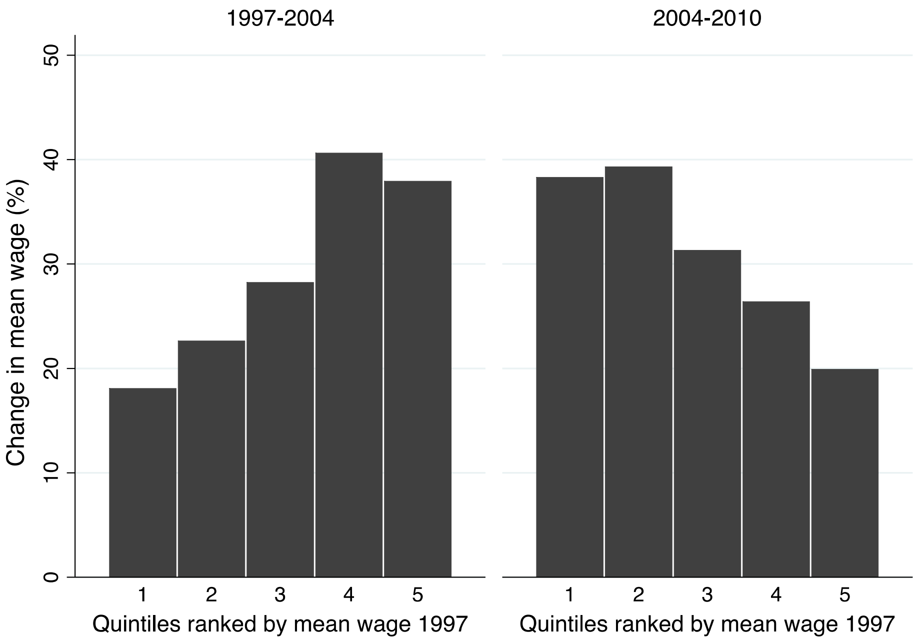
Figure 9. Percentage change in mean wage, 1997-2010



Source: Calculations done by the authors using the main data set BBGD.

Figure 10 displays the growth in mean wage for the two sub-periods of 1997-2004 and 2004-2010, and provides deeper insight into when the main changes in wage occurred. In 1997-2004, wages in middle- and high-income jobs had the highest percentage increase, while low-income jobs had the lowest. In 2004-2010, the patterns were reversed with the lowest growth in high-income jobs, and the highest in low-income jobs. The pattern in the two sub-periods does not correspond to that of wage polarization, but it also casts doubt on the pattern of reversed wage polarization as presented in Figure 9.

Figure 10. Percentage change in mean wage, 1997-2004 and 2004-2010



Source: Calculations done by the authors using the main data set BBGD.

To formally test for wage polarization, and not solely rely on visual interpretations, we estimate Equation 3 and the results are presented in Table 3. The dependent variable is the change in job-specific logged mean wage. The independent variables are the logged initial mean wage in 1997, as well as the squared version of this variable that accounts for the U-shaped relationship. The coefficient of initial mean wage is positive and the coefficient of the squared factor is negative. This translates into a reversed U-shape. Thus, the estimation results confirm the notion of a development opposite to wage polarization in the whole time period of 1997-2010, as well as in the first sub-period of 1997-2004. For the later sub-period 2004-2010 we do find any statistically significant relationship.

Table 3. Formal test for wage polarization - OLS regressions: change in job-specific log mean wage

	(1) 1997 - 2010	(2) 1997 - 2004	(3) 2004 - 2010
Log initial mean wage (1997)	2.482***	3.427***	-0.791
	(0.002)	(0.000)	(0.315)
Squared log initial mean wage (1997)	-0.182***	-0.240***	0.0472
	(0.001)	(0.000)	(0.399)
Constant	-7.930***	-11.90***	3.412
	(0.004)	(0.000)	(0.217)
N	185	191	180

p-values in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

7.2. Impact of routineness and offshorability

7.2.1. Regression results

As we find neither job nor wage polarization, it is of interest to study why this is not the case. More specifically, we will investigate how the two factors of routineness and offshorability, which are commonly mentioned as potential drivers of polarization, affect the Polish labor market. We will therefore estimate Equation 4 and
Equation 5, as presented in section 6.2.3, in order to study the effect of the routineness and offshorability of jobs on the job-specific development in terms of number of employees, as well as mean wage.

Table 4. OLS regressions: change in job-specific employment shares

	1997 - 2010		1997 - 2004		2004 - 2010	
	(1)	(2)	(3)	(4)	(5)	(6)
RTI	-0.207	-0.050	-0.178*	-0.155**	-0.030	-0.002
	(0.156)	(0.696)	(0.062)	(0.045)	(0.740)	(0.976)
Offshorability	-0.379	-0.278	-0.162	-0.017	-0.217	-0.211
	(0.400)	(0.431)	(0.517)	(0.933)	(0.310)	(0.217)
Δ Education		-0.491		0.524		-1.188**
		(0.357)		(0.211)		(0.030)
Δ Age		-0.141**		-0.056*		-0.104**
		(0.023)		(0.080)		(0.043)
Δ Share of females		0.034***		0.009		0.027**
		(0.009)		(0.219)		(0.022)
Industry dummies		YES		YES		YES
Constant	-0.145	0.363	-0.010	-0.025	-0.135	0.162
	(0.588)	(0.177)	(0.947)	(0.842)	(0.400)	(0.218)
N	208	185	208	191	208	180
Adjusted R^2	0.12	0.43	0.15	0.44	0.06	0.40

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes: The dependent variable is the change in job-specific employment share. The controls are change in education, age and share in females (changes are adjusted to the given time period) as well as dummy variables for the 14 different industries used to define job types. An increase in the control variables Δ Education, Δ Age and Δ Share of females refers to an increase in education, age and relative amount of female participants, respectively. Job types are weighted by their employment share in 1997, as well as by the average share of part-time workers. Standard errors are robust.

Table 4 reports the OLS regression results with the change in job-specific employment share as dependent variable. For each time period (1997-2010, 1997-2004 and 2004-2010) two regressions are specified, one containing only the variables of interest and one fully specified model that contains controls as well. The observations included in the regression are between 208 and 180 job types, which in turn represent between 27,500 and 31,300 individuals. The coefficients for offshorability are statistically insignificant in all periods and all specifications. The coefficients of routineness (RTI) are insignificant for the full time period of 1997-2010, as well as for the later sub-period of 2004-2010. However, for the period of 1997-2004, coefficients are negative and statistically significant in both specifications. This implies that, ceteris paribus, an increase in the level of routineness of a certain job type results in a lower employment share of this job type during the time period 1997-2004.

The effect of controls on employment appears to be more pervasive in the later sub-period. The change in education, share of females and age composition are all highly significant in the period of 2004-2010, while less or not at all significant in prior years. The adjusted R^2 shows that as controls are included up to 44 percent of the variation is explained by the model.

Table 5. OLS regressions: change in job-specific log mean wage

	1997 - 2010		1997 - 2004		2004 - 2010	
	(1)	(2)	(3)	(4)	(5)	(6)
RTI	-0.024	-0.027***	-0.051**	-0.053***	0.027**	0.012
	(0.142)	(0.03)	(0.016)	(0.000)	(0.021)	(0.193)
Offshorability	0.003	0.013	0.018	0.033**	-0.014	-0.012
	(0.828)	(0.194)	(0.414)	(0.015)	(0.454)	(0.249)
Δ Education		0.036		0.338***		0.105**
		(0.290)		(0.000)		(0.044)
Δ Age		0.003		-0.004		0.022***
		(0.297)		(0.293)		(0.000)
Δ Share of females		-0.003***		-0.004***		-0.003**
		(0.000)		(0.000)		(0.019)
Industry dummies		YES		YES		YES
Constant	0.518***	0.516***	0.263***	0.173***	0.256***	0.311***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
N	185	185	191	191	180	180
Adjusted R^2	0.04	0.35	0.11	0.61	0.04	0.38

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes: The dependent variable is the change in job-specific log mean wage. The controls are change in education, age and share in females (changes are adjusted to the given time period) as well as dummy variables for the 14 different industries used to define job types. An increase in the control variables Δ Education, Δ Age and Δ Share of females refers to an increase in education, age and relative amount of female participants, respectively. Job types are weighted by their employment share in 1997, as well as by the average share of part-time workers. Standard errors are robust.

Table 5 shows a similar regression setup but with change in log mean wage as dependent variable. Routineness (RTI) appears to have a negative effect on wages when estimated on the entire period 1997-2010. However, closer inspection of the results for the sub-periods shows that these results are driven by the negative effect on wages in the earlier period 1997-2004. The effect of routineness on wage for the later period 2004-2010 is, in fact, positive, even though not significant in the fully specified model. Offshorability of job types does not have a significant effect on wage growth for the full time period of 1997-2010, as well as the later sub-period of 2004-2010. For the earlier sub-period, however, offshorability has a statistically significant and positive effect on wage development in the fully specified model.

The coefficients of the controls included in the regression have the expected directions. The effect of an increase of female employees is negative and significant over all time periods, which implies that, ceteris paribus, an increase in the share of female employees in a job type reduces the average wage in this job type. Moreover, all else equal, an increase in the average education level per job type translates into a higher average wage; this effect is statistically significant in both sub-periods. The change in age has a significant effect only in the later sub-period, 2004-2010, where an increase in average age is predicted to result in a rise in average wage. The adjusted R^2 in the fully specified models varies between 35 percent for 1997-2010 and 61 percent for 1997-2004.

The Routine Task Intensity (RTI) index is, as explained in section 6.1.2., constructed of three different task characteristics that measure the level of routine, abstract and manual tasks in a specific occupation. In order to construct RTI, the level of abstract and manual work is subtracted from the routine level. Abstract tasks are usually performed by highly educated employees, and the measure of abstract is therefore strongly correlated (0.92) with the average level of education. The correlation between the RTI index and average education level is, however, substantially lower (-0.43). In order to investigate if the statistically significant effect of RTI on wage prevails, and to control for the possibility that it is driven by education levels, we add the average level of education to the estimation as an additional control. There are now two education variables in our estimation. The difference between the original variable, Δ Education, and the new variable, the standardized education level in 1997, is the following: Δ Education measures the absolute growth in education, that is, it subtracts the mean education level in 1997 from the mean education level in 2010. The standardized education level in 1997, however, measures the average education level of employees in a specific job type in 1997. Thus, this variable is a proxy for the skill-intensity in a specific job type, and it makes it possible to draw conclusions regarding the theory of skill biased technological change (SBTC).

Table 6 shows the regression results when the additional control variable, standardized average education level per job type in 1997, is included. The effect of the education level on wage growth is highly statistically significant throughout all periods. It is important to note, however, that the sign of the coefficient changes from the sub-period 1997-2004 to 2004-2010. This implies that, in earlier years, workers in skill-intense job are, on average, expected to experience a higher relative increase in wage than workers in less skill-intense jobs. This effect is reversed for later years. The size of the coefficients for RTI decreases slightly, that is, the predicted impact of routineness on wages is reduced. However, direction of coefficients, as well as level of significance, remains unchanged. Offshorability is still insignificant in the full time period, 1997-2010, as well as in the later sub-period of 2004-2010. For 1997-2004, the coefficient is slightly smaller in size but it remains statistically significant, now at a 10 percent level instead of a 5 percent level as in Table 5. The adjusted R^2 increases slightly.

Table 6. OLS regressions: change in job-specific log mean wage as a dependent variable with standardized education level as control

	1997-2010	1997-2004	2004-2010
	(1)	(2)	(3)
RTI	-0.019**	-0.032***	0.003
	(0.029)	(0.000)	(0.731)
Offshorability	0.006	0.019*	-0.004
	(0.485)	(0.066)	(0.672)
Std. education level	0.033**	0.057***	-0.030**
1997	(0.016)	(0.000)	(0.014)
Δ Education	0.073*	0.329***	0.054
	(0.082)	(0.000)	(0.342)
Δ Age	0.008**	0.005	0.017***
	(0.027)	(0.294)	(0.001)
Δ Share of females	-0.003***	-0.004***	-0.003**
	(0.000)	(0.000)	(0.021)
Industry dummies	YES	YES	YES
Constant	0.514***	0.185***	0.303***
	(0.000)	(0.001)	(0.000)
N	185	191	180
Adjusted R^2	0.37	0.66	0.40

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes: The dependent variable is the change in job-specific log mean wage. The main independent variables are RTI and offshorability. The control variable of interest is std. education level, which represent the standardized average education level in 1997 for each job type. Other controls are change in education, age and share in females (changes are adjusted to the given time period) as well as dummy variables for the 14 different industries used to define job types. An increase in the control variables Δ Education, Δ Age and Δ Share of females refers to an increase in education, age and relative amount of female participants, respectively. Job types are weighted by their employment share in 1997, as well as by the average share of part-time workers. Standard errors are robust.

The estimations above include variables that appear to have, at least some, variation in common, such as RTI, offshorability, Δ education and standardized average education level in 1997. Table 13 in Appendix C reports the correlation matrix for all variables. The largest correlation is between the level of education and the change in age (-0.48). The standardized education level and RTI are negatively correlated with 0.43, while offshoring and RTI are positively correlated with 0.35. Remaining correlations lie between the range 0.01 and 0.23. As none of the correlations are particularly high, multicollinearity is not likely a problem of concern.

7.2.2. Robustness checks of regression results

A number of additional regressions are estimated in order to verify the robustness of our main results. In a first set of robustness tests, we change certain specifications used in the main regressions presented in section 7.2.1. In the second set, estimations are performed on sub-samples of the data in order to investigate if the effect of RTI or offshoring on employment and wages is different, or more pronounced, in certain sub-samples. All results are found in Appendix C.[30]

Table 14 shows the results of an estimation in which the dependent variable is the log median wage, instead of the log mean wage as used in previous regressions. The predicted effect of RTI is relatively unchanged. The coefficient is now significant in the later sub-period as well, and the sign is changing between the two periods. However, as the standardized level of education in 1997 is added as a control, the effect of offshorability in the later period disappears and significance in the earlier period of 1997-2004 is reduced. These results have a close resemblance to previous results in which the logged mean wage is the dependent variable.

For the main estimations in section 7.2.1., all job types that contain less than ten employees are excluded. We also estimate the same regressions but with a changed threshold value for exclusion. In the first regression, the threshold value is lowered to five, so that those job types with fewer than five workers are excluded. In the second estimation, the threshold value is thirty. The change in threshold value is not expected to have a substantial effect on the result since all job types are weighted by their initial employment share in 1997. Thus, small job types have little influence on the estimates, and the results should therefore not change substantially when a higher number of small job types are included/excluded. The results in Table 15 illustrate that this is indeed the case, the estimates are almost unchanged as the threshold value decreases to five. In the estimations in which all job types below thirty are excluded, the significance of the coefficients is generally reduced. This is likely due to the decreased number of observations as the threshold increases.

Observations are, as explained in more detail in sections 5.2.3. and 5.2.4., weighted by their initial employment share in 1997 and by their average share of part-time workers in all regression. Table 16 shows the regression results when part-time weights are not used. Note that the observations are still weighted by their initial employment share. The size and direction of the coefficients, as well as their level of significance, closely resemble the original results. Including an interaction variable for RTI and offshorability does not change the main results either. As displayed in Table 17, the main difference is that the coefficient of offshorability in the later sub-period 2004-2010 is now significant at the ten percent level, with the direction changing between the two periods. The interaction variable itself is not significant apart from its effect on employment in the sub-period 2004-2010, which is statistically significant at a 10 percent level.

The choice of start and end years for the time periods estimated is crucial as changes in all variables are measured between these two years. In order to verify that the chosen years are not outliers distorting the results, we perform estimations for different time periods and report the results in Table 18. Regression results for the periods 1998-2010, 1997-2009, 1998-2009 and 1997-2008 are compared to the results for the original time period 1997-2010. The comparison reveals that the direction of the coefficients remains unchanged, however, the levels of significance vary slightly. The effect of RTI on wages was originally significant at a one percent level. For some of the time periods tested, the significance is reduced, but none of the coefficients become insignificant. The insignificance of RTI's effect on employment shares is not changed in any of the periods. The insignificance of the effect of offshorability on both wages and employment is generally maintained, apart from in time period 1997-2008 where its effect on wages is positive and significant at a ten percent level. The regression results for the period 2005-

[30] Regressions are estimated on the fully specified models, which include all controls. However, coefficients are only reported for the variables of interest.

2010 are compared to the results for the later sub-period of 2004-2010. While the coefficients for RTI are not significant in the 2004-2010 regression, neither for employment nor wage as dependent variable, they are both significant at the five percent level in the regressions for the time period 2005-2010. The significant coefficients predict a negative effect of RTI on employment but a positive effect on wages.

The overall conclusion from the first set of robustness tests, in which we change different specifications, is that results are not affected to a large extent. This implies that the results are robust to the use of median wage as a dependent variable (instead of mean wage), the exclusion of part-time weights, the inclusion of an interaction variable and the change in reference periods.

In the second set of robustness tests, we perform estimations on sub-samples of the data. The reasoning behind this is that the effect of offshorability might be intensified in certain sub-samples of the data, as explained in more detail in section 5.2.5. The results are presented in Table 19. First, a regression is estimated on a sub-sample that only contains observations from urban areas. We find the coefficients and significance level of offshorability to be relatively unchanged compared to the original regression on the full sample. Second, we estimate a regression on the regions most likely to attract offshoring from foreign investors. Once again, the results remain relatively unchanged.

As a last step, we estimate the regressions for a sub-sample consisting only of those industries that are rated most prone to offshoring by Blinder and Krueger (2013). The results are displayed in Table 19. In the regressions on change in employment share, coefficients and significance levels are similar to the original results. In the regressions on wage, the significance is reduced. The effect of RTI on wages is not significant for the time period of 1997-2010; it is, however, significant at a 1 percent level when the estimation is made on the full sample. The effect of offshorability for the time period 1997-2004 is no longer significant. It is important to note that the number of observations for the sub-sample decreased substantially, compared to the full sample. The regressions only contain between 72-76 observations, which is considerably lower than the 180-191 observations in the full sample regressions. This is an essential explanation behind the decrease in significance levels. The variation accounted for by this model (adjusted R^2) also decreased compared to the original regressions.

8. Discussion

8.1. Patterns in employment distribution

The employment distribution in Poland has certainly evolved over the time period 1997-2010 but there is no visual sign of job polarization, that is, an increase in employment in the lowest- and highest-paying jobs with a simultaneous decrease in the middle-income jobs. This is confirmed by the formal test for job polarization, which establishes that there is no significant U-shaped relationship. More detailed analysis shows that developments in employment patterns differ for the time period before Poland's EU membership in 2004, and after. One of the most notable changes is that employment in those jobs originally paying the highest average wage increases much more strongly after 2004, as illustrated in Figure 8. However, we do not find any signs of job polarization for the two sub-periods either.

The non-polarized employment might be less of a surprise, since we hypothesized that the effect of routineness and offshoring, in the case of Poland, might cancel each other out. However, our findings also suggest a very limited effect of routineness (RTI) and offshorability on the relative number of employees per job type. The main model (Table 4) and several robustness checks find the effect of RTI to be insignificant in estimations based on the whole time period (1997-2010). For the first sub-period (1997-2004), the impact of RTI is negative and significant, as hypothesized, but not significant for the later sub-period (2004-2010). However, as the reference period for the second sub-period is changed from 2004-2010 to 2005-2010, the effect of RTI becomes negative and significant in the second sub-period as well. Offshorability is insignificant for all time periods, in the main model as well as in all robustness checks. This suggests that offshoring is not a factor that directly affects employment patterns in Poland.

Thus, it can be said that, while we see a slight effect of routineness from 1997 up to 2004, variables included in our regressions, in general, cannot explain the changes in employment during the study period. The fact that no clear polarization has appeared in Poland might be indicative of a general difference between transition economies and highly industrialized countries. Up until now, research on job polarization has mainly focused on countries in Western Europe or the United States. It is possible that job polarization is a phenomenon that occurs mainly in highly industrialized nations, while transition economies, such as Poland, have not arrived at that point in development.

8.2. Patterns in wage development

While changes in employment tend to take time, changes in wages can occur over much shorter time horizons. This might be the reason why routineness and offshorability appear to have a more pronounced effect on wages than on employment.

In the main regression (Table 5) and the robustness checks, the effect of RTI on wages is negative and statistically significant over the whole time period of 1997-2010. However, when studying the two sub-periods, a slightly different pattern appears. RTI is negative and highly significant in the earlier sub-period (1997-2004) but insignificant in the later sub-period (2004-2010) when controls are included. The effect of offshorability on wages is less pronounced compared to RTI. For the full time period, the coefficient of offshorability is generally not significant. However, in the earlier sub-period the effect is positive and significant, as hypothesized. For the later sub-period, the effect of offshorability is, in general, insignificant in the main regression and the robustness checks.[31]

We do not find any polarization in wage over the time period 1997-2010; in fact, Figure 9 is rather suggesting the opposite, that is, a larger percentage increase in the middle-income wages than in low- and high-income wages. However, as we divide the sample into the two time periods of 1997-2004 and 2004-2010 in Figure 10, two different trends become visible. The first trend, during the time period of 1997-2004, is one of large wage growth within high-income jobs, and low wage growth within low-income jobs. In the second time period, 2004-2010, the trend is reversed, it is now the high-income jobs that have the lowest wage growth, while the highest wage growth is among the low-income jobs. This implies that Figure 9 is rather an average of two opposite trends, and it is essential to understand why the trend in wage growth is

[31] In the regression with median wage as dependent variable and in the regression including a variable for interaction the coefficient of offshorability is significant but positive in the later sub-period, which makes the effect for the later sub-period less clear.

reversed around year 2004. Therefore, the following paragraphs attempt to explain and understand the turn in wage development.

8.2.1. Skill-biased technological change

As displayed in Figure 10, the skill premium increased and income inequality grew prior to 2004. After 2004 the trend turned to the opposite with a decrease in skill premium and decreased income inequality. This is also reflected in the Gini index for Poland, as displayed in Figure 12 in Appendix B. The Gini index increased from 32.3 in 1998 to 35.9 in 2005, which represents a considerable increase in income inequality. [32] [33] After 2005, income inequality decreased. This picture could be explained by the theory on skill-biased technological change (SBTC). The theoretical model presented in Figure 1 and Figure 2, suggests that the increase in skill premium in the first time period, 1997-2004, could be the result of technological change biased towards high-skill workers, and an increase in demand for such workers. As the skill premium increases, it becomes more attractive for individuals to obtain an education. The supply of high skilled workers increases as more individuals receive a higher education. A period of high skill premium should therefore, according to theory, be followed by an adjustment in supply of high-skill workers, leading to a decrease in the skill premium. The size of the decrease, and whether or not the final skill premium is lower or higher than the initial one, depends on the size of the shifts in demand and supply.

Figure 13 in Appendix B illustrates the educational composition of the Polish labor force over time. Poland did indeed experience an increase in education during the 2000s: the education level among Polish workers increased substantially starting in 2003 and continued to do so during the second time period of our study, 2004-2010. Prior to 2003, the educational composition was relatively stable; around 13 percent of the labor force had obtained a tertiary education. By 2010, this number had increased to 26 percent. As the education level within the labor force rose, the supply of high-skill workers increased, which might have caused the decline in skill premium (relative decline in the wage of skilled workers) in the time period after 2004. Moreover, the change in employment in 2004-2010, as displayed in Figure 8, illustrates that the share of high-income workers in the fifth quintile did increase substantially. This provides additional support for an increase in the supply of skills.

Overall, the patterns displayed in Figure 10 well reflect the predictions of the theory on SBTC. To control for skill-biased technological change in the estimations, the standardized education level in 1997 is added as a control to the main wage regression in Table 6. The education level has a statistically significant effect on wage growth over the full time period, 1997-2010, as well as in the two sub-periods of 1997-2004 and 2004-2010. More importantly, the sign of the coefficient is positive in 1997-2004 and negative in 2004-2010. This implies that, in 1997-2004, wage growth increases, on average, with the skill intensity of a job type. In the later time period, 2004-2010, the pattern is reversed so that jobs with higher initial education level experienced lower wage growth on average. However, RTI remains significant after including the level of education in the estimation, which suggests that its effect on wages influences wages independently of skills. Thus, RTI seems to (at least in the earlier sub-period) have the hypothesized influence on wages, but SBTC is likely to play the more important role for the Polish labor market as it well explains the changes in the data over the period of study.

[32] No data available for our base year, 1997.

[33] The Gini index covers the range 0-100, in which 0 is perfect equality while 100 is perfect inequality.

8.2.2. Potential effects of EU membership

The radical turn in the relative wage growth takes place around 2004, which is also the year when Poland became a member of the European Union. This is an important factor to consider, since Poland's EU membership might be a key driver of the change in wage pattern. In the following we consider two different ways in which the EU membership could possibly affect labor market patterns in Poland, namely through an increase in migration flows and a further opening to trade.

Migration

In the aftermath of Poland's accession to the EU in 2004, the country experienced an unparalleled rise in migration. The removal of institutional restrictions and the successively increased access to other labor markets within the EU, resulted in a large increase in migration mainly among young and highly-educated men. Theory predicts that an upsurge in migration should, in the medium-term; result in an upward pressure on wages as labor supply is reduced.

In the Polish case, this implies that the supply of high-skill workers decreased, which represents an inward shift in relative supply of skills (see Figure 1 and Figure 2). This, in turn, should result in an increase in skill premium. However, as shown in Figure 10, this is not what has happened. Instead, the skill premium decreases after the EU accession. This might be due to the substantial increase in education levels previously discussed and the accompanying rise in relative supply of skills. The rise in supply of skills caused by increased education levels might have exceeded the fall in supply associated with increased migration of high-skill workers, resulting in an aggregate effect of decreased skill premium.

Opening to trade

After the fall of the centrally planned economy in the early 1990s, Poland has successively opened up its economy towards other countries. The accession to the EU can be thought of as a further step towards "opening up" the Polish economy to its European neighbors. Trade theory, as explained in section 3.2., can be consulted to examine the effects on the labor market of such an "opening". While Poland is not usually the country thought of as a typical skill-poor country in trade models, it might take this role in the context of trade with other EU countries in Western Europe such as Germany, Sweden or the United Kingdom. Arguably, Poland might have a comparative advantage, relative Western European countries, in tasks that involve lower-skilled labor.

In a setting in which trade barriers between Poland and Western European countries are removed, the Heckscher-Ohlin model would predict that Poland concentrates on products for which the main factor of production is lower-skilled labor, in order to export these products. Goods that require higher-skilled labor should be imported from Western European countries.
Thus, the demand for lower-skilled workers in Poland increases and inequality within the Polish labor force decreases. This corresponds to the development in wages in the second sub-period 2004-2010, after the accession to the EU, in Figure 10. The low- and middle-skill jobs experienced a higher percentage increase in wage than high-skill jobs. The Heckscher-Ohlin model is, however, generally considered weak in predicting developments in relative wages, as mentioned in section 3.2. Moreover, the increased share of the labor force with tertiary education (Figure 13), the relative growth of employment in the highest-income quintile (Figure 7 and Figure 8) and the increase in high technology exports (Figure 6) do not suggest that the Polish economy concentrates on low-skilled tasks.

Poland's EU membership simplified the process of offshoring and improved the possibility for firms to offshore jobs to Poland as the free movement of capital within the EU reduced the cost of offshoring. When the model of Feenstra and Hanson (1996) is adjusted to the case of Poland, so that offshored jobs are likely to represent middle-income jobs in the Polish labor market, it predicts that an increase in offshoring would result in a relative increase in wages of middle-income workers compared to low-and high-income workers. Figure 9 shows that for the whole time period of 1997-2010, relative wages do indeed increase the most within jobs placed in the middle of the income scale. The split of the time period in before and after Poland's EU membership in Figure 10 shows that wages for the lowest middle-income workers (quintile 2) increased the most after 2004, which is in line with the model's theoretical predictions. However, other middle-income workers (quintile 3 and 4) did not experience any significant change compared to before the EU membership, and the low-income workers (quintile 1) did have a substantial wage growth after the EU accession, which contradicts the predictions of the model. This could be due to the fact that the role of offshoring is limited: the regression results suggest that offshoring has generally very little effect on wages, especially after 2004.

9. Conclusion

We study the labor market patterns in Poland over the time period 1997-2010 in order to gain first insights on employment and wage developments in relatively well-developed countries that mainly receive offshoring. The aim is to investigate if routine-biased technological change (RBTC) and offshoring are influential factors for the Polish labor market, and in which direction they affect employment and wages.

We can conclude that job polarization has not taken place in the Polish labor market for the period of analysis, 1997-2010. Employment in the highest-income jobs increases and the lowest middle-income jobs decreases, but there is no overall pattern of job polarization. This result persists when the periods before and after 2004, the year in which Poland joined the European Union, are analyzed separately. Regarding wages, middle-income workers had the largest relative wage increase over the whole time period, which suggests the opposite of polarization. However, the division into two sub-periods, 1997-2004 and 2004-2010, reveals that this is the aggregate pattern of two opposing trends. In the earlier years, the skill premium for high-skill workers increases, while the picture is reversed in the second sub-period with a decreased skill premium. This development, together with the upsurge in education levels in the labor force after 2002; indicate that skill-biased technological change (SBTC) might be important for the Polish labor market.

RBTC, measured as the level of routineness of a job, has the expected negative effect on employment, but only for the period before 2004; for other periods the effect is insignificant. The impact of RBTC on wages is negative and highly significant for the full time period 1997-2010, as well as the sub-period 1997-2004. The effect of RBTC remains significant when SBTC is controlled for, which suggests that the level of routineness of jobs does have an impact on wages, even though the main driver of wage development appears to be the workers' educational level. The relevance of offshoring for the Polish labor market appears to be very limited. We do not find any significant effects on employment patterns. The results suggest that offshoring has a positive impact on wages, as expected, but only for the sub-period prior to 2004. In general, our results suggest that RBTC has a stronger effect on the labor market in Poland than offshoring, which is in line with the findings of Goos, Manning and Salomons (2014).

Research on highly industrialized countries has found SBTC to fit well with historical data, while RBTC is a more suitable explanation for recent developments. For a country with a slightly lower development level in comparison, such as Poland, it might be possible that the shift from SBTC to RBTC is still ongoing. This would explain our finding of both SBTC and RBTC in the context of a transition economy. It would therefore be of interest to gain a better understanding of the development path of SBTC and RBTC, and more specifically in transition economies with high education levels. Our results provide an important first insight into patterns that appear in labor markets of offshoring-receiving countries with a relatively high level of development. It is likely that neighboring countries of Poland, such as the Czech Republic, have experienced a similar development. Our results are, however, not likely to be valid in less developed offshoring-receiving countries, such as Bangladesh or Sri Lanka. Generally we believe that further research is needed to verify our results, to better understand underlying reasons for the observed developments and to gain further insight in the development path of SBTC and RBTC.

10. Appendix A

Table 7. International Standard Classification of Occupations (ISCO-88), RTI and offshorability by occupation

Two-digit code	Occupation	RTI index	Offshorability index
Group 1: Legislators, senior officials and managers			
11	Legislators and senior officials	-0.743	-0.575
12	Corporate managers	-0.560	-0.166
13	General managers	-1.469	-0.386
Group 2: Professionals			
21	Physical, mathematical and engineering science professionals	-0.678	1.292
22	Life science and health professionals	-0.829	-0.560
23	Teaching professionals	-1.285	-0.806
24	Other professionals	-0.636	0.335
Group 3: Technicians and associate professionals			
31	Physical and engineering science associate professionals	-0.248	0.089
32	Life science and health associate professionals	-0.225	-0.555
33	Teaching associate professionals	-1.655	-0.806
34	Other associate professionals	-0.246	0.336
Group 4: Clerks			
41	Office clerks	2.419	0.700
42	Customer services clerks	1.576	-0.039
Group 5: Service workers; shop and market sales workers			
51	Personal and protective services workers	-0.437	-0.743
52	Models, salespersons and demonstrators	0.207	-0.697
Group 6: Skilled agricultural and fishery workers			
61	Market-oriented skilled agricultural and fishery workers	-0.005	-0.806
62	Subsistence agricultural and fishery workers	0.313	-0.806
Group 7: Craft and related trade workers			
71	Extraction and building trades workers	-0.033	-0.740
72	Metal, machinery and related trades workers	0.632	-0.246
73	Precision, handicraft, printing and related trades workers	1.710	1.911
74	Other craft and related trades workers	1.389	1.389
Group 8: Plant and machine operators; assemblers			
81	Stationary-plant and related operators	0.471	1.841
82	Machine operators and assemblers	0.629	2.717
83	Drivers and mobile-plant operators	-1.359	-0.806
Group 9: Elementary occupations			
91	Sales and services elementary occupations	0.181	-0.611
92	Agricultural, fishery and related labourers	0.275	-0.806
93	Labourers in mining, construction, manufacturing and transport	0.607	-0.458
Group 0: Armed forces			
01	Armed forces		

Notes: The two-digit code 01, Armed forces, is not accounted for in the analysis. RTI index and offshorability index are not available for Armed forces.

Source: ILO (n.d.), RTI index and offshorability index are kindly provided by Goos, Manning and Salomons.

Table 8. Statistical Classification of Economic Activities in the European Community, NACE Rev. 1.1

Letter code	Industry
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	Activities of households
Q	Extra-territorial organizations and bodies

Notes: In the analysis, industry A and B have been grouped together, while industry P and Q are excluded.
Source: Eurostat (n.d.)

Table 9. Ranking of investment attractiveness of different voivodships, year 2010

Rank	Voivodship
1	Slaskie
2	Dolnoslaskie
3	Mazowieckie
4	Malopolskie
5	Wielkopolskie
6	Zachodniopomorskie
7	Lodzkie
8	Pomorskie
9	Opolskie
10	Lubuskie
11	Kujawsko-Pomorskie
12	Podkarpackie
13	Warminsko-Mazurskie
14	Swietokrzyskie
15	Lubelskie
16	Podlaskie

Source: The Gdansk Institute for Market Economics and Konrad-Adenauer-Stiftung (2011)

Table 10. Summary statistics

Number of observations in different years		
1997	27 501	
2004	24 996	
2010	31 920	
	Mean	**Standard deviation**
Routine Task Intensity (RTI)		
1997	0.28	1.08
2004	0.17	1.02
2010	0.07	0.96
Offshorability		
1997	0.01	0.90
2004	-0.01	0.90
2010	-0.04	0.89
Level of education		
1997	3.2	0.8
2004	3.4	0.9
2010	3.5	1.0
Age		
1997	38.8	10.0
2004	39.3	10.2
2010	39.9	11.0
Share of females		
1997	46.9	32.3
2004	47.3	31.2
2010	46.3	32.0

Notes: The summary statistics include all adults in the data set between 18 and 65 years, who have an income from employment, and for which occupation and industry code is available. Individuals working in an occupation*industry combination that have less than 10 employees in any of the years 1997, 2004 or 2010 are not included. Level of education is coded as follows: 1 = No education, 2 = Basic education, 3 = High school, 4 = Specialized education (after high school but not university level) and 5 = University.

Table 11. Ten job types with highest/lowest growth in employment share 1997-2010

Highest growth in employment share

Job type	**Change in employment share (percentage points)**
Building workers in the construction industry (F_71)	2.51
Sales persons in the wholesale and retail trade industry (G_52)	2.49
Health professionals in the health industry (N_22)	1.81
Machine operators and assemblers in the manufacturing industry (D_82)	1.49
Professionals in public administration, defense and social security (L_24)	1.12

Lowest growth employment share

Job type	**Change in employment share (percentage points)**
Craft workers in the manufacturing industry (D_74)	-3.43
Health associate professionals in the health industry (N_32)	-2.57
Extraction workers in the mining industry (C_71)	-1.25
Elementary sales and service workers in the wholesale and retail trade industry (G_91)	-1.11
Precision and handicraft workers in the manufacturing industry (D_73)	-0.88

Notes: The titles of job types often contain abbreviations of occupations and industries. For full names see Table 7 and Table 8.

Table 12. Ten job types with highest/lowest growth in wage 1997-2010

Highest growth in wage

Job type	**Change in wage (%)**
Physical and engineering science associate professionals in the transport and communication industry (I_31)	136.28
Life science professionals in the agricultural industry (A_22)	135.30
Physical and engineering science professionals in the transport and communication industry (I_21)	130.50
Associate professionals in the electricity, gas and water supply industry (E_34)	130.11
Personal and protective services workers in the transport and communication industry (I_51)	127.22

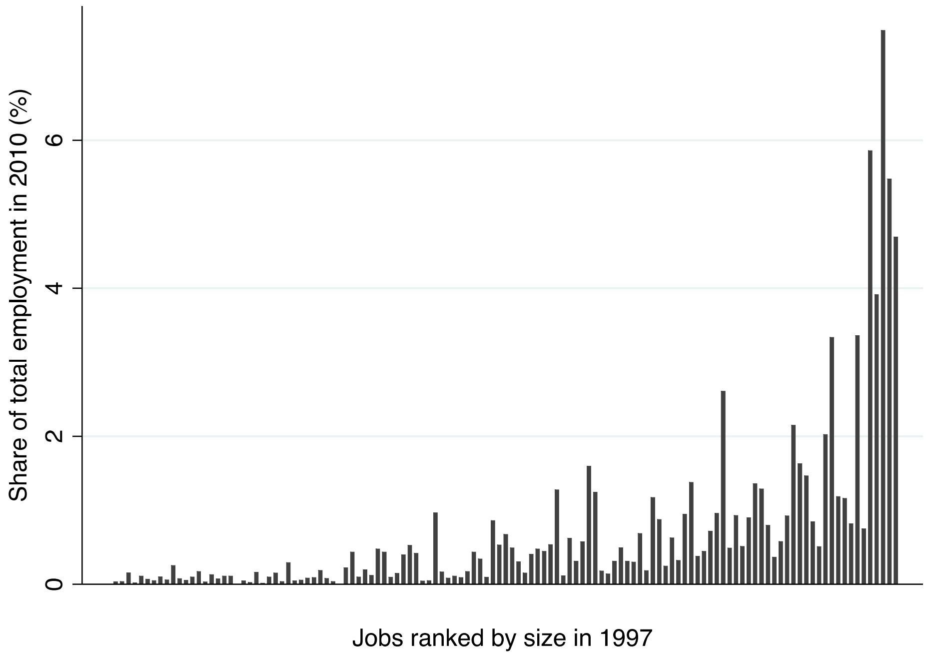
Lowest growth in wage

Job type	**Change in wage (%)**
General managers in the hotels and restaurants industry (H_13)	-5.02
Customer services clerks in the wholesale and retail trade industry (G_42)	3.03
Sales persons in the social and personal service activities industry (O_52)	12.38
Associate professionals in the mining industry (C_34)	12.70
Craft workers in the social and personal service activities industry (O_74)	18.61

Notes: The titles of job types often contain abbreviations of occupations and industries. For full names see Table 7 and Table 8.

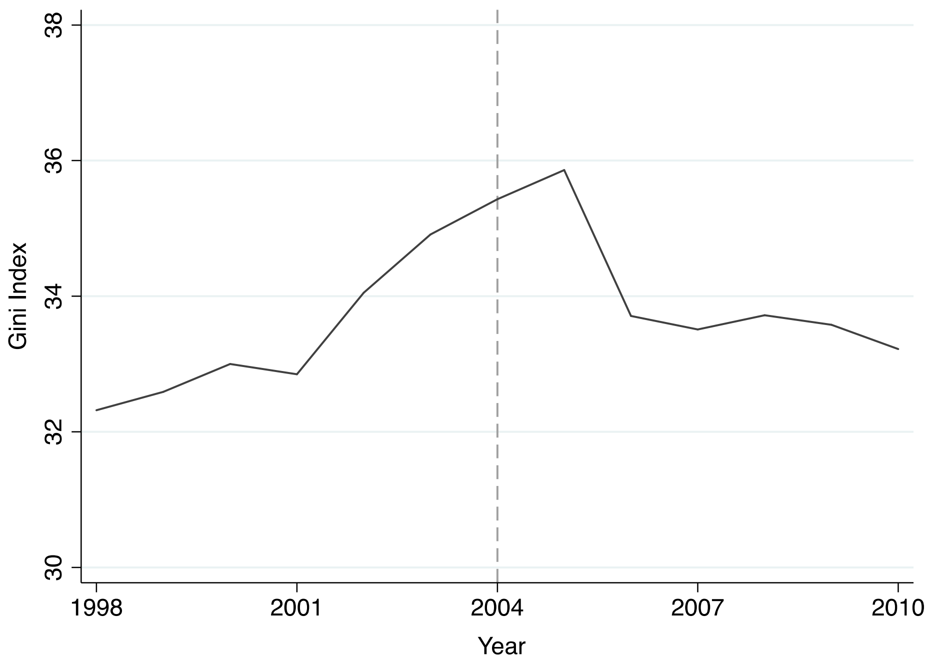
11. Appendix B

Figure 11. Size of job types in 2010 (ranked by size in 1997)



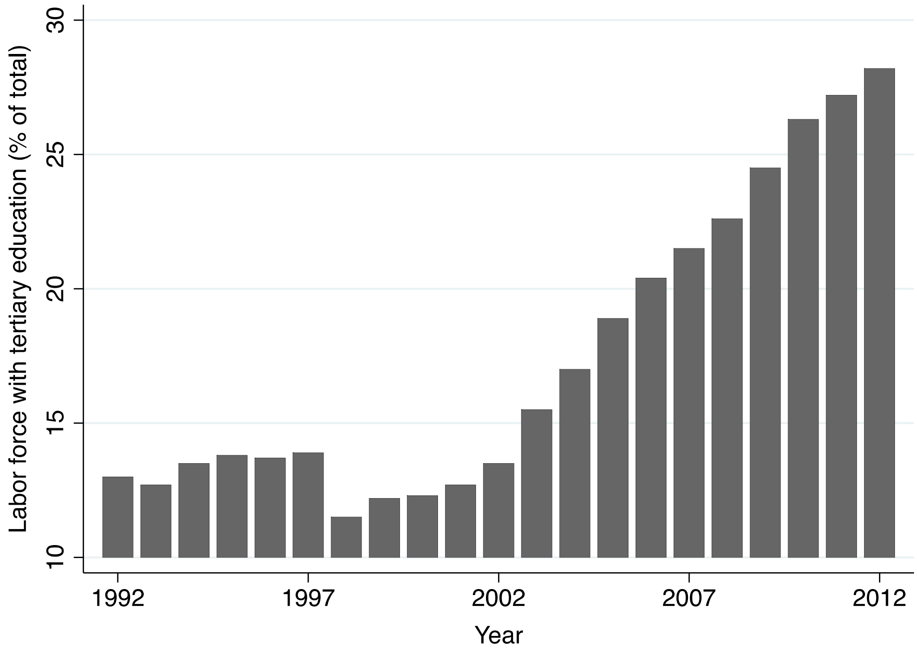
Notes: Size in 1997 refers to the share of total employment in 1997.
Source: Calculations done by the authors using the main data set BBGD.

Figure 12. Gini index for Poland, 1998-2010



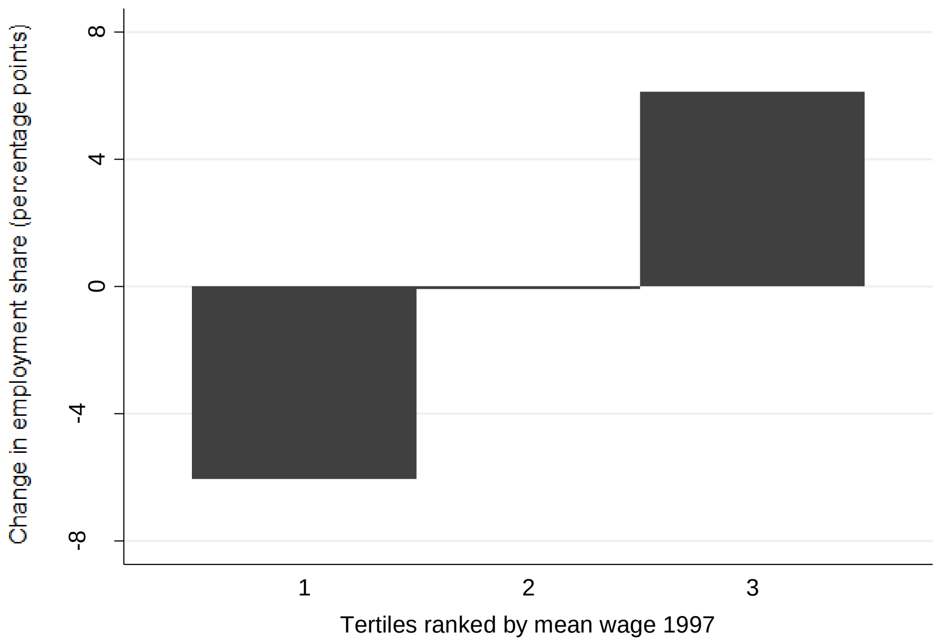
Source: World Bank (2013a)

Figure 13. Educational composition of the labor force, 1992-2012



Source: World Bank (2012)

Figure 14. Change in employment share of different job types, 1997-2010 (3 groups)



Source: Calculations done by the authors using the main data set BBGD.

Figure 15. Change in employment share of different job types, 1997-2004 and 2004-2010 (3 groups)

Source: Calculations done by the authors using the main data set BBGD.

12. Appendix C

Table 13. Correlation matrix for regression variables

	RTI	Offshorability	Education level 1997	Δ Education	Δ Age	Δ Share of females
RTI	1.00					
Offshorability	0.35	1.00				
Std. education level 1997	-0.43	0.17	1.00			
Δ Education	0.22	-0.03	-0.23	1.00		
Δ Age	0.14	-0.12	-0.48	-0.22	1.00	
Δ Share of females	-0.20	-0.09	0.01	0.03	0.08	1.00

Table 14. Log median wage as dependent variable

	1997-2010	**1997-2004**	**2004-2010**	**1997-2010**	**1997-2004**	**2004-2010**
	(1)	(2)	(3)	(4)	(5)	(6)
RTI	-0.023**	-0.047***	0.009	-0.013	-0.024***	-0.000
	(0.012)	(0.000)	(0.316)	(0.136)	(0.008)	(0.965)
Offshorability	0.008	0.032***	-0.020**	-0.000	0.016*	-0.011
	(0.392)	(0.007)	(0.046)	(0.967)	(0.095)	(0.279)
Std. education level 1997				0.041***	0.063***	-0.033***
				(0.001)	(0.000)	(0.006)
N	185	191	180	185	191	180
Adjusted R^2	0.40	0.58	0.34	0.43	0.64	0.36

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes: The dependent variable is the change in job-specific log median wage (as opposed to mean wage). All controls from Equation 5 are included in the estimations. Job types are weighted by their employment share in 1997, as well as by the average share of part-time workers. Standard errors are robust.

Table 15: Shifts in the threshold for the inclusion of job types

	Dependent variable					
	Employment			Wage		
	1997-2010	1997-2004	2004-2010	1997-2010	1997-2004	2004-2010
	(1)	(2)	(3)	(4)	(5)	(6)
Threshold < 5						
RTI	-0.080	-0.160**	-0.015	-0.027***	-0.052***	0.015
	(0.515)	(0.034)	(0.830)	(0.004)	(0.000)	(0.101)
Offshorability	-0.236	-0.008	-0.184	0.012	0.032**	-0.014
	(0.474)	(0.966)	(0.252)	(0.235)	(0.014)	(0.168)
N	222	223	217	222	223	217
Adjusted R^2	0.42	0.44	0.38	0.33	0.58	0.33
Threshold < 30						
RTI	-0.046	-0.173	0.018	-0.035***	-0.048***	0.000
	(0.781)	(0.103)	(0.859)	(0.001)	(0.000)	(0.962)
Offshorability	-0.336	-0.001	-0.281	0.019	0.026	-0.001
	(0.472)	(0.998)	(0.235)	(0.145)	(0.118)	(0.916)
N	106	109	101	106	109	101
Adjusted R^2	0.44	0.42	0.42	0.40	0.66	0.52

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is either the change in job-specific employment share or the change in job-specific log mean wage. All controls from Equation 4 and
Equation 5 are included in the estimations. Job types are weighted by their employment share in 1997, as well as by the average share of part-time workers. The threshold represents the limit of number of employees under which a job type is excluded, e.g. in the first regression, job types with less than five employees are excluded. Standard errors are robust.

Table 16. Estimation with job types not weighted by average share of part-time workers

	Dependent variable					
	Employment			Wage		
	1997-2010	1997-2004	2004-2010	1997-2010	1997-2004	2004-2010
	(1)	(2)	(3)	(4)	(5)	(6)
RTI	-0.052	-0.154**	-0.003	-0.028***	-0.054***	0.011
	(0.686)	(0.045)	(0.970)	(0.003)	(0.000)	(0.203)
Offshorability	-0.283	-0.020	-0.211	0.013	0.034**	-0.012
	(0.423)	(0.917)	(0.218)	(0.184)	(0.013)	(0.244)
N	185	191	180	185	191	180
Adjusted R^2	0.43	0.43	0.40	0.34	0.61	0.38

p-values in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Notes: The dependent variable is either the change in job-specific employment share or the change in job-specific log mean wage. All controls from Equation 4 and
Equation 5 are included in the estimations. Job types are weighted by their employment share in 1997. Standard errors are robust.

Table 17. Interaction variable

	Dependent variable					
	Employment			Wage		
	1997-2010	1997-2004	2004-2010	1997-2010	1997-2004	2004-2010
	(1)	(2)	(3)	(4)	(5)	(6)
RTI	-0.031	-0.146**	0.025	-0.029***	-0.054***	0.010
	(0.805)	(0.049)	(0.742)	(0.003)	(0.000)	(0.249)
Offshorability	-0.144	0.055	-0.100	0.003	0.026*	-0.018*
	(0.655)	(0.775)	(0.473)	(0.750)	(0.060)	(0.082)
RTI * Offshorability	-0.250	-0.130	-0.207*	0.018	0.013	0.010
	(0.205)	(0.213)	(0.094)	(0.167)	(0.330)	(0.372)
N	185	191	180	185	191	180
Adjusted R^2	0.44	0.44	0.42	0.35	0.61	0.38

p-values in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Notes: The dependent variable is either the change in job-specific employment share or the change in job-specific log mean wage. All controls from Equation 4 and
Equation 5 are included in the estimations. Job types are weighted by their employment share in 1997, as well as by the average share of part-time workers. Standard errors are robust.

Table 18: Estimation of different reference periods

		Dependent variable	
Time period		**Employment**	**Wage**
		(1)	(2)
1998-2010	RTI	-0.050	-0.017*
		(0.625)	(0.089)
	Offshorability	-0.201	0.008
		(0.457)	(0.452)
	N	186	186
	Adjusted R^2	0.44	0.25
1997-2009	RTI	-0.091	-0.035***
		(0.506)	(0.001)
	Offshorability	-0.262	0.016
		(0.493)	(0.113)
	N	185	185
	Adjusted R^2	0.40	0.36
1998-2009	RTI	-0.093	-0.021**
		(0.381)	(0.030)
	Offshorability	-0.171	0.009
		(0.564)	(0.344)
	N	187	187
	Adjusted R^2	0.41	0.25
1997-2008	RTI	-0.127	-0.040***
		(0.364)	(0.000)
	Offshorability	-0.141	0.020*
		(0.674)	(0.075)
	N	189	189
	Adjusted R^2	0.34	0.33
2005-2010	RTI	-0.145**	0.014**
		(0.024)	(0.048)
	Offshorability	-0.075	-0.008
		(0.576)	(0.382)
	N	197	197
	Adjusted R^2	0.34	0.31

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is either the change in job-specific employment share or the change in job-specific log mean wage. All controls from Equation 4 and 5 are included in the estimations. Job types are weighted by their employment share in 1997, as well as by the average share of part-time workers. Standard errors are robust.

Table 19. Estimations of sub-groups

	Dependent variable					
	Employment			Wage		
	1997-2010	1997-2004	2004-2010	1997-2010	1997-2004	2004-2010
	(1)	(2)	(3)	(4)	(5)	(6)
Urban areas						
RTI	-0.049	-0.156**	-0.000	-0.027***	-0.053***	0.011
	(0.706)	(0.043)	(0.997)	(0.004)	(0.000)	(0.200)
Offshorability	-0.291	-0.018	-0.222	0.013	0.033**	-0.011
	(0.419)	(0.926)	(0.204)	(0.181)	(0.015)	(0.287)
N	182	189	178	182	189	178
Adjusted R^2	0.43	0.44	0.40	0.35	0.61	0.37
Regions with high investment attractiveness						
RTI	0.050	-0.155**	-0.002	-0.027***	-0.053***	0.012
	(0.696)	(0.045)	(0.976)	(0.003)	(0.000)	(0.193)
Offshorability	-0.278	-0.017	-0.211	0.013	0.033**	-0.012
	(0.431)	(0.933)	(0.217)	(0.194)	(0.015)	(0.249)
N	185	191	180	185	191	180
Adjusted R^2	0.43	0.44	0.40	0.35	0.61	0.38
Industries prone to offshoring						
RTI	-0.221	-0.273**	-0.095	-0.010	-0.036**	0.014
	(0.203)	(0.027)	(0.348)	(0.541)	(0.019)	(0.430)
Offshorability	-0.326	0.035	-0.318	0.018	0.024	0.008
	(0.512)	(0.891)	(0.210)	(0.166)	(0.168)	(0.464)
N	73	76	72	73	76	72
Adjusted R^2	0.45	0.38	0.45	0.18	0.49	0.31

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes: The dependent variable is either the change in job-specific employment share or the change in job-specific log mean wage. All controls from Equation 4 and
Equation 5 are included in the estimations. The sample is split, and the estimations only include the part of the sample that is either urban, belong to a region with high investment attractiveness, or belong to a specific industry. An urban area is defined as towns with more than 100,000 inhabitants. Regions with high investment attractiveness are the ones that rank on the upper half of the investment attractiveness ranking (8 voivodships). The specific industries included is based on Blinder and Krueger (2013) measure used previously in Figure 3 Industries included are: "Manufacturing" (D), "Construction" (F), "Financial Intermediation" (J) and "Real estate, renting and business activities" (K). The estimation also includes the industry "Transport, storage and communication" (I) since the ICT-sector is covered by this industry. Job types are weighted by their employment share in 1997, as well as by the average share of part-time workers. Standard errors are robust.

13. References

Abel, Jaison R. and Deitz, Richard. 2012. "Job Polarization and Rising Inequality in the Nation and the New York-Northern New Jersey Region." *Current Issues in Economics and Finance* 18(7).

Acemoglu, Daron and Autor, David. 2010. "Skills, Tasks and Technologies: Implications for Employment and Earnings." Pp. 1043-1171 in *Handbook of Labor Economics*. Vol. 4. 4B ed., edited by Ashenfelter, O. and Card, D. Amsterdam, the Netherlands: Elsevier.

Adermon, Adrian and Gustavsson, Magnus. 2015. "Job Polarization and Task-Biased Technological Change: Evidence from Sweden, 1975–2005." *The Scandinavian Journal of Economics*. 117(3): 878-917.

Anacka, Marta, Fihel, Agnieszka, Kaczmarczyk, Pawel and Stefanska, Renata. 2011. "Recent Trends in International Migration in Poland - the 2011 SOPEMI Report." CMR Working paper 52/100. Warsaw, Poland: Centre of Migration Research.

Atkinson, Anthony. B. 2008. "The Race between Technology and Education: The Textbook Model." Pp. 7-15 in *The Changing Distribution of Earnings in OECD Countries.* Oxford, the United Kingdom and New York, NY: Oxford University Press.

Autor, David H., Dorn, David and Hanson, Gordon H. 2015. "Untangling Trade and Technology: Evidence from Local Labour Markets." *The Economic Journal* 125(584): 621-646.

Autor, David and Dorn, David. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *The American Economic Review* 103(5): 1553-1597.

Autor, David, Levy, Frank and Murnane, Richard. 2003. "The Skill Content of Recent Technological Change: An Empirical exploration." *The Quarterly Journal of Economics* 118(4): 1279-1333.

Autor, David H., Katz, Lawrence F. and Krueger, Alan B. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *The Quarterly Journal of Economics* 113(4): 1169-1213.

Bartel, Ann P. and Lichtenberg, Frank R. 1987. "The Comparative Advantage of Educated Workers in Implementing New Technology." *The Review of Economics and Statistics* 69(1): 1-11.

Belka, Marek. 2013. "How Poland's EU Membership Helped Transform its Economy." Occasional paper 88. Washington, D.C.: Group of Thirty.

Blinder, Alan S. and Krueger, Alan B. 2013. "Alternative Measures of Offshorability: A Survey Approach." *Journal of Labor Economics* 31(1): 97-128.

Büttner, Sebastian M. 2012. "Region-building and regional mobilization in Poland." Pp. 104-132 in *Mobilizing Regions, Mobilizing Europe: Expert knowledge and scientific planning in European regional development*. Abingdon, United Kingdom and New York, NY: Routledge.

Capik, Paweł and Drahokoupil, Jan. 2011. "Foreign Direct Investments in Business Services: Transforming the Visegrád Four Region into a Knowledge-Based Economy?" *European Planning Studies* 19(9): 1611-1631.

Central Statistical Office. 2011. *Informacja o Rozmiarach i Kierunkach Emigracji z Polski w Latach 2004-2010 (Information on the Scale and Directions of Emigration from Poland in 2004-2010).* Warsaw, Poland: Central Statistical Office.

Chozick, Amy. 2015. "Middle Class is Disappearing, at Least from Vocabulary of Possible 2016 Contenders." *The New York Times,* May 11. Retrieved December 3, 2015 (http://www.nytimes.com/2015/05/12/us/politics/as-middle-class-fades-so-does-use-of-term-on-campaign-trail.html).

Doms, Mark, Dunne, Timothy and Troske, Kenneth R. 1997. "Workers, Wages, and Technology." *The Quarterly Journal of Economics* 112(1): 253-290.

Dustmann, Christian, Ludsteck, Johannes and Schönberg, Uta. 2009. "Revisiting the German Wage Structure." *The Quarterly Journal of Economics* 124(2): 843-881.

Ebenstein, Avraham, Harrison, Ann, McMillan, Margaret and Phillips, Shannon. 2014. "Estimating the Impact of Trade and Offshoring on American Workers using the Current Population Surveys." *Review of Economics and Statistic*s 96(4): 581-595.

European Commission. 1998. *Regular Report from the Commission on Poland's Progress Toward Accession.* Retrieved October 14, 2015 (http://ec.europa.eu/enlargement/archives/pdf/key_documents/1998/poland_en.pdf).

Eurostat. (n.d.) "Correspondence Table NACE Rev. 1.1 - NACE Rev. 2." Retrieved September 1, 2015 (http://ec.europa.eu/eurostat/web/nace-rev2/correspondence_tables).

EY. 2015. *The Central and Eastern European Automotive Market: Poland.* Ernst & Young. Retrieved October 10, 2015 (http://www.ey.com/GL/en/Industries/Automotive/The-Central-and-Eastern-European-automotive-market---Country-profile--Poland).

Feenstra, Robert C. and Hanson, Gordon H. 1996. "Foreign Investment, Outsourcing and Relative Wages." Pp. 89-127 in *The Political Economy of Trade Policy: Papers in Honor of Jagdish Bhagwati*, edited by Feenstra, R.C., Grossman G.M. and Irwin, D.A. Cambridge, MA: MIT Press.

Fihel, Agnieszka and Okolski, Marek. 2009. "Dimensions and Effects of Labour Migration to EU Countries: The Case of Poland." Pp. 185-211 in *EU Labour Migration since Enlargement - Trends, Impacts and Policies*, edited by Galgoczi, B., Leschke, J. and Watt, A. Farnham, United Kingdom and Burlington, VT: Ashgate Publishing Company.

Friedman, William H. 2012. "On Justifying Outsourcing and Offshoring." *American International Journal of Contemporary Researc*h 2(4): 58-64.

Gandolfo, Giancarlo. 2014. *International Trade Theory and Policy*. 2nd edition. New York, NY: Springer.

Gawrycka, Małgorzata, Sobiechowska-Ziegert, Aneta and Szymczak, Anna. 2012. "The Impact of Technological and Structural Changes in the National Economy on the Labour-Capital Relations." *Contemporary Economic*s 6(1): 4-12.

Goldin, Claudia and Katz, Lawrence F. 2009. "The Future of Inequality: The Other Reason Education Matters So Much." Aspen Institute Congressional Program 24(4): 7-14. Education Reform: Sixteenth Conference. August 17-August 22, 2009. Washington, DC: Aspen Institute. Retrieved November 20, 2015 (https://dash.harvard.edu/bitstream/handle/1/4341691/GoldinKatz_EdIneq.pdf?sequence=1).

Goldin, Claudia and Katz, Lawrence F. 2008. *The Race between Education and Technology*. Cambridge, MA: The Belknap Press of Harvard University Press.

Goos, Maarten and Manning, Alan. 2007. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." *The Review of Economics and Statistic*s 89(1): 118-133.

Goos, Maarten, Manning, Alan and Salomons, Anna. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *The American Economic Revie*w 104(8): 2509-2526.

Harrison, Ann E., McLaren, John and McMillan, Margaret. 2011. "Recent Perspectives on Trade and Inequality." *Annual Review of Economics* 3: 261-289.

ILO. (n.d.) "ISCO-88: Structure and definitions." Retrieved September 1, 2015 (http://www.ilo.org/public/english/bureau/stat/isco/isco88/major.htm).

IMF. 2012. *Republic of Poland IMF Country Report no. 12/16*. Washington D.C.: IMF. Retrieved October 16, 2015 (https://www.imf.org/external/pubs/ft/scr/2012/cr12162.pdf).

Kaczmarczyk, Paweł and Okolski, Marek. 2008. "Demographic and Labour-Market Impacts of Migration on Poland." *Oxford Review of Economic Polic*y 24(3): 599-624.

Kampelmann, Stephan and Rycx, François. 2011. "Task-Biased Changes of Employment and Remuneration: The Case of Occupations." IZA Discussion Paper No. 5470. Bonn, Germany: Institute for the Study of Labor.

Katz, Lawrence F. and Autor, David H. 1999. "Changes in the Wage Structure and Earnings Inequality." Pp. 1464-1555 in *Handbook of Labor Economics*. Vol 3. 3A ed., edited by Ashenfelter, O. and Card, D. Cambridge, MA: Elsevier.

Katz, Lawrence F. and Murphy, Kevin M. 1992. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." *Quarterly Journal of Economics* 107(1): 35-78.

Levy, Frank and Murnane, Richard J. 1996. "With what Skills are Computers a Complement?" *The American Economic Review* 86(2): 258-262.

Machin, Stephen and Van Reenen, John. 1998. "Technology and Changes in Skill Structure: Evidence from Seven OECD Countries." *The Quarterly Journal of Economics* 113(4): 1215-1244.

Mark, Jerome A. 1987. "Technological Change and Employment: Some Results from BLS Research." *Monthly Labor Review* 110(4): 26-29.

OECD. 2008. *OECD Benchmark Definition of Foreign Direct Investment*. 4th ed. OECD Publishing. Retrieved November 14, 2015 (http://www.oecd.org/daf/inv/investmentstatisticsandanalysis/40193734.pdf).

OECD iLibrary (n.d.) "OECD Factbook 2011-2012: Economic, Environmental and Social Statistics." Retrieved October 16, 2015 (http://www.oecd-ilibrary.org/sites/factbook-2011-en/04/02/01/index.html?itemId=/content/chapter/factbook-2011-38-en).

OECD.Stat. (2012a). "FDI Positions by Industry." Retrieved October 12, 2015 (https://stats.oecd.org/Index.aspx?DataSetCode=FDI_FLOW_PARTNER#).

OECD.Stat. (2012b). "FDI Positions by Partner Country." Retrieved November 11, 2015 (https://stats.oecd.org/Index.aspx?DataSetCode=FDI_FLOW_PARTNER#).

Oldenski, Lindsay. 2014. "Offshoring and the Polarization of the US Labor Market." *Industrial & Labor Relations Review* 67(3 supplement): 734-761.

Piatkowski, Marcin. 2013. "Poland's New Golden Age: Shifting from Europe's Periphery to its Center." Policy Research Working Paper no. WPS6639. Washington D.C.: World Bank.

Sachs, Jeffrey D. 1995. "Shock Therapy in Poland: Perspectives of Five Years." *Tanner Lectures on Human Values* 16: 265-290. The Tanner Lectures on Human Values. April 6-April 7, 1994. Salt Lake City, UT: University of Utah. Retrieved October 16, 2015 (http://tannerlectures.utah.edu/_documents/a-to-z/s/sachs95.pdf).

Sass, Magdolna and Fifekova, Martina. 2011. "Offshoring and Outsourcing Business Services to Central and Eastern Europe: Some Empirical and Conceptual Considerations." *European Planning Studies* 19(9): 1593-1609.

Strzelecki, Pawel and Wyszynski, Robert. 2011. "Potential Implications of Labour Market Opening in Germany and Austria on Emigration from Poland." MPRA Paper no. 32586. Munich, Germany. (https://mpra.ub.uni-muenchen.de/id/eprint/32586).

Szymczak, Maciej. 2013. "Introduction." Pp. 1-8 in *Managing Towards Supply Chain Maturity: Business Process Outsourcing and Offshoring,* edited by Szymczak, M. Basingstoke, United Kingdom and New York, NY: Palgrave Macmillan.

The Gdansk Institute for Market Economics and Konrad-Adenauer-Stiftung. 2011. *The Investment Attractiveness of the Regions and the Sub-Regions of Poland 2011*. Retrieved November 15, 2015 (http://www.kas.de/wf/doc/kas_29767-1522-2-30.pdf?120323121311).

The Gdansk Institute for Market Economics and Konrad-Adenauer-Stiftung. 2010. *The Investment Attractiveness of the Regions and the Sub-Regions of Poland 2010*. Retrieved November 15, 2015 (http://www.ibngr.pl/Publikacje/Raporty-IBnGR/THE-INVESTMENT-ATTRACTIVENESS-OF-THE-REGIONS-AND-THE-SUB-REGIONS-OF-POLAND-2010).

The Gdansk Institute for Market Economics and Konrad-Adenauer-Stiftung. 2009. *Investment Attractiveness of Voivodships and Sub-Regions of Poland 2009*. Retrieved November 15, 2015 (http://www.ibngr.pl/Publikacje/Raporty-IBnGR/INVESTMENT-ATTRACTIVENESS-OF-VOIVODSHIPS-AND-SUB-REGIONS-OF-POLAND-2009).

Tinbergen, Jan. 1975. *Income Distribution: Analysis and Policies.* Amsterdam, the Netherlands: North-Holland Publishing Company.
United States Census Bureau. (n.d.) "North American Industry Classification System – Concordances 2002 NAICS to NACE Rev. 1.1." Retrieved October 16, 2015 (https://www.census.gov/eos/www/naics/concordances/concordances.html).
World Bank (2012). "World Bank Indicators: Labor Force with Tertiary Education (% of Total)." Retrieved November 2, 2015 (http://data.worldbank.org/indicator/SL.TLF.TERT.ZS).
World Bank (2013a). "World Bank Indicators: GINI Index (World Bank Estimate)." Retrieved November 27, 2015 (http://data.worldbank.org/indicator/SI.POV.GINI).
World Bank (2013b). "World Bank Indicators: High-Technology Exports (Current US$)." Retrieved November 2, 2015 (http://data.worldbank.org/indicator/TX.VAL.TECH.CD).
World Bank. (2014a). "World Bank Indicators: GDP (Current US$)." Retrieved November 2, 2015 (http://data.worldbank.org/indicator/NY.GDP.MKTP.CD).
World Bank (2014b). "World Bank Indicators: GDP Growth (Annual %)." Retrieved October 11, 2015 (http://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?page=1).
World Bank (2014c)"World Bank Indicators: Inflation, Consumer Prices (Annual %)." Retrieved October 16, 2015 (http://data.worldbank.org/indicator/FP.CPI.TOTL.ZG).
World Bank. (2014d). "World Bank Indicators: Urban Population (% of Total)." Retrieved November 4, 2015 (http://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS).
WTO Statistics Database (2014). "Time Series on International Trade." Retrieved October 16, 2015 (http://stat.wto.org/Home/WSDBHome.aspx?Language=E).