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Inward greenfield FDI and patterns of job polarization

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Abstract

The unprecedented growth in FDI in the last decades has caused drastic changes in the labour markets of the host countries. The major part of FDI takes place in low tech industries, where the wages and skills are low, or in high tech, where they offer a wage premium for the highly skilled workers. This mechanism may increase the polarization of employment into high-wage and low-wage jobs, at the expenses of middle-skill jobs. This paper looks at the effects of two types of FDI inflows, namely foreign investment in high-skill and low-skill activities, on skill polarization. We match data on greenfield FDI aggregated by country and sector with data on employment by occupational skill to investigate the extent to which differ types of greenfield FDI are responsible for skill polarization.

1 Introduction

The unprecedented growth in foreign direct investments (FDI) in the last decades has caused drastic changes in the labour markets. The increased globalization has transformed the ways firms organize their operations, as many firms transfer some stages of production abroad. Several studies have reported evidence on how globalization and MNEs activities have increased both the volatility of employment, and the demand for skilled workers, widening the wage inequality between low- and high-skill wages, especially among advanced economies characterized by flexible labour markets (Autor et al., 2006; Crinò, 2009; Acemoglu and Autor, 2011). A vast literature has focused on how

the increase in relative demand for domestic skilled labour is linked to the offshoring activities of MNEs (Autor et al., 2006; Goos et al., 2009, 2014), and there are many different views on the possible determinants of such increase. The most influential view dates back to the theoretical motivation of Skill-Biased Technical Change (SBTC) proposed by Autor et al. (2003). Their model predicts that, given the rapid adoption of computer technologies, industries that are initially intensive in routine tasks labor will reduce labor input of routine tasks, as they invest in computer capital. At the same time, they increase the demand for non-routine task labor input. Goos and Manning (2007) revisit the theoretical framework proposed by Autor et al. (2003) to explain the evidence of emerging skill polarization patterns, and argue that the computer revolution has increased the relative labor demand for nonroutine manual tasks, as these are not directly affected by technology. Their empirical predictions have been later confirmed by a number of studies, that reported empirical evidence of polarizing patterns in Europe, and US Piva et al. (2005); Goos et al. (2009, 2014).

Another channel through which internationalization can influence job polarization is inward FDI. Inward FDI can stimulate the demand for more skilled workers of the host countries, through the technology transfer to the affiliates, technology spillovers to other domestic firms, and increased investment in technological capital (Slaughter, 2004; Arnold and Javorcik, 2009; Jav, 2015).

While there are several studies that have examined the impact of inward FDI on skill upgrading and job polarization patterns (Slaughter, 2004; Blomström et al., 2003; Hakkala et al., 2010; Jav, 2015), only the work of Davies and Desbordes (2015) has analyzed the relationship between inward greenfield FDI and host countries' labour markets. Moreover, as we know from the international trade theory (Dunning, 1977; Slaughter and Ekholm, 2003), not all FDI are equal. Among other reasons, multinationals (MNEs) decide to invest abroad to access new markets, new knowledge and competencies (Franco et al., 2010), or to acquire specific resources (such as natural resources, raw materials or human capital) that are more abundant and cheaper in the host country. Different FDI activities may therefore have a diversified impact on the labour market. Indeed, MNEs might have a positive influence on host country relative demand for skilled labour, if inward FDI has an impact on technological change and if it is skill-biased (Bandick and Hansson, 2009). Therefore, treating all FDI as skill upgrading only because MNEs have superior technology may oversimplify the link between inward FDI and the relative demand for skilled labor.

In this paper, unlike previous studies, we bring forward the hypothesis that while knowledge intensive inward FDI increase the employment share of skilled labour, less

knowledge intensive FDI activities may increase the share of unskilled labour. To test our hypothesis, we use data on inward greenfield FDI activities[1] at the industry-country level for a set of European countries.

There are two clear advantages in the use of these data. The first one is that they are greenfield FDI and not cross-border mergers and acquisitions (M&A). FDI inflows have different impacts on the host countries depending on whether they are greenfield (new foreign firm) or cross-border M&A (foreign acquisition of an existing domestic firm). The traditional view on the impacts of FDI suggests that greenfield FDI is expected to have a direct impact on productivity, capital formation, and —most importantly— employment of host countries, while cross-border M&A only involves a change from local to foreign ownership of existing assets and production capacity (Norbäck and Persson, 2005; Ashraf et al., 2016). Indeed, evidence shows that the acquisitions of local firms by foreign MNEs result in less employment of skilled labor, because when the headquarters move abroad, activities such as R&D and other functions using qualified employees are also relocated to the headquarter location (Bandick and Hansson, 2009). The second advantage of these data is that the greenfield FDI projects are classified by their primary investment activities, such as manufacturing, construction, business services, R&D, etc. This distinction among activities gives us the possibility to assess if skill intensive activities, such as headquarter services and R&D, are associated to skill upgrading of labour, while low-skill intensive activities such as manufacturing correspond to an increased share of low-skilled employment.

In the next section, we describe the data sources and the variable selection. Section 4 presents the descriptive and regression analyses of changes in employment shares by skill group in Europe and the link to more and less skill intensive greenfield inward FDI. Section 5 concludes.

2 Background studies on job polarization and FDI

Job polarization and the decreasing demand for middling occupations (such as operators of machinery/electronic equipment) are raising many concerns among policymakers. Changes in the composition of labour markets imply the adaptation of institutions, and labour market policies; at the same time they present challenges on how to maintain flexible work arrangements to exploit the opportunities deriving from advances in technology and new ways of working. As a consequence, in the last decade, an increasing number

[1] A greenfield investment is the creation of a subsidiary from scratch by non-resident investors (www.imf.com)

of studies has examined the underlying causes of the hollowing-out of middle-skill occupations, pointing at a wide range of causes. Among them, the prevailing views on the determinant of such polarization are related to technological progress (the replacement of routine jobs due to the automatization of production processes; Autor et al. 2003) and/or to globalization (the decreased demand of jobs that are related to production segments and services offshored to other countries; Goos et al. 2014).

While Berman et al. (1994) and Autor et al. (1998) point to technological progress, rather than globalization, as the culprit for income inequality and skill bias, Feenstra and Hanson (1996) and Bernard and Jensen (1997) argue that the outsourcing intermediate inputs by domestic companies and exports are strong predictors of skill biases. The effect of international trade on wage inequality/skill bias has been examined in a number of studies. MNEs international activities may have a positive effects on domestic economies, as they spill-over some of their technology on domestic firms, which in turn raise their demand for skilled workers (Driffield and Taylor, 2000). However, the impact largely depend on the absorptive capacity of domestic firms (Cohen and Levinthal, 1989; Alcacer and Chung, 2007). Also, MNEs often pay higher wages (Girma et al., 2001; Lipsey and Sjoholm, 2001; Görg and Greenaway, 2004) and this further contributes to the aggregate wage dispersion. Blonigen and Slaughter (2001), using US manufacturing data from 1977 to 1994, test the impact of different types of FDI (greenfield or M&A) on skill upgrading. Despite the evidence from previous firm-level studies, they find that inward FDI did not contribute to U.S. within-industry skill upgrading, with the exception of greenfield FDI from Japanese firms. While most of the studies have mainly considered the experiences of advanced economies, Feenstra and Hanson (1997) show that rising wage inequality and the demand for skilled workers in Mexico are linked to FDI inflows. Given the mixed results regarding the effect of FDI on wage dispersion, scholars have looked into differences between developed and less developed countries (Lee and Vivarelli, 2006; Hale and Xu, 2016) or between OECD and non-OECD countries Dreher and Gaston (2008); Figini et al. (2011). Overall, these studies find that while inward FDI increase wage inequality in developing countries (even if this effect diminishes with further increases in FDI), the effects of FDI among developed countries are mixed.

Difference can be also found within the group of developed countries (Driffield et al., 2009), by investment origin (Tomohara and Yokota, 2011), by industry characteristics (Onaran and Stockhammer, 2006; Davies and Desbordes, 2015). In particular, positive effects of FDI on the reduction of wage dispersion are found in capital intensive industries that use highly skilled labour with comparatively the highest bargaining power (e.g. car industry) (Feenstra and Hanson, 1997; Lipsey and Sjoholm, 2001). However, (Görg

et al., 2009, p.18) find that "while the characteristics of the industry seem to be more important than the attributes of multinationals relative to industry average, for large domestic firms the technology of the MNEs seem to be more important than the industry average. This role of capital intensity has often been hypothesised in the literature, but to the best of our knowledge no direct evidence has been provided to sustain this claim."

Furthermore, some authors have investigated the different impact of inward FDI on the demand for skilled jobs and wages by FDI characteristics. Indeed, different FDI activities may have a diversified impact on the labour market. For example, Bandick and Hansson (2009) and Franco et al. (2010) show that MNEs might have a positive influence on the domestic demand for skilled labour, if inward FDI have an impact on technological change and if it is skill-biased. Therefore, treating all FDI as skill upgrading only because MNEs have superior technology may oversimplify the link between inward FDI and the relative demand for skilled labor. Although a vast literature address the effects of FDI on labour market (skill upgrading/wage inequality), to our knowledge there is no study that investigates how different types of FDI affect various skill groups of employees; that is, if (how much) skill intensive or low-skill greenfield FDI affect high- or low-skill employment shares of host countries.

3 Data

We match data from three different data sources. Data on cross-border greenfield investment projects announced and validated during the period from January 2003 till December 2014, comes from the *fDi Markets* database.[2] The database is an ongoing collection of information on the announcements of corporate investment projects from 2003. The data are at project level, however, to match the information with other data sources, we aggregate the total number and value of the projects per sector, country and year. *fDi Markets* contains information on the capital invested and the number of jobs created by the specific project from source to destination countries, states, regions, and cities. The projects are classified by the investment activities (e.g. R&D, design, development and testing, sales and marketing, etc.). Among the 18 different activities, we selected 6 types of greenfield FDI. More specifically, as low-skill intensive activity we chose greenfield FDI in manufacturing. Among other low-skill intensive investment

[2] *fDi Markets* is an on-line database maintained by fDi Intelligence, a division of the Financial Times Ltd. fDi Intelligence collects available information on investments since 2003 and monitors cross-border investments covering all sectors and countries worldwide, relying on company data and media sources. The database is used as the data source in UNCTAD's World Investment Report, in publications by the Economist Intelligence Unit and in recent academic research.

types (i.e., extraction, construction), manufacturing is the largest greenfield FDI one. The other 5 selected investment activities are the most high-skill intensive ones. Table 1 reports the name of the activity and the corresponding definition. Given the definitions of R&D and DD&T activities, we group them together as R&D.

Table 1: Greenfield FDI activity definitions

FDI activity	Definition
Research & Development (R&D)	Discovery, design, or development of a product – technical design centers
Design, Development & Testing (DD&T)	Project which is involved in designing, developing or testing a product. Software companies opening development centers normally under this as are involved in testing
Education & Training (E&T)	A facility providing training services or education courses. Includes internal training services for company and outsourced staff
Headquarters (HQ)	A divisional, national or regional HQ for the company
ICT & Infrastructure (ICT)	Providing the infrastructure for the ICT sector – broadband infrastructure, Internet data centres, data recovery centres, etc.
Manufacturing	Production or processing of any good – manufacturing plant, processing plant, smelter etc. It also includes operations where produce is grown (i.e., fish farm, winery forestry etc)

†Headquarter activities are high-skill activities such as R&D, marketing and management (Bandick et al., 2014). Although the decision to open a headquarter abroad is mainly driven by low corporate taxes, HQs are located in areas with similar industry specialization and with high levels of business services, which are typically knowledge intensive

Data on employment by occupational skills are extracted from ILOstat annual indicator on employment by economic activity and occupation. The International Standard Classification of Occupations 2008 (ISCO-08) provides a system for classifying and aggregating occupational information, and to group occupations into skill levels.[3] The annual data on employment by skills is collected for each country and organised by main aggregate economic activity.[4]

[3]A skill level is defined as a function of the complexity of tasks to be performed in the corresponding occupation. Given the international character of the classification, the ten major occupational groups are categorised in four broad skill levels. Therefore, occupations range from skill level 1, which corresponds to simple and routine physical or manual tasks, to skill level 4 which matches occupations that require extensive knowledge and involve complex problem-solving, creativity and decision-making.

[4]ISIC Rev.4 at 1 digit, e.g. A – Agriculture, forestry and fishing, B – Mining and quarrying, C – Manufacturing, and so on.

Finally, information on wages, capital, production, and R&D—to proxy the knowledge base or technological level of local industries—come from two databases from the OECD. The first is the OECD Main Science and Technology Indicators database (OECD-MSTI) which provides information on the activities of the OECD countries in the field of science and technology such as R&D expenditures. The second is the database for Structural Analysis (STAN) which includes measures of output and inputs at the industry level. From this database, we extract the value added, the gross capital stock, wages, and the production volume.

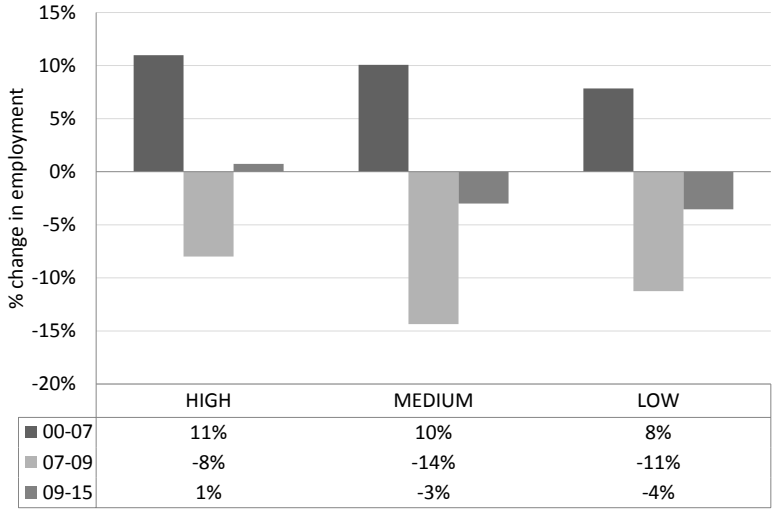
4 Analysis of European Economic Area's job structure and greenfield FDI inflows

4.1 Patterns of jobs reallocation

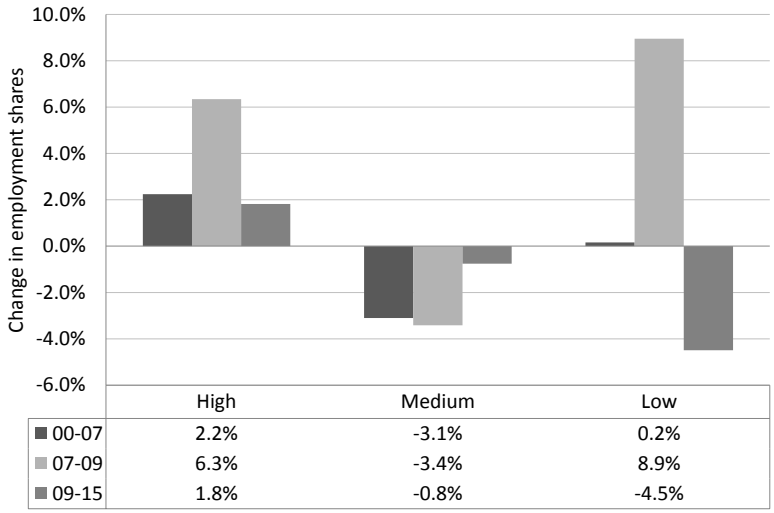
During the observed period 2000–2015, there have been some important changes in the labor market in Europe. Figure 1(a) shows the percentage growth in total employment by occupational skills before, during and after the crisis. Overall, in all three categories of occupational skill the employment has suffered the consequences of the crisis and is currently under sluggish recovery. However, employment in high skill jobs recuperated 1 percentage point during the period 2009–2015, outpacing the employment change in medium and low skill jobs, which are still picking up. Figure 1(b) confirms that, in the last period (2009–2015) employment expanded mainly at the top of the occupational hierarchy, among managers and professionals.

The evidence of job polarization in Europe and US —jobs concentrated in relatively high-skill jobs and low-skill jobs— reported by previous studies (Goos et al., 2014; Acemoglu and Autor, 2011) seems to match only the period 2000–2009 of our sample, where the U-shaped employment shares growth is evident. However, the more recent data presented in this paper shows that, in the last period (2009–2015), Europe has increased its demand for skilled workers at the expenses of job opportunities for middle and low skilled workers, pointing to a skill upgrading rather than polarization. Hence, the rigid technological argument of polarization, where machines are a substitute for labor in the middle of the employment structure, does not fit with the evidence based on most recent data presented here.

Moreover, Tables 2 and 3 show that there is more than one pattern across countries and sectors, suggesting that technology may not be enough to explain structural employment change.



(a) Percentage change in employment by occupational skills and time period



(b) Percentage change in employment **shares** by occupational skills and time period

Figure 1: Changes in employment by occupational skill (2000-2015)

Fernandez-Macias (2012) emphasizes the structuring effect of institutional frameworks, which is largely neglected in the polarization arguments. Indeed, institutions like unions, employment protection legislation, can make labor markets less responsive to technological changes. State regulation has also a direct effect on labor market composition, as it may create or reallocate jobs within certain occupations, whose function depend on politically defined social needs.

Examining the changes in employment shares by country (table 2), we find the emergence of two main patterns of employment reallocation, namely skill upgrading and polarization. Skill upgrading occurs when the employment share in medium and low skilled jobs decreases over the period 2000–2015, while that of high skill employment increases. Skill polarization is the situation where the relative share of middling jobs falls, while high and low skill employment shares grow. Table 2 reports the average initial employment shares in 2000 and the change in percentage point between 2000 and 2015 of the employment shares in high, medium and low skill occupations by country and by patterns of job reallocation. The results in Table 2 show that the changes in employment structure, via polarization or skill upgrading, vary considerably across countries in the European Economic Area.

Table 3 shows the within and between industry differences in employment. Differently from other studies, we investigate the changes in the shares of skilled, unskilled and middling employment within sectors, and categorize them into patterns of restructuring. Skill upgrading sectors are information and communication, financial and insurance services and public administration and construction. The manufacturing sector is undergoing an important transformation. Mining and quarrying, manufacturing, health and social services, and electricity and gas are skill polarization sectors, as they have lost between 4 and 32 percentage points of the share of middling occupations.

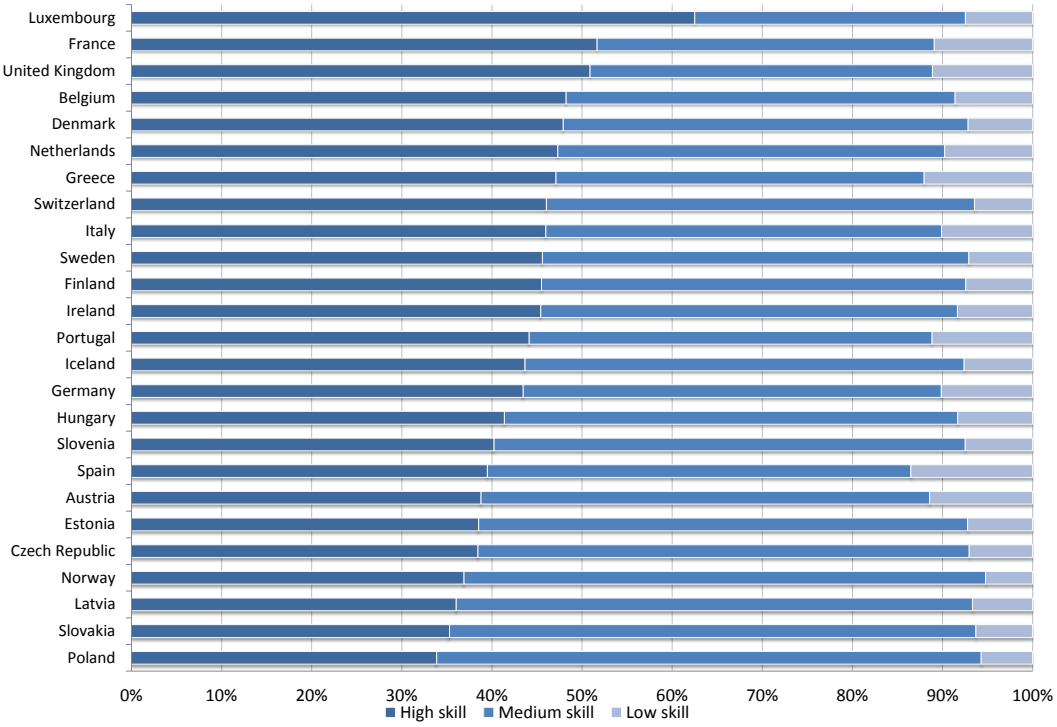
In addition to skill upgrading and polarization patterns, we identify two additional trends, which we called *skill midgrading* and *downgrading*. Skill midgrading is defined as a situation where the share of middle skill employment increases, while both the shares of high and low skill jobs decrease. Real estate, education, technical, professional, and other services belong to this group of sectors. These sectors are characterized by large shares of high skill occupations (apart from other service) and very small shares of low skill ones. The share of high skill jobs dropped only marginally compared to the levels of 2000, and the redistribution seems to have occurred from low skill to middle skill jobs, possibly as a consequence of national investment in high-quality education and training. Moreover, the middle skill jobs in these sectors may be less susceptible to machine replacement, given the relevant non-routinized human component of jobs such

Table 2: Employment shares in 2000 and percentage points change (%, 2000-2015) by occupational skills and country

Country	high		medium		low	
	initial share	change	initial share	change	initial share	change
Skill upgrading						
Netherlands	47.3	0.5	43.9	0.1	8.8	-0.5
Switzerland	42.7	8.3	52.4	-7.3	4.9	-1.0
Finland	41.5	4.7	50.6	-3.0	7.9	-1.7
Germany	39.5	4.9	52.0	-4.6	8.4	-0.3
Ireland	38.3	2.7	52.8	-2.7	8.8	0.0
Luxembourg	37.9	20.5	51.7	-18.8	10.3	-1.7
Norway	37.5	14.7	56.5	-12.7	5.9	-2.0
Denmark	37.0	8.3	49.7	-6.0	13.3	-2.3
Estonia	36.3	8.1	52.7	-5.3	11.0	-2.8
Latvia	33.9	7.4	52.4	-6.0	13.7	-1.4
Czech Republic	33.7	3.9	58.1	-1.4	8.2	-2.5
Poland	28.7	9.3	63.0	-7.7	8.3	-1.6
Spain	26.7	6.3	58.2	-4.0	15.1	-2.3
Portugal	19.9	16.0	65.9	-12.8	14.2	-3.2
Skill polarization						
Sweden	42.7	8.1	53.0	-8.5	4.3	0.5
United Kingdom	39.8	8.2	52.1	-8.9	8.1	0.7
Belgium	39.0	6.8	50.5	-7.0	10.5	0.1
France	34.2	10.9	58.8	-14.2	7.0	3.3
Iceland	32.8	15.8	63.4	-19.1	3.8	3.3
Slovakia	32.8	-0.7	57.4	2.0	9.8	-1.2
Hungary	32.0	3.1	60.4	-5.9	7.7	2.9
Austria	30.9	9.8	61.5	-10.2	7.6	0.4
Italy	30.3	5.7	60.6	-8.0	9.0	2.2
Slovenia	30.3	12.4	64.6	-15.1	5.1	2.7
Greece	26.6	3.8	67.8	-5.3	5.7	1.6

Note Long difference 20002015. Occupational employment pooled within each country. Occupations are grouped according to the ISCO-08 skill level definition.

as teachers and instructors, legal advisors and representatives, or real estate advisors.



Note : *High skill sectors* include: electricity and gas, information and communications, financial and insurance activities, scientific and technical services, public administration and defense, education, and health services. *Medium skill sectors* include: mining and quarrying, manufacturing, construction, wholesale and retail, real estate, transportation and storage. *Low skill sectors* are: agriculture, forestry and fishing, water supply and waste management, accommodation and food services, real.

Figure 2: Sectoral composition in value added, by skill employment share and countries

Sectors with a trend of increasing trend low skill employment share are business support services, wholesale and retail, accommodation and food services, agriculture, transport and storage, and water supply and waste management. These sectors are characterized by a relatively large average share of medium skill employment, but they are also some of the sectors that have the highest proportion of jobs facing potential high risks of automation.[5] Moreover, with the growth of low skill jobs there is a corresponding loss of high skill employment share. In particular, the sector of water and waste management has suffered the negative effect of environmental reforms and climate change, that reduced water availability and intensified competition for water among users,leading to

[5]Source: https://www.theguardian.com/technology/2017/mar/24/millions-uk-workers-risk-replaced-robots-study-warns

Table 3: Employment shares in 2000 and percentage points change (%, 2000-2015) by occupational skills and sector

Sector	high		medium		low	
	initial share	change	initial share	change	initial share	change
Upgrading						
Construction	16.1	6.4	75.4	-6.2	8.5	-0.2
Information & communication	21.1	60.9	67.1	-51.1	11.8	-9.7
Financial & insurance	45.0	19.0	54.1	-19.0	0.9	0.0
Public administration & defence	47.9	6.8	44.0	-6.4	8.1	-0.5
Polarization						
Mining & quarrying	23.5	10.9	70.7	-11.9	5.7	1.1
Manufacturing	25.0	5.2	67.6	-5.6	7.5	0.4
Electricity & gas	24.6	30.9	73.3	-31.6	2.0	0.7
Health & social services	56.6	3.0	36.9	-4.1	6.4	1.1
Midgrading						
Real estate	68.2	-9.5	14.5	20.5	17.3	-11.0
Technical services	86.8	-7.5	3.0	16.1	10.2	-8.6
Education	77.4	0.4	13.6	2.3	9.0	-2.7
Other services	35.0	-12.3	43.4	11.4	21.5	0.9
Downgrading						
Agriculture, forestry & fishing	7.0	-3.5	82.3	-3.9	10.7	7.4
Water supply	45.9	-17.4	47.3	-5.3	6.9	22.6
Wholesale & retail	29.9	-5.7	64.2	4.4	5.9	1.3
Transportation & storage	23.3	-5.6	70.2	3.5	6.4	2.1
Accommodation & food services	77.5	-58.6	18.8	44.2	3.7	14.4
Business support services	25.6	-5.1	49.6	-1.8	24.8	7.0

Note Long difference 20002015. Occupational employment are pooled within each sector. Occupations are grouped according to the ISCO-08 skill level definition.

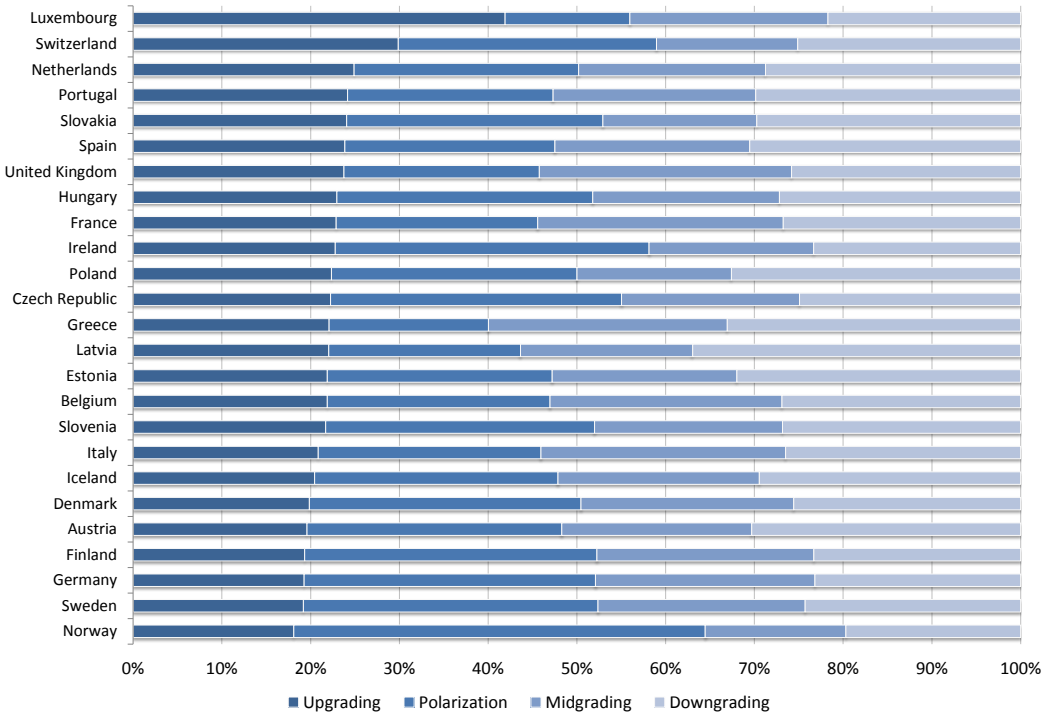


Figure 3: Sectoral composition in value added, by sectoral dynamics and countries

a reduction of job opportunities. [6]

To connect the evidence on country and sectoral pattern of jobs reallocation, Figures 2 and 3 show the shares of value added by group of sectors and country. Figure 2 list the countries in order of value added in sectors with the largest shares of high skill employment.[7] Figure 3 list the countries by value added in skill upgrading sectors defined in Table 3. Overall, the two sector classifications give divergent pictures. For example, while the United Kingdom has the third largest value added in sectors with high skill employment share (Figure 2), it also has a medium value added in sectors that have experienced skill upgrading and one of the largest added value in midgrading sectors.

In conclusion, we find that, rather than a unique polarizing pattern, there are several

[6] Source: United Nations World Water Development Report 2016 http://unesdoc.unesco.org/images/0024/002439/243938e.pdf

[7] Sectors are defined "high skill" if they have at least an average of 50 percent employment in high skill occupations, "medium skill" if they have at least 50 percent employment in medium skill jobs and less that 10 percent in low skill occupations, "low skill" if they have at least 10 percent of low skill employment share.

trends in the labour markets within countries and sectors. There are two patterns (skill upgrading and polarization) within countries, and four patterns within sectors. Examining the sectoral structure of each country, we were not able to detect any job reallocation pattern regularity, pointing to the striking evidence that, contrary to previous studies, there is no uniform polarization of European employment structures.

4.2 Inward greenfield FDI in high and low skill intensive activities

Most of the literature explains the skill upgrading and polarization phenomena with the skill-biased technological change, offshoring and/or routinization of medium skill intensive activities. Another channel through which the increased internationalization may affect the relative demand for skills is inward FDI. This is attributed to the assumption that MNEs use higher levels of technology and require relatively more skilled labour than domestic firms. However, not all FDI should be treated as equal. Labour-intensive, low-cost, low-skill manufacturing FDI may increase the demand for unskilled labour, while capital-, knowledge- and skill-intensive FDI may lead to more demand for high skill workers.

During the period 2003–2014, countries in the European Economic Area received nearly 10,000 greenfield investment projects—of which more than 40% in manufacturing activities—corresponding to approximately Euro 370 billion and more than 1 million jobs. Table 4 reports the total number of greenfield FDI projects, jobs and total amount of capital expenditure, by investment activity. We grouped the investment activities into *Skill intensive* and *Low skill*. Skill intensive activities are Education & Training (E&T), Headquarters (HQ), ICT and R&D activities. Low skill activities are the building of manufacturing plants. Despite the similar number of HQ and R&D greenfield projects, HQ activities have created a larger number of jobs with a less capital invested compared to R&D activities.

Table 4: Greenfield FDI inflow in Europe (2003-2014, total)

Investment activity		N. projects	Capex	Jobs	Capex/N	Jobs/N	Capex/jobs
Skill intensive	Education & Training	292	3,924.1	12,209	13.4	41.8	0.3
	Headquarters	2,337	30,649	152,634	13.1	65.3	0.2
	ICT	643	59,330.3	44,260	92.3	68.8	1.3
	R&D	2,477	51,349.9	181,599	20.7	73.3	0.3
Low skill	Manufacturing	4,100	227,994.5	740,374	55.6	180.6	0.3

Note : Capex figures are in Euro millions. Number of jobs and capital expenditure are partly based on estimated figures provided by the Financial Times.

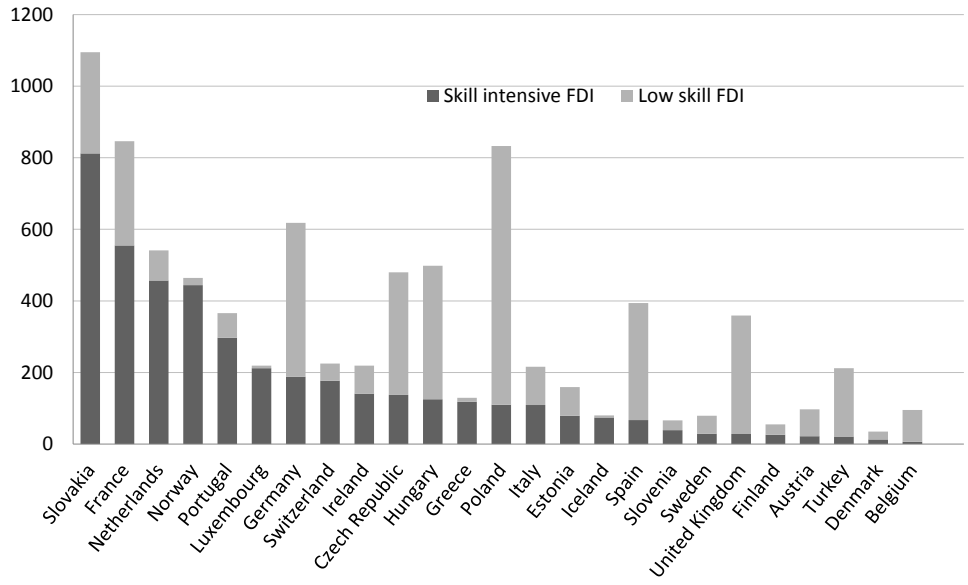


Figure 4: Greenfield FDI by destination country (2003-2014, total number of projects) – Manufacturing vs Skill intensive activities

Greenfield projects in ICT have the largest amount of capital per project (92 Euro millions per project), while FDI in manufacturing activities create the highest average

number of jobs per project. The last two columns compare the average number of created jobs per project and capital investment per job across FDI activities. FDI in ICT have the highest capital per job, while FDI in manufacturing create the largest number of jobs per project.

Figure 4 shows the number of inward greenfield FDI in skill intensive and low skill activities during the period 2003-2014 by destination country. The countries are ordered, from left to right, by total number of skill intensive greenfield projects received. Slovakia is the country that received most skill intensive greenfield projects and overall, while Poland has received mainly FDI in low skill activities. In the next subsection, we analyze the link between different types of inward greenfield FDI and the patterns of job polarization of the European labour markets.

4.3 The link between high- and low-skill intensive greenfield FDI and employment shares

Our empirical analysis borrows the methodological framework of previous studies on SBTC. Differently from previous empirical analyses, we assume, for the purpose of this study, that inward greenfield FDI activities rather than offshoring are the factors that shift the demand for skilled or unskilled labour. For each time period t, the representative firm operates in sector j of country c and produces a certain output using capital, skilled, medium skilled and unskilled labour, and a specific level of technology. Under the assumptions of short-run translog cost function, linear price homogeneity and symmetry, the employment share S of skill type $h = H, M, L$ (high, medium, low) takes the following functional form

$$S^h_{jct} = \beta_0 + \beta_h w^h_{jct} + \beta_k k_{jct} + \beta_r r_{jct} + \beta_q q_{jct} + \sum_{i \in I} \beta_i GFDI^i_{jct} + \varepsilon_{jct}, \tag{1}$$

where w is the log of wage, k and r are respectively the logs of capital and R&D intensity, which proxy the level of technology, q is the log of output, and $GFDI$ is the log number of inward greenfield FDI projects of type $i = E\&T, HQ, ICT, R\&D, Manu.$[8] The error term ε_{jct} includes country, sector and year fixed effects. Also, we use lagged independent variables, not to solve the endogeneity issues, but because we believe that it may take at least a year before the local labour markets react to MNEs' investment. Indeed, lagging independent variables would yield causal identification only if there were

[8]We also use different measures of FDI inflows such as log of capital investment or log of number of jobs created by the MNEs FDI projects. These additional results are used mainly to check the robustness of the analysis and are available upon request.

serial correlation in the potentially endogenous explanatory variables, and if there were no serial correlation among the unobserved sources of endogeneity. Therefore, all our results are best interpreted as associations rather than causal relationships.

Table 5 displays the results of a generalized least squares estimation of equation (1), which allows for heteroskedasticity among the residuals. The left part of the table reports the results of a simpler specification where greenfield FDI are regressed on the share of high-, medium- and low-skill employment. The right part displays the results from the full specification, which controls for wage, capital, value added, and technology (R&D intensity). We find that FDI in R&D increase the share of high skill workers, while it decreases the share of medium-skill employment. Manufacturing investment corresponds to a lower share of high skill employment, and to higher shares of medium- and low-skill employment. FDI in ICT activities seem to correspond to a larger (smaller) share of medium-skill (high-skill) employment. Finally, investment in E&T reduce the share of low-skill occupations. When including the wage, capital, value added and R&D intensity, the sample reduces to around 2,200 observations (3,000 observations lost), because of missing data in the OECD databases. However, the inclusion of this set of regressors does not change the statistical significance nor the sign of the effect of greenfield FDI on shares of employment.

The results from Table 5 seem to point to a shifting effect of FDI activities. To test polarization patterns, in Table 6 we report the results of regressing FDI inflows on the ratio between high- and medium-skill S_{HM}, between low- and medium-skill S_{LM}, and between high- and low-skill employment S_{HL}. If all FDI had a polarizing effect, we would find a positive coefficients for both S_{HM} and S_{LM}. However, we find evidence of skill upgrading due to FDI activities, especially for Education & Training (E&T), that reduces low-skill employment share compared to the medium-skill one, while it increases the share of high-skill over low-skill workers.

Table 5: FGLS Estimation results

Dep. var.s	S_H	S_M	S_L	S_H	S_M	S_L
E&T$_{t-1}$	-0.001	0.004	-0.007***	0.001	-0.001	-0.008***
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)
HQ$_{t-1}$	0.002	-0.006***	0.000	-0.000	-0.003	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
ICT$_{t-1}$	-0.014***	0.011***	0.000	-0.014***	0.013***	0.001
	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.002)
R&D$_{t-1}$	0.021***	-0.017***	0.001	0.015***	-0.011***	0.002
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Manu$_{t-1}$	-0.009***	0.004**	0.000	-0.011***	0.008***	0.003***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
w_{t-1}				-0.049***	0.028***	0.029***
				(0.004)	(0.005)	(0.002)
k_{t-1}				0.009***	-0.015***	-0.003**
				(0.002)	(0.003)	(0.002)
q_{t-1}				0.044***	-0.016***	-0.019***
				(0.004)	(0.005)	(0.002)
r_{t-1}				0.854***	-0.005***	-0.002***
				(0.070)	(0.001)	(0.000)
constant	0.094***	0.768***	0.126***	-0.016	0.838***	0.103***
	(0.004)	(0.006)	(0.003)	(0.024)	(0.028)	(0.013)
Y/C/S dummies	✓	✓	✓	✓	✓	✓
N. obs	5,289	5,336	5,144	2,513	2,316	2,248

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: FGLS Estimation results — Skill shifting

Dep. var.s	S_{HM}	S_{LM}	S_{HL}	S_{HM}	S_{LM}	S_{HL}
E&T$_{t-1}$	0.100	-0.020***	0.803*	0.076	-0.021**	1.961***
	(0.069)	(0.008)	(0.426)	(0.066)	(0.009)	(0.681)
HQ$_{t-1}$	0.003	0.002	-0.447**	0.015	-0.000	-0.578**
	(0.027)	(0.003)	(0.201)	(0.024)	(0.004)	(0.291)
ICT$_{t-1}$	-0.078	0.019***	0.077	-0.132*	0.007	-0.238
	(0.068)	(0.006)	(0.669)	(0.073)	(0.008)	(0.929)
Manu$_{t-1}$	-0.035	-0.006*	-0.011	-0.028	0.005	-0.932***
	(0.023)	(0.003)	(0.163)	(0.024)	(0.004)	(0.252)
R&D$_{t-1}$	0.053	0.007*	0.254	0.015	0.010**	0.089
	(0.032)	(0.004)	(0.237)	(0.031)	(0.004)	(0.336)
w_{t-1}				-0.293***	0.056***	-1.545***
				(0.035)	(0.006)	(0.389)
k_{t-1}				0.038*	0.006	0.159
				(0.021)	(0.005)	(0.239)
q_{t-1}				0.130***	-0.047***	2.044***
				(0.038)	(0.007)	(0.465)
r_{t-1}				0.030***	-0.000	0.092
				(0.007)	(0.001)	(0.079)
constant	-0.013	0.190***	0.743*	0.498**	0.119***	-8.916***
	(0.050)	(0.007)	(0.429)	(0.199)	(0.030)	(2.288)
Y/C/S dummies	✓	✓	✓	✓	✓	✓
N. obs	5,235	5,111	4,729	2,303	2,247	2,128

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Manufacturing and Headquarter activities seem to have a downgrading effect, by increasing the demand for low-skill labour (relative to the high-skill). The positive effect of FDI in R&D on S_{LM} is deriving from the fact that R&D activities reduce the demand for medium-skill occupations (see Table 5).

Up to now, we have considered the employment shares to be independent from each other. However, there may be interactions between the individual equations. To take into account the correlation among shares of employment across the three skill groups, we estimate eq.(1) using a simultaneous system of seemingly unrelated regression (SUR) equations. Results are reported in Tables 7 and 8.

As before, Table 7 reports the results for the individual shares of employment. Results remain unchanged: foreign R&D investment increase the demand for high-skill jobs, and reduces that of middling occupations; manufacturing activities increase the shares of medium- and low-skill employment shares; FDI in ICT has a negative (positive) effect on high-skill (medium-skill) workers; E&T reduces the demand for low-skill jobs.

The right part of the table displays the results of a regression specification that includes the four sectoral pattern found in Section 4.1 (see Table 3 and Figure 3). Specifically, we include three dummy variables, *upgrading, polarization, midgrading* (*downgrading* is chosen as base variable). For example, *polarization* equals 1 if the sectors are mining&quarrying, electricity&gas, or construction, 0 otherwise.

Table 7: SUR Estimation results

Dep. var.s	S_H	S_M	S_L	S_H	S_M	S_L
E&T$_{t-1}$	0.009	0.009	-0.020***	0.044***	-0.015	-0.030***
	(0.009)	(0.010)	(0.007)	(0.019)	(0.019)	(0.010)
HQ$_{t-1}$	0.004	-0.005	0.000	0.003	0.006	-0.009**
	(0.005)	(0.005)	(0.004)	(0.008)	(0.008)	(0.005)
ICT$_{t-1}$	-0.023***	0.019**	0.005	0.078***	-0.088***	0.010
	(0.007)	(0.008)	(0.006)	(0.013)	(0.013)	(0.006)
R&D$_{t-1}$	0.014***	-0.015***	0.001	0.023**	-0.030***	0.008
	(0.005)	(0.006)	(0.004)	(0.010)	(0.010)	(0.005)
Manu$_{t-1}$	-0.019***	0.010**	0.007**	-0.153***	0.117***	0.037***
	(0.005)	(0.005)	(0.004)	(0.008)	(0.008)	(0.004)
w_{t-1}	-0.058***	0.021***	0.040***	0.028***	-0.050***	0.024***
	(0.006)	(0.007)	(0.005)	(0.007)	(0.007)	(0.004)
k_{t-1}	0.020***	-0.015***	-0.003	0.065***	-0.059***	-0.006*
	(0.004)	(0.005)	(0.003)	(0.007)	(0.007)	(0.003)
q_{t-1}	0.039***	-0.013*	-0.027***	-0.056***	0.089***	-0.034***
	(0.007)	(0.008)	(0.005)	(0.011)	(0.011)	(0.006)
r_{t-1}	0.010***	-0.008***	-0.002	0.018***	-0.008***	-0.010****
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
constant	-0.018	0.881***	0.121***	-0.060	0.699***	0.354***
	(0.032)	(0.036)	(0.025)	(0.041)	(0.041)	(0.021)
Y/C/S dummies	✓	✓	✓	✓	✓	✓
Upgrading				0.280***	-0.184***	-0.100***
				(0.009)	(0.009)	(0.005)
Polarization				0.242***	-0.152***	-0.100***
				(0.010)	(0.010)	(0.005)
Midgrading				0.381***	-0.339***	-0.047***
				(0.011)	(0.011)	(0.006)
N. obs	2,288	2,288	2,288	2,288	2,288	2,288
R-squared	0.904	0.851	0.671	0.654	0.575	0.375
χ^2	21579.44***	13111.06***	668.54***	3077.74***	2058.20***	1371.59***

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

When considering the sectoral patterns of labour market structuring, we find that E&T activities are not only decreasing the share of low-skill workers, but, at the same

time, increase the share of high-skill employment. FDI in ICT has now the same effect of R&D, that is positive on high-skill employment and negative on middling occupations, while foreign R&D is not statistically significant. In addition, investment in HQ reduce the share of low-skill occupations, and the relation with FDI in manufacturing remains unchanged.

Table 8 confirms that E&T activities are skill upgrading (increase S_{HM} and decrease S_{LM}, shifting resources from low- to medium- to high-skill employment).

Table 8: SUR Estimation results — Skill shifting

Dep. var.s	S_{HM}	S_{LM}	S_{HL}	S_{HM}	S_{LM}	S_{HL}
$E\&T_{t-1}$	-0.033	-0.080***	3.034	0.523***	-0.051*	2.510
	(0.116)	(0.024)	(2.170)	(0.174)	(0.030)	(2.772)
HQ_{t-1}	0.100*	0.016	-1.644	0.060	-0.012	1.409
	(0.058)	(0.012)	(1.079)	(0.087)	(0.015)	(1.379)
ICT_{t-1}	-0.233**	0.027	-6.413***	1.153***	0.067***	6.930***
	(0.097)	(0.020)	(1.810)	(0.118)	(0.020)	(1.878)
$R\&D_{t-1}$	-0.104	0.011	1.654	0.106	0.025	2.221
	(0.065)	(0.014)	(1.221)	(0.096)	(0.016)	(1.524)
$Manu_{t-1}$	0.043	0.016	-1.091	-0.958***	0.048***	-12.279***
	(0.059)	(0.012)	(1.096)	(0.072)	(0.012)	(1.147)
w_{t-1}	-0.269***	0.095***	-4.431***	0.513***	0.089***	-3.369***
	(0.084)	(0.018)	(1.575)	(0.070)	(0.012)	(1.119)
k_{t-1}	-0.026	0.003	-1.759	0.486***	0.026**	-0.260
	(0.058)	(0.012)	(1.093)	(0.063)	(0.011)	(0.996)
q_{t-1}	0.114	-0.088***	6.503***	-0.923***	-0.147***	2.270
	(0.098)	(0.021)	(1.834)	(0.110)	(0.019)	(1.754)
r_{t-1}	0.035*	-0.001	0.108	0.166***	-0.032***	4.758***
	(0.019)	(0.004)	(0.355)	(0.018)	(0.003)	(0.280)
constant	0.795*	0.246**	-13.835	0.510	0.837***	-2.407
	(0.458)	(0.096)	(8.565)	(0.392)	(0.069)	(6.400)
Y/C/S dummies	✓	✓	✓	✓	✓	✓
Upgrading				1.576***	-0.159***	25.614***
				(0.090)	(0.016)	(1.468)
Polarizing				0.948***	-0.136***	5.831***
				(0.099)	(0.017)	(1.579)
Midgrading				3.201***	0.094***	19.008***
				(0.100)	(0.018)	(1.637)
N.obs	2,168	2,168	2,168	2,168	2,168	2,168
R-squared	0.785	0.525	0.644	0.520	0.250	0.397
χ^2	7893.16***	2396.68***	3920.58***	2091.19***	706.99***	1398.82***

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The relationship between job polarization dynamics and FDI in ICT depends on the set of regressors. Concretely, when considering the dummies of sectoral patterns, ICT activities have a polarizing effect, in line with the routinization hypothesis, while when omitting these sectoral dynamic characteristics, they have a downgrading effect (negative effect on S_{HM} and S_{HL}, shifting the employment from high- to medium- an from high- to low-skill). Foreign investment in manufacturing continue to have a downgrading effect on labour composition.

5 Conclusions

Empirical studies have reported evidence of job polarization in US and Europe. The evidence has been matched by a theoretical framework that explains the underlying dynamics. The main views are, on the one hand, that that technological change sparked a long-term shift from routine to non-routine tasks, whereby workers are becoming more concentrated in either high-paid/high-skill jobs or low-paid/low-skill non-routine jobs. On the other hand, the increasing internationalization of commercial activities has changed the job structure in the richest countries, because they relocate low-skill occupations to developing countries, where labour costs are lower. The relocation of middle- and low-skill activities caused an upward shift in the demand for high-skill jobs.

Another channel through which the increased internationalization may influence the job restructuring is inward FDI. While there are several studies that have examined the impact of inward FDI on skill upgrading and job polarization patterns (Slaughter, 2004; Blomström et al., 2003; Hakkala et al., 2010; Jav, 2015), only the work of Davies and Desbordes (2015) has analyzed the relationship between inward greenfield FDI and host countries' labour markets. The advantage of using greenfield FDI is that, differently from cross-border mergers and acquisitions, the decision to open a new facility abroad (i.e., greenfield) is mainly dependent on the relative factor prices, rather than competition or technology acquisition. However, not all greenfield FDI should be treated as equal. Labour-intensive, low-cost, low-skill manufacturing FDI may increase the demand for unskilled labour, while capital-, knowledge- and skill-intensive FDI may lead to more demand for high skill workers. In this paper, we test this assumption, by studying the relationship between inward greenfield FDI in five distinct activities (one low-skill and four high-skill intensive activities) and the share of employment by occupational skill of countries of the European Economic Area.

Overall, this paper contributes to the literature on internationalization and job polarization in Europe, by providing new evidence on the role of greenfield FDI for the relative

demands of skills. Our empirical analysis provides two main relevant results. First, we find that pan-European countries have experienced a polarization of their labour markets up to the period right after the crisis. In the last years (2009–2015), however, a skill upgrading pattern emerges. Moreover, we find that, rather than a unique polarizing pattern, there are several trends in the labour markets within countries and sectors.

Second, we find evidence that FDI in R&D and education and training activities contribute to skill upgrading, while manufacturing activities lead to skill downgrading, by increasing the relative demand of low-skill workers. We also find that, when considering the heterogenity of sectoral labour market structures, foreign investment in ICT are the only activity that is associated with skill polarization.

Our interpretation is that, besides the technological upgrade brought about by high-skill FDI activities or the increased demand for low-skill employment due to manufacturing FDI, there are additional country- and sector-specific dynamics that contribute to or withhold to the polarization of jobs. Indeed, technology and the skill intensity of international activities may not be enough to explain structural employment change and other factors, such as institutional frameworks, may play a role in the employment composition by making labor markets more or less responsive to technological change.

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