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Abstract

This paper aims to identify factors that determine functional specialisation (FS) in global value chains (GVCs) in European Union countries. We focus on fabrication and R&D as two opposite business functions in terms of their character and their potential of creating value-added. To make our results robust two different approaches to measuring functional specialisation are used – an FDI-based approach and a trade-based approach. To assemble a relative functional specialisation index, for each approach we use the same metric – a revealed comparative advantages index. Our results suggest a positive effect of wages on specialisation in an R&D function, and a negative impact on FS in fabrication. Increasing labour productivity boosts both specialisation in fabrication and in R&D. The results are robust to different model specifications and different time intervals. The instrumental variables method allows us to interpret the results as causal relationships. Additionally, human capital and labour skills foster FS in R&D (only in FDI data), and growing employment makes FS in fabrication increase. The growth of GDP per capita positively affects functional specialisation in R&D activities. Among GVC participation measures, we confirm the importance of increasing backward linkages to explain the boost in fabrication activities. Dividing a full sample into a group of EU15 countries and a group of Central Eastern European countries we observe that patterns for the EU15 are similar to those for the full sample, while for CEE countries wages are insignificant and labour productivity affects FS in fabrication only.

Keywords: functional specialisation, global value chains, smile curve, factory economy, headquarters economy

JEL classification: F15, F21, F23, F63, L23

CONTENTS

TABLES AND FIGURES

1. Introduction

For a long time international trade has mainly focused on the trade of final products, with the market being seen as the only platform for exchange. However, the rapid decline in ICT costs and technological advances have led to the development of more complex structures that are very different from the simple exporter-importer relationship. The emergence of global value chains (GVCs), characterised by companies dividing the production process among different countries and specialising in specific tasks, has diametrically changed global trade (Pleticha, 2021). Trade in GVCs, especially in intermediate goods and services produced by different companies in different places in the world, grew rapidly until the outbreak of the global financial crisis in 2008 and has stagnated since then, but still accounts for more than 70% of world trade (World Bank, 2020).

Over the past two decades, the GVC framework has become an influential development paradigm in economic policy, and also in EU policy. There is much evidence that GVCs are powerful drivers of countries' economic growth (Hermida et al., 2022), increase productivity (Pahl and Timmer, 2020), and create jobs (Van Assche, 2017). A variety of governments and international organisations have therefore incorporated the GVC framework into regional, national, and global development strategies (Taglioni and Winkler, 2016). The benefits listed above are not distributed evenly among participants in global value chains (Chong-Sup et al., 2019). Although countries can benefit from participation in GVCs in multiple ways, the gains appear to be more significant for high-income countries (Ignatenko et al., 2019). This can be represented as a smile curve showing where value is added in a typical industrial value chain, i.e. there are high value-added service activities at the two edges, such as innovation, R&D, design, and branding (usually located in developed countries such as the EU15, called headquarters economies), while at the center are assembly lines, which typically add little value (and are located in middle-income countries such as the EU13, called factory economies). This division of the benefits from GVCs raises the fundamental question: what determines the fact that some countries benefit more than others?

Two mechanisms are mentioned in the literature: knowledge connectedness and functional specialisation (Pietrobelli et al., 2021). By global knowledge connectedness we mean the set of knowledge-based linkages established between geographically dispersed innovative actors of value chains, which provide access to knowledge that can strengthen domestic technological capabilities needed for economic upgrading. The European Central Bank (European Central Bank, 2020) finds that GVCs are a crucial channel for the transfer of know-how, technology, and process innovation within European regions and between European countries and the rest of the world.

The second mechanism, often described as the most important, is functional specialisation (FS), i.e. specialisation in exports of value-added in different activities such as fabrication, R&D, management, and marketing. Nowadays, production specialisation includes two dimensions: spatial and functional (Timmer et al., 2019). A typical example is iPhones that have 'Designed by Apple in California Assembled in China' printed on the back, meaning that they are designed by Apple in California, the United States, and then assembled in China (Wang et al., 2020).

Why is functional specialisation so important? Some researchers argue that it is necessary to better understand the potential for a country's development in the context of global integration. GVCs have been found to lead to a finer international division of labour, which takes place at the level of tasks[1] and complements specialisation at the product level, allowing countries or regions to specialise functionally at those stages of the value chain where they have a comparative advantage (Grossman and Rossi-Hansberg, 2008). According to the World Bank (2020), specialisation in business functions is seen as critical not only for developing countries that lack the capabilities to produce complete products, but also for developed countries as European countries, which can specialise in intangible, value-added tasks such as R&D, management, and marketing while de-specialising in production (Buckley, 2021).

For us, rather than answering the question of why functional specialisation is so important, we want to find an answer to the question: What are the determinants of functional specialisation? What determines whether a particular country has a comparative advantage in more complex and profitable business functions such as R&D, and which factors determine whether it has an advantage over its competitors in production and assembly activities? The main interest of our analysis are determinants of FS related to the labour market (especially wages and skills) because the concept of functional specialisation connects labour market features with a country's participation in value chain activities that generate differentiated value-added levels.

We begin with an analysis of the existing literature to identify the potential determinants of functional specialisation. Next, we calculate the functional specialisation indices. We use two approaches. The first approach, proposed by Stöllinger (2021), refers to foreign direct investment projects. Functional specialisation is measured as the share of jobs created due to inward greenfield FDI projects in a given country *c* serving a particular function *f* in the total number of jobs created due to inward projects in the country relative to the corresponding share at the world level. This approach enables us to identify five types of activities performed in global value chains, such as (i) headquarter services, (ii) R&D, (iii) fabrication, (iv) sales and distribution services (including marketing, sales, logistics, marketing, business services), and (v) technical support services and training. The second approach we call the trade approach. It is based on the work of Koopman et al. (2014) and Los et al. (2016), which has been greatly extended by Timmer et al. (2019). The idea is to combine detailed occupational and wage data with a world input-output database to track value-added trade flows between countries. This second approach allows for the identification of four types of activities performed in global value chains, i.e. (i) R&D, (ii) management services, (iii) fabrication, and (iv) marketing services. Based on the index of revealed comparative advantages (RCA), specialisation in each business function is calculated. In the same section, we present an empirical model and the strategy of model estimation.

In the next section we focus on data selection and description, and we move to empirical results, assessing the impact of identified determinants on changes in functional specialisation patterns in the group of EU27 countries along with the United Kingdom. The last section presents conclusions.

1 In this study, we use the term "tasks" synonymously with "business functions"

2. Literature review

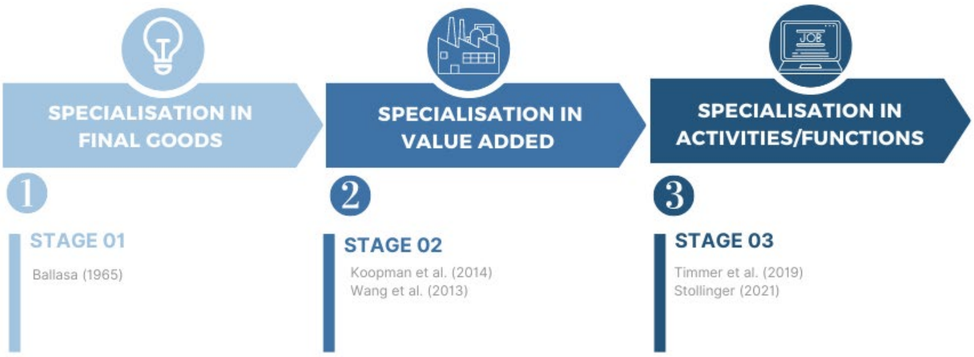
2.1. THE EVALUATION OF TRADE SPECIALISATION CONCEPTS

Functional specialisation in GVCs is a fairly new term, whose roots are related to trade specialisation concepts and can be found in the oldest economic theories as well as in the newest literature on GVCs. In classic economic theory, trade specialisation is the central idea in Adam Smith's (1776) theory, in which gains from trade are explained by the division of labour even when all individuals ex-ante are identical. This concept is further developed by Ricardo (1817), who emphasises the role of exogenous comparative advantage in explaining trade patterns and the division of labour between countries. The concept of specialisation was popularised by Balassa (1965), who proposed a standard tool for analysing patterns of specialisation, called Revealed Comparative Advantage (RCA). According to Balassa a country has a comparative advantage for a given product if the share of that product in the country's exports is larger than the share at the level of the trade area under consideration (world exports or a regional trade area). A country reveals comparative advantages if its RCA value is greater than 1 or comparative disadvantages if its value is smaller than 1.

More recently, the idea of trade specialisation has been challenged by the increasing importance of production fragmentation in GVCs (Jones and Kierzkowski, 1990), offshoring (Arndt, 1997), outsourcing (Grossman and Helpman, 2002), and vertical specialisation (Hummels et al., 2001). As mentioned earlier, two-thirds of world trade takes place through global value chains, where products cross at least one border before final assembly (Degain et al., 2017). Thanks to the accounting framework of Koopman et al. (2014), which allows us to break down a country's gross exports into different value added components, we can estimate how much each country contributes to the value of a product during its production process (known as domestic value added). The traditional approach to measuring trade specialisation based on gross exports of (final) products proposed by Balassa (1965) is thus replaced by the second generation of trade specialisation measurement (Figure 1), i.e. the measurement of value added included in exports, which captures the international fragmentation of production and provides a more accurate picture of trade specialisation. Since then, foreign trade policy makers have focused on improvements to the RCA from a value added trade perspective, analysing a country's export specialisation in the context of GVCs.

The new method of measuring trade specialisation based on value-added trade helps overcome two limitations (Wang et al., 2020). The traditional approach to measuring trade specialisation ignores the fact that a country's industries (products) may be hidden in the exports of its other industries (products) to realise indirect export. It also ignores the fact that a country's industrial (product) exports may hide part of other countries' value added and therefore its export in gross value terms is not necessarily the 'real export' of the industries (products).

Figure 1 / The evaluation of trade specialisation concepts



Source: Timmer et al. (2019), Stöllinger (2021).

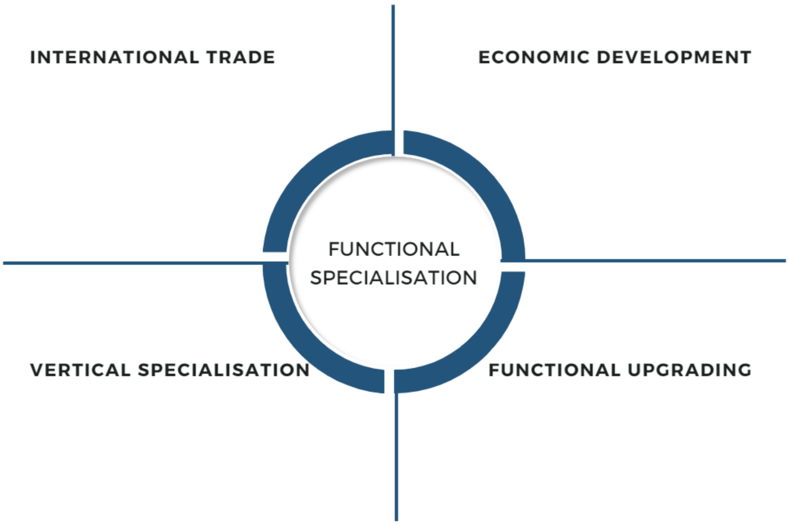
However, the concept of trade specialisation in value-added does not solve all problems, because it is still based on official products/sectors statistics. Two phenomena distort the correct assessment of a country's specialisation in GVCs. First, is the servicification of manufacturing, which means that firms classified as manufacturers sell more services than goods, as in the case of 40% of French firms (Crozet and Millet, 2017). Nowadays, goods are produced with services, and services are produced with goods, and companies tend to sell solutions to customers by bundling goods and services together (Miroudot, 2019). So even if we express the value of exports in terms of value added, this does not solve the problem of correctly assigning production to a service or manufacturing sector and the proper measurement of a country's specialisation in GVCs. Second, firm activity statistics are different from industry statistics and there is no simple one-to-one mapping. On the basis of an analysis of US industrial statistical systems, Fontagné and Harrison (2017) state that a mere statistical classification of industries cannot be relied on. Although administrative data is organised by classifying establishments (or firms) according to their primary activity, which is the activity that makes the most significant contribution to value added, in reality, establishments perform various activities and combine them in-house. For example, firms that design goods and coordinate production networks are often registered as manufacturers, but they are not *de facto* engaged in fabrication activity (Bernard et al., 2017).

In an effort to solve the above problems, a new understanding of specialisation (referred to as functional specialisation) has been developed. It was created by combining two concepts: specialisation in value added together with the concept of trade-in of different tasks among GVCs (Grossman & Rossi-Hansberg, 2008). The new approach identifies domestic value added exports of a particular function by the labour income of workers that perform that function. The idea is to combine detailed occupational and wage data with a world input-output database to track value-added trade flows across countries. Based on the revealed comparative advantage index, this approach allows us to identify the four types of activities performed in global value chains, i.e. fabrication, R&D, marketing, and management. The idea is developed by Timmer et al. (2019).

2.2. DETERMINANTS OF FUNCTIONAL SPECIALISATION: A THEORETICAL FRAMEWORK

The concept of functional specialisation has a multidimensional character, even if its roots are in trade theories. In our opinion, the search for the determinants of this phenomenon should also be based on theories of vertical specialisation, functional upgrading, and economic development (Figure 2).

Figure 2 / The framework of functional specialisation determinants



Source: Humphrey and Schmitz, (2004); Taglioni and Winkler, (2016), Buckley et al. (2020), Mehta (2021).

The core of international trade theory is David Ricardo's theory of comparative advantage. This theory states (under the assumption that international trade barriers are removed) that countries can derive comparative advantage from two sources: differences in resource endowments and differences in technology. While Ricardo's theory was originally formulated in terms of final goods, it also applies in a world of GVCs, and Baldwin and Evenett (2015) argue that the effects of comparative advantage are even amplified when fragmentation of production is possible. Buckley et al. (2020) present a simple example: consider two goods, A and B, and two countries, one of which is rich in skilled labour (say Germany) and the other rich in unskilled labour (say Poland). Good A is skilled labour-intensive and B is unskilled labour-intensive, so initially, Germany has a comparative advantage in A and Poland in B. Following Ricardo's theory, Germany is likely to produce more A and export it to Poland, while Poland is likely to produce more B and export it to Germany. Now suppose that the production process can be unbundled into separate tasks: A into A1 and A2, and B into B1 and B2. And let us assume that A1 and B1 are skill-intensive compared to A2 and B2. According to the logic of comparative advantage, we would expect activities A1 and B1 to be carried out in Germany, while the A2 and B2 activities to be carried out in Poland. So after unbundling, each country is fully specialised in tasks, not products, according to its comparative advantage. Timmer et al. (2019) provide evidence of a strong international division of labour in the world economy, i.e. Mexico and Poland have an obvious comparative advantage in exporting fabrication activities, Italy and South Korea in marketing activities, the Netherlands and the US in management activities, and Germany and Sweden in R&D activities. As the theory of comparative advantage is valid, so the potential determinant of functional specialisation could be differences in resource endowments, i.e. prices and quantity of resources (employment, wages, human capital, skills, technology).

The framework of upgrading in GVCs introduced by Humphrey and Schmitz (2004) is a useful tool for identifying determinants of functional specialisation. According to Lee and Gereffi (2015) upgrading ‘focuses on the strategies used by countries, regions, and other economic actors to maintain or improve their position in the global economy’. In literature, we have four forms of upgrading in GVCs, i.e., product, process, intersectoral, and most interesting for us, functional upgrading, by which we mean the entry of a company into a new, higher value-added function or level in the value chain. Functional upgrading can occur when an individual producer or group of producers acquires or develops production capacity at a higher value level to capture a greater share of the product value. However, upgrading in GVCs is not automatic. Giuliani et al. (2005) note that while process or product upgrading occurs, functional upgrading is more difficult. A successful catch-up model would be to shift from the production of low-value-added goods to the production of high-value-added goods. This requires first of all higher productivity and better labour qualifications (Salido and Bellhouse, 2016). Also, Kaplinsky’s (2015) analysis indicates that functional upgrading refers to the improvement of a firm’s productivity and competitiveness through the creation of technological and managerial capacity to ensure its inclusion in GVCs. Additionally, Taglioni and Winker (2016) underline that functional upgrading is strongly connected with the development of employees’ skills and the capacity to innovate is associated with producers’ ability to increase value added. To sum up, based on the concept of functional upgrading, the determinants of functional specialisation could thus be differences in labour skills, labour productivity, and technology.

To find the determinant of functional specialisation, we also refer to the measurement of vertical specialisation (VS), as the root of the concept of integration in GVCs. VS is often calculated as the share of imports in export products (Balassa, 1967). It tends to be high when production is organised in GVCs and leads to an increase in trade in intermediate goods (Hummels et al., 2001). In the GVC literature, VS is measured in terms of backward linkages (use of imported inputs to produce for exports, i.e foreign value added in own gross exports) which together with forward linkages (share of domestic value added in exports) are the two best-known measures of industry integration in GVCs (Johnson, 2014). Mehta (2021) proposes joining backward and forward indices with the upgrading concept and proposes the new theoretical hypothesis named ‘upgrading within GVC in four stages’. In Stage I, both backward and forward linkages are low with lower productivity growth, but it provides a ‘window of opportunity’ to increase GVC participation. Firms enter the II phase when their backward linkages increase. Only those companies with sufficient technological capabilities to transform into high value added activities that are participating in the GVC with increasing forward linkages, are in the III phase. In the IV phase, both backward and forward linkages decrease again, albeit at a higher level of productivity growth, where firms divide their production processes among different locations. Based on Mehta's (2021) hypothesis, one should conclude that an appropriately high level of integration in GVCs, i.e., both strong backward and forward linkages in the economy, can play a key role in the acquisition or adoption of new value chain functions/ activities.

Finally, to create a framework of functional specialisation determinants we connect the FS concept with economic development. We start with the assumption that GVCs reshape not only trade in goods and services but also the cross-border movement of know-how, investment, and human capital, which are the effects of economic growth (Taglioni and Winkler, 2016). It is why GVCs have become ubiquitous in the analysis of globalisation and economic development (Gereffi and Lee, 2012). UNCTAD (2013) as the first states that developed countries tend to source more goods from abroad and sell a higher share of their gross exports as intermediate goods. Kowalski et al. (2015) confirm that the level of development determines participation in GVCs, so the higher the per capita income, the higher the backward engagement. In turn, according to Taguchi (2014), positive correlations between GVC participation and the squared term of GDP per capita, suggests that Asian countries' GVC participation is nonlinear with economic development. Lee et al. (2018) and Mao (2022) also confirm the nonlinear (U-shaped) relationship between GVC participation and economic growth. Based on the above-mentioned empirically established relationships, we believe that a given country’s level of development must be taken into account in a theoretical framework of FS determinants.

2.3. EMPIRICAL EVIDENCE AND HYPOTHESES

Little is known in the empirical literature about the determinants of functional specialisation. Kordalska and Olczyk (2022) have attempted to identify upgrading factors for different types of functional specialisation in GVCs, but the analysis is only for selected CEE countries. They find that the wage convergence of CEE economies with developed economies and strong linkages with GVCs (backward linkages) support the path to higher value-added in almost all business functions. Higher GDP per capita levels and lower economic distance from Germany have allowed these countries to escape the status of ‘factory economies’ and achieve higher value added in R&D. In turn, Timmer et al. (2019) and Stöllinger (2019) find in their analysis that GDP per capita plays an important role in explaining the functional specialisation pattern. In our analysis, we focus on the following factors-determinants of functional specialisation:

Wages. In our analysis, wages are the first potential determinant of functional specialisation. Baldwin and Venables (2013) argue that the development of ICT enabled the relocation of production, but this could only be profitable if wage differentials existed. Trade-in-task models (Grossman and Rossi-Hansberg, 2008) highlight the centrality of wages and wage differentials to offshoring decisions. The wage gap between foreign and domestic firms in the host country is often the main reason for FDI (Markusen and Venables, 1997). Kersan-Škabić (2019) finds in her study for CEE economies that wage level is an important determinant of FDI location choice. The most recent studies by Duc (2019) for Vietnam and Gagliardi et al. (2019) for Belgium confirm that the shift to upstream sectors in GVCs requires higher productivity of skilled workers, which improves company profits and increases skilled workers’ wages.

Labour productivity. The beginnings of research on the relationship between labour productivity and participation in GVCs should be sought in analyses measuring offshoring at the industry level, from the perspective of the offshoring country (Egger and Egger, 2003). In the literature, we can find a lot of analyses based on both industry and firm-level data, in which participation in GVCs is connected with productivity growth through a variety of channels (Kummritz, 2016; Taglioni and Winkler, 2016; Criscuolo and Timmis, 2017; Banh et al., 2021). Thanks to strong backward linkages firms experience knowledge spillovers from foreign firms, and pro-competitive effects of foreign competition, which implies the growth of productivity (Criscuolo and Timmis, 2017). Since functional specialisation is related to workers’ activities, it is worth paying attention to the work of Pahl et al. (2022). The authors find that expansion in GVCs is positively correlated with labour productivity both across countries and over time, but also that more important GVC jobs are more productive than non-GVC jobs.

GDP per capita. We will use GDP per capita as the explanatory variable for functional specialisation. We rely on the relationship between GDP per capita and GVC participation, which is well-known from empirical analyses. UNCTAD (2013) found that countries that have improved their performance in GVCs over the past 20 years have average GDP growth per capita of 3.4%, compared with 2.2% for countries that have not improved their domestic value added. Ignatenko et al. (2019) find in their analysis of 189 countries that changes in GVC participation and potential progress in GVCs are strongly associated with income convergence. In turn, Stöllinger (2019) estimates that incomes in a factory economy range from about USD 11,500 to USD 14,800 and that a typical functional specialisation pattern in a factory economy is associated with lower growth rates.

Linkages in GVCs. We will use forward and backward linkages as variables in our analysis. These linkages indicate the nature of participation in GVCs, i.e., each country participates in GVCs through forward linkages (when the country supplies inputs for other countries' exports) or backward linkages (when the country imports intermediate goods used in its exports). Linkages are measured as the sum of 'foreign value added in own gross exports' (backward linkages) and 'domestic value added in gross exports of other countries' (forward linkages). In the empirical literature, Sydor (2011), Kowalski et al. (2015), and Ignatenko et al. (2019) confirm that countries with strong forward linkages tend to have a better position in GVCs. In turn, Bartelme and Gorodnichenko (2015) and Tian et al. (2019) identify backward linkages as a determinant of progress in GVCs, i.e., growth in developed countries is generally correlated with stronger backward linkages. However, Pahl et al. (2022) find that backward participation may become lower for countries in the innovative group because their activities are less dependent on imported inputs.

Distance. In addition, we take into consideration a variable 'distance to Germany' that indicates the country's proximity to major producing countries or a selected hub. Meng (2019) finds that current production systems in the EU are more complex, but also more regional rather than global. For EU countries, Stöllinger et al. (2018) confirm that European countries participate 50% in GVCs and 50% in regional value chains. Inomata (2017) also confirms that a country's proximity to a hub increases its prospects for integration into GVCs.

Skills and Employment. Here we refer to the literature on the relationship between the labour market and GVC participation (Wood and Berge, 1997) and the determinants of GVC upgrading (Eichengreen et al., 2013; Tian et al., 2019). Hollweg's (2019) analysis shows that higher employment within sectors and firms is associated with GVC integration. In turn, Eichengreen et al. (2013), in their analysis of countries avoiding the middle-income trap, underline that skilled workers are needed to move up the value chain from low value added industries to develop higher value added activities. Farole (2016) analyse the relationship between GVCs and labour markets and suggest that the gap between skilled and unskilled labour matters for gains from GVC integration. Wang et al. (2018) find that upgrading in GVCs requires higher-skilled labour. This is mainly because the high value added activities in GVCs also require special skills and knowledge. The skill-biased nature of GVC trade is associated with the increased complexity of global supply chains as well as increased use of skill-intensive inputs.

FDI. We also want to test whether the inflow of foreign direct investment has an impact on functional specialisation patterns. We find some indirect evidence for this in the empirical literature. FDI inflows are cited in the empirical literature as a potential determinant of upgrading activities in GVCs. FDI is a channel for importing high-value inputs (OECD, 2013), increases the fragmentation of cross-border production between countries (Head and Mayer, 2017), and supports domestic firms' participation in GVCs (Martınez-Galan and Fontoura, 2019). The best example is Vietnam, where Samsung has invested in cell phone production since 2009, bringing the country into the global electronics manufacturing market (Tong et al., 2019).

So, **the hypotheses** tested on determinants of functional specialisation patterns can be summarised as follows:

H1: Wages and GDP per capita of EU member states affect their functional specialisation patterns. Growing wages/GDP per capita stimulates the achievement of comparative advantages in the R&D business function.

H2: Labour productivity positively affects both functional specialisation in fabrication and in R&D-oriented activities

H3: The nearer the vicinity to the GVC hub and the stronger the backward relationships with the GVC partners are – the more intensive functional specialisation in fabrication function is.

H4: Employment growth supports specialisation in fabrication activities, but in turn, achieving comparative advantages in the R&D function requires the development of skilled workers.

H5: The inflow of foreign direct investment has a positive impact on EU countries' functional specialisation patterns.

3. Functional specialisation measure, empirical model, and estimation strategy

3.1. MEASURING FUNCTIONAL SPECIALISATION

In our empirical analysis, we consider two alternative approaches to measuring functional specialisation at the country-industry level to test the hypotheses set in Section 2. These two different perspectives allow us to look at the bigger picture of the way particular factors affect the phenomenon analysed, and to form wider conclusions.

The first approach focuses on the number of jobs related to inward greenfield FDI projects (hereafter: FDI-based approach, Stöllinger, 2021), whereas the second solution combines information from the labour market about workers' occupations and their income with trade data derived from input-output tables (hereafter: trade-based approach, Timmer et al., 2019). Based separately on the number of jobs created due to greenfield FDI projects[2] on the one hand side, and domestic value added that is carried out by workers divided into groups according to their occupations,[3] on the other hand, and using the revealed comparative advantages index adopted from Balassa (1965), the two dimensions of functional specialisation are presented. Formally, to calculate the relative functional specialisation index (RFS) for individual value chain function *f*, for industry *j*, country *c*, and period *t*[4] in each of the two methodologies we employ the following formula:

$$(1) \quad RFS_{jc}^{f} = \frac{J_{jc}^{f}/\Sigma_f J_{jc}^{f}}{\Sigma_c J_{jc}^{f}/\Sigma_c \Sigma_f J_{jc}^{f}},$$

where J_{jc}^{f} is the number of jobs created by greenfield FDI projects or labour income in trade serving function *f* in country *c* and industry *j*. Likewise, $\sum_f J_{\mathrm{jc}}^{f}$ is the total number of jobs created by greenfield FDI projects or the total labour income in trade in country *c* across all value-chain functions. Analogous definitions apply for the number of jobs (labour income in trade) in the denominator, where jobs are summed up over countries to yield the EU-wide number of jobs created by greenfield FDI (labour income in trade is summed up across countries and presented in relation to labour income for all countries in their total exports and across all value-chain functions).

To be in line with the approach of Laursen (2015) to revealed comparative advantage measures we normalise RFS indices and in econometric specification we use them in the following form:

$$(2) \quad normRFS_{jc}^{f} = \frac{RFS_{jc}^{f}-1}{RFS_{jc}^{f}+1}.$$

2 Details of the mapping of 'activities' into value chain functions are in Appendix, Table A.1.1, and details of the mapping of fDi Markets industries into NACE Rev.2. are provided in Kordalska et al. (2022)

3 Details of mapping occupations into value chain functions – Appendix, Table A.1.2.

4 Subscript *t* is omitted in formula (1) to make the formula more legible. Available data allow us to calculate the FDI-based relative functional specialisation index for the period 2003-2019. Trade-based data is limited to 2000-2014.

This conversion makes RFS indices symmetric and allows us to specify them in the range of -1 to 1.

Each of the methods provides information about relative specialisation for slightly differing value chain functions. Greenfield FDI projects allow for the identification of five value chain functions: (i) headquarter services, (ii) R&D, (iii) fabrication, (iv) sales and distribution services (including marketing, sales, logistics, marketing, and business services), and (v) technical support services and training. The trade-based methodology enables us to identify four functions: (i) management, (ii) R&D, (iii) fabrication, and (iv) marketing. The functions which are common to both methodologies relate to fabrication and R&D. At the same time, these two functions are located on the two poles in terms of their behaviour, and in terms of those countries which specialise in these activities. That is why in a main empirical analysis we focus on these two business functions. The comparison of both methodologies applied to EU countries is described in Kordalska et al. (2022).

3.2. EMPIRICAL MODEL AND ESTIMATION STRATEGY

Based on the discussion of the potentially relevant determinants of functional specialisation, we develop a general empirical model. For this model we estimate separate specifications for the fabrication function and R&D function, using FDI-based functional specialisation indices for the period 2003-2019, and alternatively, trade-based functional specialisation measures for the period 2000-2014. All regressions use country-industry data.

Taking all of this into account, the general model for relative functional specialisation (*RFS*) measuring comparative advantages in function *f* (fabrication and R&D, separately), recorded in industry *j*[5], country *c*, and in period *t*, is presented as follows:

$$(3)\quad RFS^{f}_{jct} = \alpha + \underbrace{\beta^{f}_{1} Wages_{jct} + \beta^{f}_{2} GDPperCap_{ct}}_{H1} + \underbrace{\beta^{f}_{3} LabProd_{jct}}_{H2} + \underbrace{\beta^{f}_{4} GVCparticipation_{jct} + \beta^{f}_{5} DistHub_{c}}_{H3} + \underbrace{\beta^{f}_{6} Employment_{jct} + \beta^{f}_{7} HumanCapital_{jct} + \beta^{f}_{8} HsLsRatio_{jct}}_{H4} + \underbrace{\beta^{f}_{9} FDI_{jct}}_{H5} + \delta_j + \delta_c + \delta_t + \varepsilon_{jct},$$

where H1 to H5 refer to the hypotheses to be tested. The main explanatory variable $Wages_{jct}$ reflects annual real wages in industry *j*, country *c*, period *t*, and is expressed in logarithms. $GDPperCap_{ct}$ is a logarithm of country level real GDP per inhabitant. To test the second hypothesis, we take country-industry real labour productivity – $LabProd_{jct}$ in logarithm form. Variables related to GVCs comprise a country-industry $GVCparticipation_{jct}$ which in estimated models is decomposed into GVC backward participation and GVC forward participation ($BWparticipation$ and $FWparticipation$ in tables with models estimates, respectively). Both variables are presented as a percentage of gross exports. In this group we also consider a logarithm of geographical distance to GVC hub/main trading partner in export – $DistHub_c$. To test hypothesis 4 we use a set of human capital factors. $Employment_{jct}$ reflects the logarithm of the total number of persons engaged and $HsLsRatio_{jct}$ presents the ratio between high-skilled and low-skilled workers. These factors are recorded at the country-industry level. $HumanCapital_{jct}$ which is a human capital index derived from the Penn World Table 10.0 (Feenstra et

5 Information about industries considered in this analysis is presented in Appendix, Table A.1.3.

al., 2015), is observed at the country level. The last variable FDI_{jct} describes the ratio between inward and outward foreign direct investment. Additionally, δ_j, δ_c, δ_t indicate industry, country and time fixed effects, and ε_{jct} is the error term. The detailed description of all variables included in regression (3) is presented in Section 4. 1, whereas information about the expected direction of impact of individual factors is included in the hypotheses formulated in Section 2.

As a starting point, regression (3) is estimated with the aid of OLS with groups of variables for particular hypotheses added sequentially, remembering that the main variable of interest is wages. To avoid the problem of potential endogeneity, all explanatory variables in the OLS regression come into the model in the form of their first lags. This potential endogeneity issue may appear mainly due to the simultaneous causal relationship between functional specialisation measures and wages - our main variable of interest. Unobservable industry, country, and time effects are incorporated into the model as fixed effects. The OLS model is treated as a baseline model; however, due to the problem of endogeneity mentioned above, we will skip interpreting the results and focus on more reliable estimations.

This simple procedure incorporating first lags of explanatory variables into a model specification may not be sufficient. In our empirical investigation, we deal with the endogeneity problem by considering instrumental variables techniques. We test alternative approaches to building instruments and incorporating them into models' specifications. In each approach, instruments are constructed at the country-industry level.

In looking for an instrument for the variable of interest (wages), in the first step, we go beyond the sample of EU countries. Such a solution originates from Autor et al. (2013) who assessed the US labour market's exposure to rising import competition from China. To build the instrument we use information on the compensation of employees and the size of employment in non-EU economies[6] which come from the Trade in Employment database (OECD, 2021a).[7] This 'out-of-sample' approach allows us to increase the chance of overcoming the problem of endogeneity. The construction of the instrument is based on the economic proximity between wages for country-industry pairs over time. This economic proximity between EU country-industry and non-EU country-industry pairs is measured individually by the correlation coefficient[8]. Next, for a particular country-industry EU panel unit, we look for five non-EU 'siblings' in the same industry which has the highest correlation coefficients in terms of their wages[9]. Finally, we calculate both the average and correlation coefficient weighted value of wages which form the instruments for EU countries' wages.[10]

We also consider natural candidates as instruments for wages – i.e. minimum wages, and trade union density.

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6 The sample of non-EU economies that is used to construct the instrument/instruments consists of 23 countries: Argentina, Australia, Brazil, Canada, China, Chile, Columbia, Costa Rica, Iceland, India, Indonesia, Israel, Japan, Korea, Mexico, New Zealand, Norway, Russia, Saudi Arabia, South Africa, Switzerland, Turkey, and the United States.

7 To make data comparable to data on real wages in EU countries that is used in the analysis we deflate it with the aid of CPI (2015=100) for US dollars and next express it in million euros. The correlation coefficient between real wages from our sample and real wages from the TiM database for EU countries =0.73

8 Due to size considerations, a complete table with correlation coefficients is available upon request only.

9 E.g. for the Polish food and beverages industry (PL, C10T12) we look at industry C10T12 in other non-EU countries – taking those which have the highest correlation coefficient for wages over the period analysed

10 The same is done for labour productivity. To instrument GDP per capita, we use the instrument constructed for wages.

Additionally, we use an IV estimation with heteroskedasticity-based instruments proposed by Lewbel (2012). Lewbel's estimator utilises heteroskedasticity of error terms to identify the structural parameters in a model with endogenous regressors if traditional identifying information, such as external instruments or repeated measurements, are absent. We test this kind of instrument, as well as heteroskedasticity-based instruments supported by the external instruments described above.

4. Data and descriptive statistics

4.1. VARIABLES DESCRIPTION

FDI-based functional specialisation. The information for calculating the FDI-based RFS is obtained from the cross-border investment monitor fDi Markets, maintained by the Financial Times Ltd. The underlying database compiles individual greenfield FDI projects and major extensions from 2003 onwards. Since the database is composed of single greenfield FDI projects, a large number of characteristics of each individual greenfield FDI is available, including the investor company, the name of the subsidiary established, the origin and destination locations of the project, as well as the industry affiliation. Of these characteristics we exploit in particular information on the purposes for which the subsidiary is established, that is the business (or value chain function) it serves. These functions labelled ‘activities’ in the database, largely correspond to business functions that can be used directly for the categorisation of projects by function. The information on value chain functions is available at the industry level, though the industry classification of the fDi Markets database had to be mapped to the NACE Rev.2 industry classification.

Trade-based functional specialisation. The trade-based RFS rely on the international input-output tables from the World Input-Output Database (WIOD) Release 2016 (Timmer et al. 2015) to calculate the domestic value added in trade. WIOD contains information about input-output flows, final demand, gross value added, and gross output for 43 countries (27 EU countries, the United Kingdom, and 15 non-EU countries), and the rest of the world, and for 56 industries according to the NACE rev.2 classification. Given the coverage of the data, this measure is available for the period 2000-2014. The information from WIOD is combined with data on employment and labour compensation for 13 occupational groups across European countries at the industry level, which has been kindly provided by Timmer et al. (2019) and Buckley et al. (2020).

Wages. Wages are derived by dividing industry-level data on the nominal labour compensation and the number of employees, taken from Eurostat’s Structural Business Statistics (SBS). We take into account the change in industry classifications from NACE rev.1 to NACE rev.2 in 2008 using a correspondence table, to obtain a time series running from 2000 to 2019. As certain industries in the SBS were particularly prone to a large number of missing observations, these had to be filled in from other data sources. Hence, where information was unavailable, we supplemented the SBS dataset with the employment and compensation data accompanying the OECD Inter-Country Input-Output (ICIO) database. Given methodological differences, however, the two datasets are not entirely comparable. Therefore, rather than directly transferring the ICIO values to SBS, we derive the growth rates of the respective ICIO values over time and use these growth rates to infer the missing values in the SBS dataset. Since ICIO data only contains information up to the year 2018, where values for 2019 are missing, these are inferred based on the growth rates of the overall manufacturing sector (C) taken from SBS. All values are deflated to obtain real 2015 values using national harmonised consumer price indices (HCPI).

Labour productivity. We obtain industry-level labour productivity in a similar way to the steps described above related to wages. The relevant information has been taken from Eurostat's SBS, namely value added and the number of employees, and has been complemented with the corresponding data from OECD ICIO. Here too, we relied on the respective growth rates of the ICIO data (value added and the number of employees) to fill in the gaps in the SBS dataset. In turn, labour productivity is calculated as value added per employee. In order to be aligned with wages, labour productivity was deflated using the country-level HCPI to obtain real 2015 values.

GDP per capita. Country-level information about GDP per capita is derived from the Eurostat Database. It is expressed in current prices and million EUR. All GDP per capita values are deflated with the aid of the price index (implicit deflator) and presented in 2015 prices.

GVC backward and forward participation. Information about country-industry GVC participation comes from the Trade in Value Added (TiVA) database (OECD, 2021b).[11] This database contains observations for backward and forward participation for the period 2000-2018. Data for the year 2019 is imputed. GVC backward participation is represented by foreign value added embodied in particular country-industry gross exports, and GVC forward participation is measured as domestic value added embodied in country-industry gross exports. These measures enter into the model specification as a share of gross exports.

Distance to GVC hub/main trading partner. Geographical information about particular countries' distance to Germany – a factory Europe hub and the main trading (importing) partners is the distance measured from particular EU countries and their most important cities/agglomerations to hub/main importers (their most important cities/agglomerations) and is expressed in logarithms. The data on distances are derived from the CEPII database (Mayer and Zignago, 2011).[12] Distance to the factory Europe hub is data that varies between countries only. Distance to the main trading partner is country-level data with a slight variability over the years analysed.

The size of employment. Statistics on domestic employment by industry are drawn from the Trade in Employment database (OECD, 2021a). Employment is defined as the total number of persons engaged in the production activity of a particular industry within the National Accounts boundary of the resident institutional unit. It covers both employees and self-employed.

Employment skills. Data on the educational attainment of workers according to the International Standard Classification of Education (ISCED) are not generally available for EU countries. Therefore, we had to resort to the first generation of the Socio-Economic Accounts (SEA) of the World Input-Output Database (WIOD 2013 Release)[13]. The SEA of the WIOD 2013 Release contain information on employment of high, medium and low-skilled workers for the period 1995-2009. An inspection of the data suggested that the variation is often not across industries but by industry groups and technology content. Nevertheless, the SEA of the WIOD 2013 is the most suitable source of data on employment by skills. We complement the data beyond 2009 with the country-level data on employment by skill group from

[11] Available at: https://www.oecd.org/sti/ind/measuring-trade-in-value-added.htm#access

[12] Available at: http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=6

[13] Available at: https://www.rug.nl/ggdc/valuechain/wiod/wiod-2013-release?lang=en.

Eurostat. Hence, the trends over time within any country are the same for all industries for the period 2010-2019. Given the data constraints, this is a limitation we have to accept.

Human capital. The data on human capital comes from the Penn World Table 10.0 (Fenstra et al., 2015).[14] The human capital index is based on the average years of schooling (Barro and Lee, 2013) and an assumed rate of return to education, based on Mincer equation estimates around the world.

FDI IN-OUT ratio indicates a country-industry ratio between inward and outward FDI flows (Eurostat data).

The choice of fabrication function and R&D function has been motivated not only by overlapping these two functions in both considered methodologies but also due to their opposite character confirmed by de Vries et al. (2019), Stöllinger (2021) and Kordalska et al. (2022). Regardless of how fabrication and R&D specialisation are identified, and regardless of the time span, this opposite character is also visible in terms of the functions' relation to the main factor we are interested in, i.e. wages, but also GDP per capita (Table 1). RFS in fabrication is negatively correlated with wages, whereas we observe a positive interrelation between RFS in R&D and wages. The same pattern is also true for GDP per capita. For labour productivity we expect positive relationships. This can be seen for RFS in R&D (both FDI- and trade-based), but unfortunately, for fabrication this relationship is either insignificant or negative.

Table 1 / Correlation between FDI-based and trade-based functional specialisation in fabrication and R&D, and selected explanatory variables – wages, GDP per capita, and labour productivity

	FDI-based		trade-based		FDI-based		trade-based	
	RFS in fabrication	RFS in R&D	RFS in fabrication	RFS in R&D	RFS in fabrication	RFS in R&D	RFS in fabrication	RFS in R&D
	2003-2019		2000-2014		2003-2014			
Wages (2015=1.000) EUR m	-0.2417*	0.3444*	-0.0289	0.2147*	-0.2234*	0.3347*	-0.0504*	0.2091*
GDP per capita (2015=1.000) EUR per capita	-0.2611*	0.3671*	-0.0632*	0.1966*	-0.2576*	0.3411*	-0.0858*	0.1822*
Labour productivity (2015=1.000) EUR per emp	-0.1697*	0.2960*	0.0334	0.2486*	-0.1479*	0.2969*	0.0175	0.2445*

Note: * indicates a statistically significant correlation at the 1% level.

In addition to the above table, we present the correlation matrix for all explanatory variables considered in the empirical model (Table 2). The highest correlation coefficient is for wages, GDP per capita, and labour productivity. That is why to avoid the problem of multicollinearity between these variables, we will consider them in separate model specifications. In these specifications' wages, GDP per capita, and labour productivity will be followed by groups of other explanatory factors related to tested hypotheses. For none of these factors, except for FDI, are high correlation coefficients observed. FDI will be added to the models as a last variable.

[14] Available at: https://www.rug.nl/ggdc/productivity/pwt/?lang=en

Table 2 / Correlation matrix for explanatory variables

	Wages (log)	GDP-per-Capita (log)	Labour productivity (log)	BW-participation	FW-participation	BW-participation × GDP	FW-participation × GDP	Distance-MP (log)	Employment (log)	Human Capital Index	HS-LS ratio	FDI IN-OUT-ratio
Wages (log)	1											
GDP-per-Capita (log)	0.9046*	1										
Labour productivity (log)	0.9297*	0.8205*	1									
BW-participation	-0.1773*	-0.1362*	-0.1509*	1								
FW-participation	0.0991*	0.0624*	0.1010*	-0.0825*	1							
BW-participation × GDP	-0.0076	0.0284	0.0073	0.9511*	-0.0575*	1						
FW-participation × GDP	0.1991*	0.1604*	0.1900*	-0.1435*	0.9785*	-0.0655*	1					
Distance-MP (log)	0.1865*	0.1625*	0.1857*	-0.3142*	0.0468*	-0.2084*	0.1275*	1				
Employment (log)	0.1852*	0.1878*	0.1561*	-0.2415*	0.1659*	-0.0438*	0.2897*	0.3088*	1			
Human Capital Index	0.1266*	0.2058*	0.0851*	0.0815*	0.1300*	0.0808*	0.1437*	-0.1381*	0.0661*	1		
HS-LS ratio	0.0007	0.1209*	0.0033	0.1378*	0.0456*	0.0988*	0.0141	-0.0868*	-0.2271*	0.4461*	1	
FDI IN-OUT-ratio	-0.6287*	-0.6379*	-0.5257*	0.2312*	-0.0324	0.1036*	-0.1168*	-0.2219*	-0.2186*	-0.0522*	0.0808*	1

Notes: * indicates a statistically significant correlation at the 1% level.

4.2. EMPIRICAL RESULTS

Aiming to identify factors affecting functional specialisation in the two selected business functions – fabrication and R&D – we estimate different specifications of the model (3) using (i) alternative databases – FDI-based data for the period 2003-2019 and trade-based data for the years 2000-2014, (ii) alternative estimators – OLS, the instrumental variables method, as well as the instrumental variables method with heteroskedasticity based instruments (Lewbel 2012)[15], (iii) alternative instruments as described in Section 3.2, (iv) different time periods – i.e. periods that are specific for the two databases used in our analyses (2003-2019 and 2000-2014), and a period that is common for these two databases (2003-2014), and finally (v) different subsamples – EU15 countries and CEE countries which expose different patterns in terms of functional specialisation (Kordalska et al. 2022). Models for the fabrication function and R&D function are separate models.

As mentioned in Section 3.2, we estimate model (3) adding groups of variables for testing particular hypotheses sequentially. The only exemption concerns hypotheses 1 and 2 where we consider the impact of wages, GDP per capita, and labour productivity on functional specialisation. The correlation coefficient for these variables fluctuates between 0.82 and 0.93 (Table 2) and that is why we incorporate them in separate model specifications. In this case, we take the following approach. We start with specifications that contain wages only (specification (1) for the fabrication function, specification (6) for the R&D function); then as described above we add groups of variables one by one for hypotheses 3, 4, and 5. Next, we present models that include GDP per capita instead of wages, and all other factors at once to make the table with estimations readable. An analogous way of presenting results is for labour productivity and the factors for the remaining hypotheses.[16]

Because of the potential endogeneity problem described in Section 3.2, to interpret our results we rely on instrumental variables models. Table 3 contains estimation results for FDI-based relative functional specialisation, while Table 4 presents estimation results for trade-based data. For reasons of comparison, the OLS results for FDI- and trade-based indicators are presented in Appendix, Table A.2.1 and Appendix, Table A.2.2.

Following the results presented in Table 3, we find that country-industry wages increase functional specialisation in the R&D function in EU countries. The same results are obtained with OLS estimations with 1-period lagged explanatory variables (Appendix, Table A.2.1). The coefficients are robust to different model specifications ((6)-(10)) both in IV and OLS estimations. These results are in line with the findings by Duc (2019) and Gagliardi et al. (2019) and allow us to confirm the part of the first hypothesis which states that increasing wages support functional specialisation in R&D-oriented activities. At the same time, the growth of these wages limits functional specialisation in the fabrication function (specifications (1)-(5)). Taking into account the differentiation of functional specialisation patterns across EU countries and that they form two clusters – the EU15 and CEEs (Kordalska et al., 2022) we can expect that the growth of wages may support the functional upgrading of CEE countries. Taking a closer

[15] Finally, we have rejected Lewbel's (2012) method, both with heteroskedasticity-based instruments and heteroskedasticity-based instruments supported by external instruments as described in Section 3.2. In each case, we rejected the null hypothesis on an overidentification test of all instruments.

[16] In the case of model specifications containing labour productivity and GDP per capita (separately) we have taken analogous steps as in the case of wages models – i.e. we sequentially added groups of variables for hypotheses 3, 4, and 5. Due to space limitations, in Table 3, Table 4, and Table A.2.1 and A.2.2 in the Appendix, we present the most expanded models.

look at the impact of real GDP per capita on fabrication and R&D function (specifications (11) and (12)) we clearly observe an analogous pattern as in the case of wage specifications. That is why we fully confirm hypothesis H1.

The test of the importance of labour productivity in explaining comparative advantages in business functions is presented in columns (13) and (14). An increase in labour productivity fosters further specialisation in both functions, and thus hypothesis H2 cannot be rejected. According to FDI-based models, the effect of labour productivity on functional specialisation in fabrication is stronger than that on functional specialisation in R&D.

Employing FDI-based functional specialisation measures, our results also support hypothesis H3 which relates to the importance of GVC backward participation for strengthening comparative advantages in fabrication function. Regardless of model specifications, (2), (3), (4), (11), and (13), and the method of estimation (IV/OLS) the coefficients remain robust. Hypothesis H3, next to GVC relations, assumes that countries with the closest geographical distance to the hub or to main trading partners develop their specialisation in fabrication. Unfortunately, though the coefficients are negative, they are mainly insignificant, so we do have no clear evidence to not reject this hypothesis in the area related to distance.

The next group of factors focuses on employees and their skills. Using FDI-based data our results confirm a positive and significant impact of employment growth on increasing comparative advantages in fabrication, but this impact is not observed to support the R&D function. In turn, the growth of human capital measured by years of schooling, and the growth of the number of higher-skilled workers over low-skilled ones result in fostering specialisation in R&D activities. Functional upgrading resulting in the ability to move up along the smile curve and create higher value-added requires well-educated employees. Eichengreen et al. (2013), Farole (2016), and Wang et al. (2018) reach the same conclusion. Our results are also in line with Miroudot’s (2019) analysis of GVCs, in which he states that high-skilled jobs are required for the R&D, design, and engineering of activities in GVCs. Thereby we confirm hypothesis H4.

The last hypothesis – H5 states that the inflow of foreign direct investment has a strong positive impact on EU countries’ functional specialisation patterns. Both OLS (Appendix, Table A.2.1) and IV (Table 3) estimations reveal a very specific pattern of FDI influence on fabrication and the R&D function. The growth of inflows in comparison to outflows of FDI leads to increased specialisation in fabrication and a drop in R&D specialisation.

Table 3 / FDI-based functional specialisation in fabrication and R&D, 2003-2019, instrumental variable regression with fixed effects

	FDI-based FAB					FDI-based R&D					FAB	R&D	FAB	R&D
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Wages (log)	-0.191	-0.278**	-0.386**	-0.325**	-0.267*	0.170***	0.141**	0.117*	0.111*	0.114*				
	(0.128)	(0.131)	(0.159)	(0.159)	(0.153)	(0.062)	(0.062)	(0.063)	(0.064)	(0.064)				
GDP-per-Capita (log)											-0.189*	0.676**		
											(0.107)	(0.320)		
Lab-Prod (log)													0.438***	0.286***
													-0.149	-0.110
BW-participation		0.903***	0.754***	0.794***	0.304		-0.557***	-0.575***	-0.577***	-1.362***	0.884***	-0.579***	0.537***	-0.494**
		(0.123)	(0.127)	(0.126)	(0.257)		(0.194)	(0.197)	(0.200)	(0.411)	(0.116)	(0.206)	-0.122	-0.241
FW-participation		0.823***	0.991***	1.175***	0.201		0.511	0.546	0.615	-1.001	1.085***	0.736	0.563**	-0.237
		(0.233)	(0.232)	(0.227)	(0.414)		(0.420)	(0.414)	(0.429)	(0.714)	(0.209)	(0.458)	-0.254	-0.500
BWpart×GDP					0.045**					0.069**				
					(0.022)					(0.033)				
FWpart×GDP					0.087***					0.143**				
					(0.031)					(0.056)				
Distance-MP (log)		-0.035*	-0.035*	-0.031	-0.029		-0.011	-0.004	-0.001	-0.002	-0.030	0.031	-0.014	-0.081*
		(0.021)	(0.021)	(0.021)	(0.020)		(0.036)	(0.036)	(0.035)	(0.035)	(0.021)	(0.039)	-0.021	-0.042
Employment (log)			0.113***	0.109***	0.106***			0.021	0.018	0.018	0.098***	0.014	0.060***	-0.027
			(0.013)	(0.013)	(0.013)			(0.017)	(0.017)	(0.017)	(0.011)	(0.017)	-0.021	-0.024
Human-Capital-Index			0.146	0.207	0.177			0.819***	0.903***	0.912***	0.164	0.850***	-0.111	1.222***
			(0.168)	(0.169)	(0.168)			(0.303)	(0.316)	(0.315)	(0.161)	(0.327)	-0.176	-0.370
HS-LS ratio			0.004	-0.001	-0.008			0.053**	0.055**	0.052**	-0.011	-0.004	-0.075***	0.080**
			(0.022)	(0.021)	(0.021)			(0.025)	(0.025)	(0.025)	(0.018)	(0.041)	-0.021	-0.035
FDI IN-OUT-ratio				0.034**	0.035***				-0.115***	-0.113***	0.030**	-0.116***	0.029**	-0.066**
				(0.014)	(0.014)				(0.023)	(0.023)	(0.012)	(0.024)	-0.015	-0.027
Observations	2,884	2,884	2,884	2,806	2,806	2,986	2,986	2,986	2,888	2,888	2,815	2,888	2,785	1,938
R-squared	0.279	0.275	0.273	0.283	0.304	0.307	0.313	0.317	0.321	0.323	0.343	0.304	0.220	0.322
F	26.88	27.32	28.85	26.96	26.76	41.51	41.90	41.27	39.89	38.97	28.89	38.10	22.75	23.90
p for K-P rk LM	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
K-P rk Wald F	85.40	84.70	64.79	63.11	67.58	130.1	135.5	102.9	86.49	87.92	465.8	33.94	18.46	75.86

Note: * p<0.10, ** p<0.05, *** p<0.01, robust standard errors in parentheses, in all specifications, constant, country, industry, and time effects are included. All explanatory variables are 1-period lagged. FAB=fabrication, p for K-P rk LM refers to p-vaue for Kleibergen-Paap underidentification test, K-P rk Wald F refers to the Kleibergen-Paap weak identification test.

Comparing these results with those obtained for the trade-based relative functional specialisation measure (Table 4) we observe a similar pattern for the impact of wages on comparative advantages in the R&D business function. Similarly to the first approach, in each model specification, higher real annual wages increase functional specialisation in R&D. This positive coefficient supports hypothesis H1 in the area of the relation between functional specialisation and wages, but the positive impact of GDP per capita on R&D-oriented specialisation cannot be tested through trade-based models due to weak instruments.

In the case of labour productivity and trade-based data, once again we are not able to fully confirm hypothesis H2. An increase in labour productivity promotes comparative advantages in R&D services but not in the fabrication function.

A group of factors reflecting GVC linkages supports us in confirming hypothesis H3 as regards GVC backward participation and its positive impact on increasing specialisation in fabrication activities. Similarly to FDI models, the hypothesis on the negative relation between the fabrication function and geographical distance to hub/exporting partners cannot be proved.

The incorporation of human capital variables significantly increases R-squared (specifications (3) and (8)). In contrast to FDI-based models, the trade based regressions indicate that growth of the number of employees positively influences not only specialisation in the fabrication function but also in the R&D function, both using OLS and IV. This can be the result of a way to measure functional specialisation with the aid of trade-based data. To do that, information about the structure of employment is used. Hypothesis H4 postulates that workers' skills matter for achieving comparative advantages in R&D. None of the wage models ((8), (9), (10)) confirm hypothesis H4. Only in the labour productivity specification (13) is a positive impact of the human capital index recorded.

As regards hypothesis H5 – we fully reject it. A significant and positive impact of FDI flows on functional specialisation patterns does not exist.

In spite of significant differences between ways of measuring FDI- and trade-based functional specialisation, and difficulties in proving some of the hypotheses on the basis of trade data, we confirm the positive impact of growing wages on comparative advantages in R&D-oriented activities. This is confirmed not only with the use of two different databases but also with the aid of different model specifications, different estimators, and different time periods. The use of the IV technique and positively tested instruments leads to the interpretation of these results as causal relations.

Next to the estimates presented in Tables 3 and 4 we provide additional results based on FDI and trade data and covering the period 2003-2014, i.e. the period in which both databases overlap (Appendix, Table A.2.3). The removal of 5 years from the FDI database and 3 years from the trade database affected the results, although the positive impact of real wages, real GDP per capita, and labour productivity on specialisation in the R&D function is still valid (trade database). Moreover, the negative impact of wages, GDP per capita, and the positive impact of labour productivity on the fabrication function is confirmed in the FDI database once again. Similarly to the previous results, the increase in comparative advantages in the fabrication function is supported by the strengthening of GVC backward linkages and the growth of the number of employees. Unfortunately, this limited period of time prevents us from confirming the influence of employees' skills on R&D specialisation.

Table 4 / Trade-based functional specialisation in fabrication and R&D, 2000-2014, instrumental variable regression with fixed effects

	Trade-based FAB					Trade-based R&D					FAB	FAB	R&D
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Wages (log)	0.094	0.008	-0.072	-0.090	-0.065	0.236***	0.259***	0.266***	0.262***	0.261***			
	(0.082)	(0.092)	(0.073)	(0.075)	(0.072)	(0.045)	(0.046)	(0.068)	(0.072)	(0.072)			
GDP-per-Capita (log)											-0.062		
											(0.054)		
Lab-Prod (log)												-0.127*	0.744***
												(0.067)	(0.100)
BW-participation		0.814***	0.418***	0.410***	0.151		0.557***	0.204***	0.213***	-0.094	0.428***	0.392***	0.032
		(0.126)	(0.071)	(0.074)	(0.164)		(0.109)	(0.077)	(0.076)	(0.167)	(0.070)	(0.083)	(0.122)
FW-participation		-0.951***	-0.406**	-0.424***	0.429		-0.747***	-0.195	-0.167	0.354	-0.447***	-0.391**	-0.671**
		(0.258)	(0.159)	(0.163)	(0.365)		(0.231)	(0.179)	(0.177)	(0.313)	(0.160)	(0.182)	(0.282)
BWpart×GDP					0.024*					0.028**			
					(0.013)					(0.013)			
FWpart×GDP					-0.078***					-0.048**			
					(0.026)					(0.023)			
Distance-MP (log)		-0.005	-0.008	-0.010	-0.009		0.015	0.018	0.016	0.015	-0.010	-0.009	-0.013
		(0.018)	(0.012)	(0.012)	(0.012)		(0.020)	(0.012)	(0.013)	(0.013)	(0.012)	(0.013)	(0.025)
Employment (log)			0.382***	0.383***	0.382***			0.367***	0.370***	0.369***	0.381***	0.398***	0.354***
			(0.010)	(0.010)	(0.010)			(0.009)	(0.010)	(0.010)	(0.010)	(0.013)	(0.011)
Human-Capital-Index			-0.016	-0.133	-0.109			0.070	0.031	0.048	-0.097	-0.074	1.225***
			(0.140)	(0.149)	(0.147)			(0.129)	(0.134)	(0.133)	(0.148)	(0.157)	(0.275)
HS-LS ratio			-0.000	-0.003	-0.008			-0.017	-0.027	-0.029*	-0.004	-0.001	-0.022
			(0.016)	(0.017)	(0.016)			(0.016)	(0.017)	(0.017)	(0.016)	(0.017)	(0.031)
FDI IN-OUT-ratio				-0.005	-0.003				-0.020	-0.019	-0.002	0.005	-0.031*
				(0.012)	(0.012)				(0.013)	(0.013)	(0.011)	(0.012)	(0.017)
Observations	2,799	2,624	2,624	2,497	2,497	3,346	3,346	3,346	3,137	3,137	2,497	2,474	1,604
R-squared	0.358	0.390	0.752	0.752	0.758	0.422	0.435	0.723	0.730	0.732	0.760	0.737	0.666
F	45.28	53.05	194.5	187.6	183.6	76.46	78.06	205.0	192.8	187.6	188.1	174.5	94.59
p for K-P rk LM	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
K-P rk Wald F	117.2	95.80	59.88	57.80	62.34	299.4	298.5	239.1	175.5	174.6	921.6	34.52	31.37

Note*:* * p<0.10, ** p<0.05, *** p<0.01, robust standard errors in parentheses, in all specifications, constant, country, industry, and time effects are included. All explanatory variables are 1-period lagged. FAB=fabrication, p for K-P rk LM refers to p-vaue for Kleibergen-Paap underidentification test, K-P rk Wald F refers to the Kleibergen-Paap weak identification test.

The preliminary analyses of functional specialisation patterns in EU countries allowed us to classify them into two separate clusters – the EU15 cluster and the CEE cluster (Kordalska et al. 2022). In Table A.2.4 of the appendix we present regressions for functional specialisation in fabrication and in R&D for these two clusters separately. A group of EU15 countries reveals a similar pattern in terms of factors determining functional specialisation to the pattern presented by the whole sample, i.e we observe the negative impact of real wages and real GDP per capita on the fabrication function, and a positive impact of these factors on the R&D function. Labour productivity positively affects both types of FS. We can see the great importance of the number of employees. What distinguishes CEE countries from EU15 countries is the strength of workers' skills. Even though our results do not support hypotheses 1 and 2 in CEE countries, in these countries both the human capital index and the relation between highly-skilled and low-skilled workers strongly affects functional specialisation in R&D. This means that CEE countries' move along the smile curve towards more profitable activities requires a highly skilled labour force.

Conclusions

The dominant channel of world trade is related to a country's participation in global value chains (GVCs), in which goods and services are produced by different companies in different places in the world and cross borders many times. Changes in international trade have affected not only international flows of goods and services but also the demand for skills and relative wages, bringing benefits and creating new policy challenges. Additionally, the increasingly interconnected global economy has posed significant challenges to understanding how firms and countries participate in the global economy. This is why our analysis aims to better understand the nature and determinants of EU countries' involvement in global value chains, by using the new concept of specialisation, namely functional specialisation.

The development of GVCs led to the emergence of headquarters and factory economies (Timmer et al., 2019). Based on the criterion of technological classification of exports, Bontadini et al. (2021) reveal in the case of Europe, Germany is a headquarters economy with factory Eastern Europe integrating into GVCs by providing low technology intermediates. But such an analysis shows us only a part of the true story. Products in GVCs cross borders many times before they reach the final clients and a country may have technologically advanced products in its exports, which are only assembled in a country. This is why we use the concept of functional specialisation, which concentrates not on products but on different activities in GVCs such as fabrication and R&D. Functional specialisation allows us to assess in which business functions a country has competitive advantages. This is crucial to the governance and control of value chains. Our results highlight the dualism - or functional clubs - within the EU, i.e. CEE countries are particularly specialised in the fabrication stage ('factory economies') and western EU countries are mainly involved in R&D activities (‘headquarters economies’) (Kordalska et al., 2022).

The revealed crucial discrepancies between EU15 and CEE countries in their functional specialisation patterns underline the importance of understanding the factors that determine these patterns. Our results confirm the positive effects of wages on specialisation in the R&D function and the negative effects on FS in fabrication. Increasing labour productivity promotes specialisation in fabrication and R&D. Thus, it appears that there is no place for a single, common wage policy to strengthen functional specialisation in the EU; i.e. possessing comparative advantage in R&D functions (mainly by the EU15) is associated with wage growth, in contrast to countries with a comparative advantage in fabrication (mainly by CEE). These results have important implications for EU economic policy, especially for CEE countries. We state that the low wage profile is not only a historical legacy for CEE but has become an obstacle to future development. The CEE region's low wage profile defines its role in the international division of labour based on a low value-added function, i.e assembly and subcontracting activities with no future prospects. The CEE region has established itself as an important location for foreign direct investment, with clusters in the automotive and electronics sectors embedded in a large supplier network that cannot be easily relocated. We strongly recommend implementing a strategy to achieve additional comparative advantages in the R&D function by CEE countries. Galgóczi's (2017) analysis shows that there is room for rising wages in the economies of CEE, which would strengthen specialisation in the

R&D function. He finds that the wage share[17] is seven percentage points lower in CEE than in Western Europe. In terms of wage-adjusted labour productivity[18] in manufacturing, all CEE countries fare far better than Germany, i.e there is a 'productivity reserve' in these economies that provides scope for wage increases.

Our results show that raising wages alone will not help foster the functional specialisation patterns in R&D unless the skill base is improved. Investing in the skills of workers in the EU is *a sine qua non* for moving up the smile curve and achieving higher value added. It is why export performance is primarily determined by supply chains and often depends on past decisions to build or expand these capabilities. So, these decisions are mostly influenced by the availability of skilled labour and competencies. Human capital development could be considered a centrepiece of the EU15 policy to strengthen these countries' specialisation in R&D functions, but also as the core of a new policy for the CEE countries to climb the smile curve. The development of FS based on a relatively highly skilled workforce would allow some CEE countries to achieve additional specialisation in R&D functions, as some Asian countries have done (de Vries et al. 2019).

Our results also confirm that GDP per capita positively affects functional specialisation in R&D activities. In a country which has achieved higher income status, institutions can help leverage GVC engagement by fostering skill-building, innovation, and efficient access to capital, by supporting the inclusion of more local enterprises and workers in the GVC network; and by focusing on structural reforms that increase domestic labour productivity and skills (World Bank 2017).

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[17] A wage share is a t indicator that shows how value added is distributed between capital and labour in the whole economy.

[18] Wage-adjusted productivity is the apparent labour productivity (defined as value added at factor costs divided by the number of persons employed) divided by average personnel costs (defined as personal costs divided by the number of persons employed). For example, in 2013 the German manufacturing sector, with labour costs of EUR 51,500 per employee, achieved value added of EUR 67,900 per employee, which means (67900/51500 equals 1,32) that for EUR 100 of labour costs, value added of EUR 132 was achieved; in Hungary, on the other hand, value-added of EUR 211 was achieved for EUR 100 in labour costs. All CEE countries, but in particular Poland, Latvia and Romania had significantly higher wage-adjusted productivity in manufacturing than Germany.

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Appendix

APPENDIX 1: CLASSIFICATION OF FUNCTIONS AND INDUSTRIES

Table A.1.1 / Mapping of activities into value chain functions

Activity in the fDi cross-border monitor	Value-chain functions (narrow categories)	Value-chain functions (broad categories)
Research & Development	R&D and related services	Pre-production
Design, Development & Testing		
Headquarters	Headquarter services	
Manufacturing	Production	Production
Recycling		
Extraction*		
Business Services	Sales, marketing, logistics, retail and other business services	Post-production
Logistics, Distribution & Transportation		
Retail		
Sales, Marketing & Support		
Customer Contact Centre		
Shared Services Centre		
ICT & Internet Infrastructure	Technical services, maintenance & training	
Technical Support Centre		
Education & Training		
Maintenance & Servicing		

Note: * For chemicals sector only.

Table A.1.2 / Functional specialisation in trade approach – business functions and ISCO88 occupations

Occupations	1-digit ISCO88	3-digit ISCO88	Business functions	Example of occupation
Legislators, Senior Officials and Managers	1	111–131	management	directors and chief executives
Professionals	2	211–235	R&D	mathematicians, statisticians and related professionals
		241-247	marketing	business professionals
Technicians and Associate Professionals	3	311–323, 331-334	R&D	physical and engineering science technicians
		341-348	marketing	business services agents and trade brokers
Clerks	4	411–422	marketing	client information clerks
Service Workers and Shop and Market Sales Workers	5	511–522	marketing	shop, stall and market salespersons and demonstrators
Skilled Agricultural and Fishery Workers	6	611–615	fabrication	fishery workers, hunters and trappers
Craft and Related Trades Workers	7	711–744	fabrication	electrical and electronic equipment mechanics and fitters
Plant and Machine Operators and Assemblers	8	811–834	fabrication	automated-assembly-line and industrial-robot operators
Elementary Occupations	9	911-916	marketing	street vendors and related workers
		921–933	fabrication	manufacturing labourers

Source: Authors' elaboration based on Timmer et al. (2019), 'Online appendix with replication files.

Table A.1.3 / NACE Rev. 2 industries used for the analysis at the function-industry-country level

Description	NACE Rev. 2
Manufacture of:	
food and beverages	10
textiles; wearing apparel; leather	13-15
chemicals	20
pharmaceuticals	21
metals and metal products	24-25
computer, electronic and optical products	26
electrical equipment	27
machinery and equipment	28
motor vehicles	29
other transport equipment	30

Table A.2.1 / FDI-based functional specialisation in fabrication and R&D, 2003-2019, OLS regression with fixed effects

	FDI-based approach – Fabrication					FDI-based approach – R&D					FAB	R&D
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Wages (log)	0.015	0.026	-0.000	0.008	0.010	0.118**	0.106**	0.088*	0.089*	0.091*		
	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)	(0.049)	(0.049)	(0.049)	(0.051)	(0.051)		
Lab-Prod (log)											0.052***	0.011
											(0.017)	(0.032)
BW-participation		0.564***	0.496***	0.504***	-0.124		-0.229	-0.224	-0.307	-1.144***	0.516***	-0.334*
		(0.102)	(0.094)	(0.097)	(0.206)		(0.190)	(0.189)	(0.192)	(0.402)	(0.096)	(0.190)
FW-participation		0.367***	0.582***	0.676***	-0.247		0.579	0.608	0.553	-0.865	0.651***	0.546
		(0.140)	(0.133)	(0.152)	(0.313)		(0.411)	(0.406)	(0.419)	(0.705)	(0.152)	(0.418)
BWpart×GDP					0.056***					0.073**		
					(0.017)					(0.032)		
FWpart×GDP					0.082***					0.127**		
					(0.023)					(0.055)		
Distance-MP (log)		-0.017	-0.016	-0.014	-0.015		-0.018	-0.010	-0.006	-0.007	-0.014	-0.009
		(0.017)	(0.017)	(0.017)	(0.017)		(0.036)	(0.036)	(0.036)	(0.036)	(0.017)	(0.036)
Employment (log)			0.120***	0.117***	0.116***			0.006	0.005	0.006	0.112***	0.008
			(0.009)	(0.009)	(0.009)			(0.016)	(0.016)	(0.016)	(0.009)	(0.016)
Human-Capital-Index			-0.018	0.061	0.067			0.930***	1.011***	1.025***	0.093	1.016***
			(0.132)	(0.135)	(0.134)			(0.294)	(0.304)	(0.304)	(0.136)	(0.305)
HS-LS ratio			-0.033***	-0.035***	-0.037***			0.061**	0.065***	0.061**	-0.039***	0.070***
			(0.011)	(0.011)	(0.011)			(0.025)	(0.025)	(0.025)	(0.011)	(0.025)
FDI IN-OUT-ratio				0.021**	0.022**				-0.124***	-0.122***	0.021**	-0.125***
				(0.010)	(0.010)				(0.024)	(0.024)	(0.010)	(0.024)
Observations	3,960	3,960	3,960	3,833	3,833	3,102	3,102	3,102	2,993	2,993	3,832	2,992
R-squared	0.303	0.311	0.357	0.347	0.350	0.301	0.303	0.307	0.315	0.316	0.349	0.313
F	33.54	34.04	38.98	35.67	34.97	41.21	40.82	40.62	39.28	38.49	36.57	39.61

Note: * p<0.10, ** p<0.05, *** p<0.01, robust standard errors in parentheses, in all specifications, constant, country, industry, and time effects are included. All explanatory variables are 1-period lagged. FAB=fabrication.

Table A.2.2 / Trade-based functional specialisation in fabrication and R&D, 2000-2014, OLS regression with fixed effects

	Trade-based approach – Fabrication					Trade-based approach – R&D					FAB	R&D
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Wages (log)	0.145***	0.169***	0.103***	0.087***	0.089***	0.186***	0.204***	0.132***	0.121***	0.124***		
	(0.030)	(0.036)	(0.028)	(0.027)	(0.027)	(0.037)	(0.045)	(0.037)	(0.038)	(0.038)		
Lab-Prod (log)											0.120***	0.162***
											(0.014)	(0.019)
BW-participation		0.594***	0.304***	0.306***	0.056		0.398***	0.106	0.134*	-0.126	0.308***	0.134*
		(0.099)	(0.063)	(0.065)	(0.147)		(0.101)	(0.073)	(0.076)	(0.165)	(0.061)	(0.072)
FW-participation		-1.056***	-0.648***	-0.506***	-0.062		-0.974***	-0.573***	-0.364*	0.095	-0.570***	-0.451**
		(0.178)	(0.148)	(0.172)	(0.334)		(0.184)	(0.170)	(0.195)	(0.315)	(0.168)	(0.186)
BWpart×GDP					0.023*					0.023*		
					(0.012)					(0.013)		
FWpart×GDP					-0.041					-0.043*		
					(0.026)					(0.023)		
Distance-MP (log)		0.007	0.007	0.005	0.005		0.013	0.015	0.013	0.012	0.003	0.009
		(0.018)	(0.011)	(0.012)	(0.011)		(0.020)	(0.012)	(0.013)	(0.013)	(0.011)	(0.012)
Employment (log)			0.368***	0.369***	0.369***			0.369***	0.371***	0.371***	0.361***	0.360***
			(0.008)	(0.008)	(0.008)			(0.008)	(0.009)	(0.009)	(0.008)	(0.008)
Human-Capital-Index			0.016	-0.048	-0.034			0.053	0.001	0.015	-0.005	0.059
			(0.109)	(0.115)	(0.114)			(0.126)	(0.132)	(0.131)	(0.113)	(0.129)
HS-LS ratio			-0.028**	-0.029**	-0.030**			-0.002	-0.010	-0.012	-0.035***	-0.019
			(0.013)	(0.012)	(0.012)			(0.014)	(0.014)	(0.014)	(0.012)	(0.013)
FDI IN-OUT-ratio				0.011	0.012				-0.030**	-0.029**	0.009	-0.033***
				(0.011)	(0.011)				(0.012)	(0.012)	(0.011)	(0.011)
Observations	3,750	3,500	3,500	3,272	3,272	3,750	3,500	3,500	3,272	3,272	3,271	3,271
R-squared	0.347	0.379	0.731	0.745	0.746	0.410	0.426	0.721	0.731	0.732	0.753	0.742
F	59.59	67.39	233.4	223.6	219.2	76.53	71.77	194.8	182.5	178.2	223.7	195.2

Note: * p<0.10, ** p<0.05, *** p<0.01, robust standard errors in parentheses, in all specifications, constant, country, industry, and time effects are included. All explanatory variables are 1-period lagged. FAB=fabrication.

Table A.2.3 / FDI- and trade-based functional specialisation in fabrication and R&D in overlapping period 2003-2014, instrumental variable regression with fixed effects

	FDI-based approach						Trade-based approach					
	Fabrication			R&D			Fabrication			R&D		
Wages (log)	-0.319*			0.047			0.015			0.137***		
	(0.176)			(0.110)			(0.098)			(0.046)		
GDP-per-Capita (log)		-0.181*			0.499			0.007			0.868***	
		(0.102)			(0.496)			(0.065)			(0.149)	
Lab-Prod (log)			0.141*			0.079			0.043			0.163***
			(0.085)			(0.083)			(0.050)			(0.036)
BW-participation	0.672***	0.788***	0.263**	-0.766***	-0.486**	-0.506**	0.372***	0.367***	0.163*	0.204**	0.293***	0.201***
	(0.138)	(0.117)	(0.126)	(0.245)	(0.236)	(0.231)	(0.081)	(0.071)	(0.084)	(0.101)	(0.094)	(0.075)
FW-participation	0.643***	0.637***	0.502***	0.555	0.501	0.377	-0.284	-0.284	-0.398*	0.164	-0.042	-0.365*
	(0.226)	(0.220)	(0.191)	(0.510)	(0.518)	(0.487)	(0.174)	(0.175)	(0.224)	(0.223)	(0.213)	(0.200)
Distance-MP (log)	0.005	0.005	0.075	0.068	0.071	0.067	0.008	0.008	0.027	-0.027	0.018	-0.007
	(0.026)	(0.026)	(0.052)	(0.058)	(0.059)	(0.058)	(0.013)	(0.013)	(0.027)	(0.032)	(0.016)	(0.013)
Employment (log)	0.112***	0.108***	0.114***	0.042*	0.027	0.024	0.375***	0.375***	0.386***	0.366***	0.372***	0.367***
	(0.012)	(0.012)	(0.016)	(0.022)	(0.022)	(0.023)	(0.007)	(0.007)	(0.010)	(0.009)	(0.008)	(0.007)
Human-Capital-Index	-0.120	0.072	-0.044	0.171	-0.027	0.227	0.035	0.027	0.013	0.079	-0.208	0.245
	(0.230)	(0.232)	(0.256)	(0.531)	(0.567)	(0.518)	(0.145)	(0.138)	(0.180)	(0.208)	(0.191)	(0.152)
HS-LS ratio	-0.002	-0.016	-0.030	0.074*	0.035	0.086**	-0.008	-0.007	-0.008	0.008	-0.098***	-0.006
	(0.025)	(0.020)	(0.020)	(0.045)	(0.073)	(0.043)	(0.017)	(0.015)	(0.015)	(0.016)	(0.025)	(0.014)
FDI IN-OUT-ratio	0.030**	0.035**	0.001	-0.140***	-0.160***	-0.156***	0.013	0.013	0.027**	-0.007	-0.036***	-0.034***
	(0.014)	(0.014)	(0.017)	(0.034)	(0.035)	(0.034)	(0.012)	(0.012)	(0.013)	(0.015)	(0.013)	(0.012)
Observations	2,546	2,546	1,860	1,998	2,070	2,069	2,747	2,747	1,993	2,007	2,866	2,865
R-squared	0.314	0.348	0.326	0.327	0.310	0.321	0.763	0.762	0.777	0.733	0.678	0.759
F	25.12	25.92	16.34	41.11	38.37	40.40	233.3	232.7	221.0	172.2	144.9	224.2
p for K-P rk LM	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
K-P rk Wald F	46.38	349.2	29.48	48.24	52.18	780.7	45.21	423.0	37.92	206.5	88.36	1120

Note: * p<0.10, ** p<0.05, *** p<0.01, robust standard errors in parentheses, in all specifications, constant, country, industry, and time effects are included. All explanatory variables are 1-period lagged. p for K-P rk LM refers to p-vaue for Kleibergen-Paap underidentification test, K-P rk Wald F refers to the Kleibergen-Paap weak identification test.

Table A.2.4 / FDI-based functional specialisation in fabrication and R&D for EU15 and CEE countries 2003-2019, instrumental variable regression with fixed effects

	EU15 countries						CEE countries					
	Fabrication			R&D			Fabrication			R&D		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Wages (log)	-0.645*			0.247**			-0.322			-0.078		
	(0.382)			(0.104)			(0.348)			(0.093)		
GDP-per-Capita (log)		-1.157**			2.509**			-0.743			-0.074	
		(0.554)			(1.084)			(0.713)			(0.436)	
Lab-Prod (log)			0.113***			0.132*			0.020			-0.016
			(0.026)			(0.070)			(0.044)			(0.081)
BW-participation	1.293***	1.203***	0.770***	0.641**	0.922***	1.025***	-0.303	-0.185	0.029	-1.414***	-1.330***	-1.314***
	(0.134)	(0.133)	(0.138)	(0.267)	(0.311)	(0.247)	(0.282)	(0.166)	(0.127)	(0.277)	(0.261)	(0.286)
FW-participation	1.793***	1.262***	1.253***	3.072***	3.429***	3.049***	-0.842***	-0.878***	-0.348*	-0.233	-0.183	-0.156
	(0.358)	(0.263)	(0.247)	(0.588)	(0.629)	(0.572)	(0.310)	(0.320)	(0.195)	(0.486)	(0.492)	(0.487)
Distance-MP (log)	-0.059**	-0.048**	-0.015	0.041	0.090*	0.017	0.022	-0.061	0.015	-0.005	-0.011	-0.005
	(0.029)	(0.024)	(0.019)	(0.041)	(0.051)	(0.041)	(0.049)	(0.094)	(0.048)	(0.121)	(0.127)	(0.119)
Employment (log)	0.060***	0.045***	0.060***	0.059***	0.052**	0.016	0.082***	0.076***	0.063***	0.082***	0.080***	0.073***
	(0.020)	(0.012)	(0.012)	(0.022)	(0.023)	(0.022)	(0.017)	(0.013)	(0.013)	(0.026)	(0.026)	(0.025)
Human-Capital-Index	0.336	-0.829	0.426*	0.190	2.704**	0.314	-0.330	-0.554	-0.048	1.402***	1.438***	1.540***
	(0.258)	(0.627)	(0.219)	(0.534)	(1.216)	(0.538)	(0.290)	(0.445)	(0.153)	(0.384)	(0.387)	(0.359)
HS-LS ratio	0.057	0.039	-0.051**	-0.080	-0.220**	-0.024	-0.029**	-0.024*	-0.028**	0.135***	0.136***	0.137***
	(0.056)	(0.044)	(0.025)	(0.052)	(0.092)	(0.049)	(0.013)	(0.013)	(0.012)	(0.031)	(0.032)	(0.030)
FDI IN-OUT-ratio	-0.028	0.018	0.025*	-0.147***	-0.168***	-0.170***	0.016	0.006	0.007	0.092***	0.089**	0.076**
	(0.029)	(0.015)	(0.014)	(0.032)	(0.032)	(0.031)	(0.017)	(0.013)	(0.012)	(0.036)	(0.035)	(0.034)
Observations	2,008	2,008	2,130	1,861	1,861	1,949	1,681	1,681	1,712	1,036	1,036	1,053
R-squared	0.307	0.463	0.487	0.314	0.260	0.309	0.201	0.211	0.252	0.357	0.358	0.363
F	34.74	40.71	46.77	30.17	27.94	26.24	7.946	7.486	8.059	24.02	24.30	25.26
p for K-P rk LM	0.008	0.000	0.000	0.000	0.000	0,000	0.003	0.000	0.000	0.000	0.000	0.000
K-P rk Wald F	4.898	29.02	826.8	37.11	18.32	786.7	5.661	7.870	205.4	50.89	16.25	119.9

Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$, robust standard errors in parentheses, in all specifications, constant, country, industry, and time effects are included. All explanatory variables are 1-period lagged. p for K-P rk LM refers to p-vaue for Kleibergen-Paap underidentification test, K-P rk Wald F refers to the Kleibergen-Paap weak identification test.

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