Koerner and Moigne *J Labour Market Res* (2023) 57:25
https://doi.org/10.1186/s12651-023-00346-7

Journal for Labour Market Research

ORIGINAL ARTICLE

Open Access

FDI and onshore task composition: evidence from German firms with affiliates in the Czech Republic

Konstantin Koerner[1*] and Mathilde Le Moigne[2,3]

Abstract

How does a firm's foreign direct investment (FDI) in a low-wage country change its onshore task demand in a high-wage country? Is the shift more intensive for jobs that the literature has designated offshorable? We address these questions using a matched difference-in-differences (DiD) approach with data on German firms that have similar propensities to conduct FDI in the Czech Republic. Our novel matching procedure draws on post-lasso logit estimates and shows that high task intensities of managing, administration, and labor legislation play a major role in firms' engagement in international expansion. The outcomes of the DiD estimation show that after acquiring a foreign affiliate, multinational enterprises (MNEs) increase the intensities of their activities typical of headquarters such as *managing*, *analyzing*, and *negotiating* relative to the corresponding task intensities among non-MNEs. We also find sector-specific decreases, such as a reduction in typical production tasks (*monitoring*, *producing*, *measuring*) in manufacturing MNEs or typical service tasks (*informing*, *medical*, *repairing*) in service MNEs.

Keywords FDI, Tasks, Trade, Offshorability, Central and Eastern Europe, Germany

JEL Classification F16, F66, J24

1 Introduction

Globalization is increasingly becoming characterized by the exchange of ideas and tasks. Multinational enterprises (MNEs) benefit from different expertise clusters around the world, where online knowledge distribution and cross-border exchanges of information have become the standard rather than the exception. This brings new challenges to the quantification of the effects of globalization on the domestic labor market, since the value-added flows are often difficult to measure. While it has become clear that the new forms of internationally fragmented production have heterogeneous effects on domestic labor demand (recently, e.g., in Borrs and Knauth 2021; see also the survey by Hummels et al. 2018), this heterogeneity in terms of tasks is still understudied. Even from a theoretical perspective, the implication is ambiguous: while the increased sourcing of tasks from abroad may replace some kinds of domestic jobs, the cost savings from imports drive up productivity and may induce scaling effects and expansion of demand for other jobs (e.g., Grossman and Rossi-Hansberg 2008). The net effect on domestic labor is, hence, an empirical question. Prior studies have addressed this question within manufacturing industries and for broad distinctions of labor such as a worker's skill level or whether the worker is blue or white collar (Feenstra and Hanson 1999). However, particularly when we consider the service sector, these groups are too aggregated. More recent papers have thus considered MNEs and distinguished jobs by their tradability or offshorability (see, e.g., Blinder and Krueger 2013; Brändle and Koch 2017) or by their task profile,

*Correspondence:
Konstantin Koerner
konstantin.koerner@iab.de
[1] Institute for Employment Research, Nuremberg, Germany
[2] Princeton University, Princeton, USA
[3] University of Zurich, Zurich, Switzerland

such as task routineness, interactivity or production (e.g., Autor et al. 2003; Becker et al. 2013).[1] However, even using these measures, it is unclear whether the onshore demand changes (e.g., in the share of interactive tasks) are driven by the need for management and coordination tasks to participate in an international network or by substituting forces (e.g., of noninteractive tasks).

In this paper, we analyze firms' onshore demand changes for very specific tasks (e.g., *legal, measuring, selling*) by following their outward FDI in a low-wage country. Specifically, we use a unique dataset covering the universe of German MNEs with affiliates in the Czech Republic. The key challenge in identifying these effects is accounting for the endogeneity of the treatment deriving from firms' selectivity in conducting FDI and particular firm characteristics. While some of these MNE characteristics, such as high productivity and large size, have been broadly studied (e.g., Helpman et al. 2004; Antras and Helpman 2004; Antràs and Rossi-Hansberg 2009; Yeaple 2006; Nocke and Yeaple 2008), surprisingly little is known about these firms' typical task intensities and how they differ from non-MNEs. We contribute to the literature by addressing this shortcoming by identifying the firms' typical task intensities through the development of a novel two-step matching strategy that combines machine learning methods (lasso) with propensity score matching[2] and conducting a difference-in-differences (DiD) analysis that explores the effective shifts in MNEs' task demand in response to FDI.

In the first step, we explore the particular task intensities of firms engaging in FDI on the cusp of their international expansion and obtain a notion of FDI-facilitating tasks, i.e., tasks that may decrease the cost–benefit ratio of FDI. In detail, we apply cross-validation to logit regressions with a least absolute shrinkage and selection operator (lasso). The outcome is a data-driven specification that identifies, among others, *managing*, *administration*, and *labor legislation* as tasks with high predictive power for the firm's propensity to conduct FDI (dynamic correlations).[3] We then use the propensity scores from the post-lasso logit regression to match MNEs with similar firms that have not invested in any foreign country (non-MNEs).

The model selection greatly improves the quality of the matches (e.g., lower Mahalanobis distances) and, hence, mitigates concerns about firms' selectivity in conducting FDI. Employing the matched sample, in a second step, we perform a DiD analysis to study how FDI changes MNEs' task intensities relative to those of non-MNEs. We show that in manufacturing MNEs, the relative share of jobs comprising many unskilled manual tasks decreases while the shares of managers and jobs involving skilled commercial and administrative tasks increase. In service MNEs, we find relative decreases in the share of jobs involving typical service-related tasks such as medical tasks and informing/consulting and, again, relative increases in the shares of managers and jobs featuring skilled commercial and administrative tasks.

Our new approach is possible because it draws on a newly available dataset compiled by the Institute for Employment Research (IAB), namely, the *Research on Locational and Organizational Change* (IAB-ReLOC).[4] The dataset is designed for event studies and contains precise FDI dates for the universe of German MNEs with affiliates in the Czech Republic as of 2010 and data on a sample of control firms. The control firms have no foreign affiliates or indirect foreign investments, and their sample is stratified and oversamples larger firms within industries such that they are more comparable to MNEs. The dataset traces the firms from 1985 to 2011 and contains detailed information on the onshore employment of these firms from high-quality administrative accounts of the Federal Employment Agency. In particular, it contains the workers' occupation codes, which we link to survey data about the specific task content of jobs.

Although the specific country pair restricts external validity, we still expect our findings to be transferable to similar trade relationships. This is particularly the case because the Czech Republic is a well-chosen target country for German FDI due to its marked wage differentials with respect to Germany and because it illustrates the increasing significance of Central European states for German offshoring activities.[5,6] Within this country

[1] Autor (2013, p. 195) states the following: "*It is regrettably the case that there are almost as many distinct task classifications as there are papers in the task literature*".

[2] The two-step matching procedure should not be confused with the two-step estimation in IV approaches or in the procedure of Helpman et al. (2008) to correct for selectivity in gravity equations. We use two steps for matching and account for the nonrandom sampling using clustered standard errors at the match level.

[3] This is an approach suggested by Athey and Imbens (2019); Mullainathan and Spiess (2017) that has thus far primarily been employed in the forecast literature, such as in Verme (2020).

[4] The data are confidential but can be accessed upon application for noncommercial research via on-site use at the IAB.

[5] The OECD (2021) reports that in 1995, the average yearly wages in the Czech Republic amounted to 14,386 USD (at 2021 PPPs), while that in Germany was 45,840 USD. In 2010, average wages were 24,808 USD in the Czech Republic and 49,085 USD in Germany.

[6] According to OECD Globalization/FDI statistics, the Central and Eastern European countries were the largest recipients of German FDI among low-wage countries in 2010 (together receiving more than the sum of the outward FDI stock from China, Russia, and Turkey). Bundesbank (2014) approximates that the Czech Republic represents 24% of German MNEs' workforce in Central and Eastern European countries.

group, the Czech Republic is the largest recipient of German FDI (Marin 2004, p. 4), most of which targets offshoring activities, as approximately 76% of the German affiliates in this country exchange inputs with their parent firms (Marin 2006, p. 614). In the IAB-ReLOC administrative data, we cannot distinguish the motive for FDI (vertical or horizontal), but we would refrain from drawing such a distinction in any case since FDI most likely follows complex integration strategies, as convincingly shown by Yeaple (2003).[7] Moreover, the data do not record whether the MNEs have FDI in any other country or the timing of such events. If the timing of those events is long before FDI to the Czech Republic, our estimates could be attenuated and represent a rather conservative estimate of the effect size. If the timing of those events is close to the FDI to the Czech Republic, we could overestimate the effect of the specific FDI to the Czech Republic. Thus, we need to interpret the effects more generally as an effect due to FDI.

Beyond these limitations, the data have several advantages for the analysis of MNEs' onshore employment. First, German MNEs have substantial weight in the global economy and account for 87% of revenue concentration within Europe (Melitz 2020, p. 11).[8] Second, compared to other prevalently used FDI data for Germany, our data are not impaired by selectivity concerns with respect to small or medium-sized companies. Third, we do not have to merge these data with trade measures in coarse industry classifications but already have detailed firm-level information on the date of FDI events. Finally, German occupations can be mapped directly to task information in the BiBB Employment Survey, which has already been used in prominent task analyses (Spitz-Oener 2006; Becker et al. 2013; Becker and Muendler 2015). Thus, unlike other precise employer–employee data such as those for Denmark or France, we do not need to employ several crosswalks to map jobs to the American O*net directory.[9] Both datasets are derived from the same population, i.e., employees in Germany, so we have no extra noise from occupational differences in task performance across countries.

We find that the high task intensities in (labor) legislation, management, and administrative tasks are associated with a firm's decision to engage in FDI. These tasks seem to accompany a firm's capability of bearing the high (fixed) costs of conducting FDI, so an important share of the organizational costs of international coordination pertains to legal contracting (labor legislation), management, and international coordination.[10]

The matched DiD design then allows us to identify the MNEs' shifts in task intensities relative to the task intensities in non-MNEs. For manufacturing MNEs, we find relative declines in low-wage production-related tasks such as *monitoring*, *producing*, *measuring*, and *repairing*. In service MNEs, the declining task intensities are also characterized by below-average wage compensation. We find decreases in the demand for some typical service tasks, such as *informing*, *medical tasks* (in private nonhealth service industries, e.g., nursing homes or labor recruitment agencies for nursing assistance at private homes), and *repairing*. On the positive side, the estimates show that regardless of the economic sector, MNEs increase headquarters activities such as *organizing the work of others* and *analyzing*. These are also tasks that positively correlate with future FDI decisions (e.g., *management*) in the logit regressions.

Our paper integrates well into a large and expanding body of literature on the effect of international integration on domestic labor demand. Offshoring affects individual employment, labor market transitions, and wages, as shown, for example, by Geishecker (2006) for Germany, Egger et al. (2007) for Austria, Munch (2010) for Denmark, and Feenstra and Hanson (1996) for the US. Boehm et al. (2020) highlight the importance of MNEs in this context. The majority of papers from this strand of literature focus on the effect of arm's-length trade in the manufacturing sector and on skill groups. Ebenstein et al. (2014) and Baumgarten et al. (2013) shift the focus to the occupation level, which can explain a higher fraction of the labor market changes induced by offshoring, especially since they include measures for nonroutine and interactive tasks. We expand the scope of the analysis by also considering the service sector, similarly to Crino (2010) and Liu and Trefler (2019) for the US and Eppinger (2019) for Germany. Instead of measuring cross-border flows of services, however, we consider FDI (Sethupathy 2013), which we suspect to be a more precise

[7] Distinguishing the FDI motive is only possible by using the IAB-ReLOC survey, which has a low response rate among MNEs. A corresponding analysis by Moritz et al. (2020) has already concluded that German MNEs follow complex integration strategies with their FDI in the Czech Republic.

[8] The concentration is measured by the Herfindahl–Hirschman Index with data from 2000 to 2017. See also Bighelli et al. (2020).

[9] By Danish employer–employee data, we are referring to the administrative registers at Statistics Denmark, which include the Firm Statistics Registers (FirmStat) and the Integrated Database for Labor Market Research (IDA). The respective data for France are available in the Panel for Annual Declaration of Social Data by the INSEE. In the US, MNE data rarely contain information on occupational titles, which are needed for the analysis of tasks. The BEA Survey of Direct Investment Abroad does not include information on workforce composition.

[10] Antràs (2005); Helpman et al. (2004) highlights the tradeoff between contract incompleteness with foreign suppliers and organizational fixed costs.

measure for capturing the effects of globalization in the service sector because not all cross-border exchanges of service tasks can be quantified by flow data. For example, in the service sector, information or consultation is a prevalent activity that can be conducted over the phone (and internally within the firm without any direct cross-border payments).[11]

Using FDI-conducting MNE data, Hakkala et al. (2014) and Becker et al. (2013) analyze the onshore employment changes along unidimensional indices that quantify nonroutine or interactive occupations (but not tasks directly). In a subsequent work, Becker and Muendler (2015) investigate offshoring effects separately for the tasks from the BiBB Employment survey and find increased specialization of the German workforce into nonoffshorable workplace activities and knowledge requirements. They propose a general industry-level analysis, however, whereas we can directly map tasks to the MNE workforce and analyze firm-level effects following FDI.

Our analysis is complementary to those of Koerner et al. (2022) and Koerner et al. (2023), who use the same firm-level dataset and a similar matching approach. The former paper shows that FDI negatively affects employment growth relative to that of noninvesting firms. The latter further registers the effects of FDI on employment and reveals that the separation rates of incumbent workers (in the MNEs) are not affected. Firms adjust to the altered labor needs of these workers by assigning them to different task sets (occupations). In this paper, we add to these findings and identify demand changes for nuanced tasks.

Most of the associated offshoring and trade literature (e.g., Hummels et al. 2014; Dauth et al. 2014; Kovak et al. 2021; Bernard et al. 2020) addresses endogeneity concerns via instrumental variable (IV) approaches. Since our outcome variables involve a battery of different tasks, it is difficult to construct an instrument for the timing of a firm's FDI that satisfies all validity assumptions. Additionally, the high quality of our data, especially those for FDI, mitigates measurement bias from the independent variables. We are thus convinced that using a DiD approach of matched firms has only weak disadvantages regarding causality relative to using IV.

Our focus on employment recomposition also contributes to the literature on job polarization, which includes seminal works on skill-biased technical change by ALM and Autor et al. (2006). This change has been narrowed down to the disappearance of routine jobs, which represent a large fraction of middle-income jobs (Michaels et al. 2014; Cortes 2016; Cortes et al. 2017, 2020; Atalay et al. 2020) that either become automated (Dauth et al. 2021; Autor and Salomons 2018; Graetz and Michaels 2018) or move to low-wage countries (Goos et al. 2014; Cortes and Morris 2020). While we cannot trace the aggregate cross-border movements of middle-income jobs (since the IAB-ReLOC does not contain sufficient data on the affiliates' employment), our negative estimates still exhibit a relative decrease in demand for low- and medium-wage (production) tasks in German (manufacturing) MNEs. This paper also adds to the discussion on workplace specialization (Cortes and Salvatori 2019; Becker et al. 2018; Bernard et al. 2020), as we find that FDI to a low-wage country expands the intensity of high-wage social tasks, such as management and commercial-related activities. The growing importance of these social tasks in the long-run trend of within-firm job polarization has recently been emphasized by Cortes et al. (2021) and contrasts with the findings of Marin et al. (2018) that German MNEs offshore management tasks to the CEECs.

This strand of literature is highly related to the field of job offshorability. The latter addresses questions on how many and/or which jobs could be performed from abroad and has been based predominantly on subjective judgments regarding the set of occupational activities (Blinder 2009; Blinder and Krueger 2013) or tasks (Brändle and Koch 2017; Hummels et al. 2014; Becker et al. 2013) that can be deemed offshorable or on other questionable measures, such as the measurement of geographical concentration (e.g., Jensen and Kletzer 2010)[12] or the use of information and communication technology (e.g., Van Welsum and Vickery 2005). Notably, there is a choice between either a subjective forward-looking analysis of *potentially* offshorable jobs or an objective data-driven approach to determining which jobs have actually been traded. In this paper, we focus on the latter and observe how tasks respond in the domestic part of an MNE when it invests in a low-wage country. This approach thus enables us to compare observed employment shifts with the corresponding categorization of already established offshorability and task indices in Appendices C and E.

The remainder of the paper is structured as follows. We present the dataset in Sect. 2. Section 3 analyzes which task intensities correlate with an FDI decision, according to the logit-lasso approach. Anticipating these insights, in Sect. 4, we match firms by propensity scores and use a DiD design to identify the employment adjustment of

[11] The majority of international statistics on trade in services use FDI as the primary source of measurement. See, for example, the Manual on Statistics of International Trade in Services from OCDE et al. (2010).

[12] For instance, Blinder (2009) criticizes the value of offshorability (of 96%) of lawyers and judges obtained with this method.

onshore tasks to FDI events. Finally, Sect. 5 concludes the paper.

2 Data and descriptive statistics

This section introduces the various sources of our data. The integral components of our dataset are the classification of occupations and measures of task content. Combined with administrative worker- and firm-level FDI data, these data are exceptionally suitable for our analyses.

2.1 IAB-ReLOC

Our dataset is derived from several administrative sources compiled within the scope of the IAB ReLOC project. The data cover the universe of German MNEs with one or more affiliates (having an MNE ownership share of at least 25%) reported in the Czech Commercial Register as of 2010, with precise information on the date of the FDI event but no information about the type of FDI (vertical, e.g., efficiency seeking, or horizontal, e.g., market seeking) or the arm's-length trade of the firm.[13] Firms in the reference group (non-MNEs) have neither a foreign sister company nor any direct or indirect FDI in any country.[14] Since the reference group was directly created to ensure its suitability for comparison with the MNE group, the sample of non-MNEs is stratified and oversamples medium-sized and large firms by industry. We focus on the manufacturing and private service sectors, which include 2549 German MNEs and 7138 non-MNEs during our observation period, which ranges from 1985 to 2011.[15]

The German firms' names are linked to the IAB Establishment History Panel following the record-linkage procedure described by Schäffler (2014). The establishment data are derived from administrative accounts at the German Federal Labor Agency and contain information on the establishments' corresponding industry, location and foundation date.[16] For multisite firms, we choose the region and industry that make up the highest share of the firm's employment. A readily available plant identifier enables us to directly connect the plants with employment information from the IAB Integrated Employment Biographies. The latter dataset covers all employees from the German social security system. The labor force of the parent MNEs in our sample amounts to 1.9 million workers (in 2008), or approximately 6% of all workers in Germany subject to social security. The worker-level information includes daily wages, gender, age, contract type (marginal, part-time or full-time) and, most important, up to 330 (3-digit) occupation codes (*Klassifikation der Berufe* 1988, KldB88) with respect to economic activity. These can be linked to on-the-job tasks and knowledge requirements from the *BiBB Employment Survey*.

2.2 BiBB employment survey

The BiBB Employment Survey is a representative cross-section of the German labor force that asks workers about their career histories and detailed workplace and job characteristics, such as working conditions, formal qualifications, other knowledge requirements, and specific tasks performed on the job. The survey is conducted every 6 years by the Institute for Vocational Education and Training (BiBB) and other institutes, such as the IAB or the Federal Institute for Occupational Safety and Health.[17] The longitudinal scope of the survey is limited due to changes in the methodology between the waves and because only a small fraction of questions are repeated throughout the different waves. To avoid any disturbance due to differences in the measurement of the tasks, we focus solely on the wave that is closest to the middle of our sample period, i.e., 1998/1999. In this survey, workers answered the following generic question about various workplace tasks on a 1–3 scale (where the numbers correspond to the responses "often", "rarely", and "never", respectively):

> *Would you say that you perform the following activity in your job? How often?*

They also rated several knowledge requirements on a binary scale (yes–no) in response to the following question:

> *In which areas do you need special knowledge in your current job, not just basic knowledge?*

Since the frequency of the performance of the task may be unrelated to the task's importance for the job, we convert the answers to binary responses {0; 1}; that is, we register whether the worker either performs (even rarely) or does not perform a particular task. We then take the average of affirmative responses by three-digit occupation code and consider a given occupation to be

[13] The compilation of the dataset follows Yeaple (2003) in considering complex integration strategies to be the motive for FDI. The data do not include MNEs that exited before or entered after 2010. See Hecht et al. (2013b) for further details on the compilation of the treatment and control groups.

[14] The information about the reference firms was compiled by TNS Infratest Sozialforschung and is based on the database of a commercial provider. See Hecht et al. (2013a, p. 16 f.) for further details.

[15] East German firms are recorded from 1992 onward.

[16] We use the terms *site plant* and *establishment* interchangeably.

[17] Formerly, the survey was named the German Qualification and Career Survey. Waves are available for the years 1979, 1985/86, 1991/92, 1998/99, 2006, and 2012. Each wave covers between 20,000 and 35,000 individuals.

associated with that task or knowledge if the positive responses exceed 50% of all responses.[18] We proceed similarly for the type of knowledge requirements. For the sake of brevity, we subsume the term *knowledge requirements* into our definition of tasks since specific knowledge can directly be associated with certain job activities (e.g., the use of computer software).

Table 1 reports the tasks in the BiBB 1998 survey, the average daily wages (in 2010) of all workers who perform the particular task, and examples of representative jobs.[19] The best-paid task is *researching and developing*, while *producing* is the worst paid. Regarding knowledge content, we observe that *management* skills are at the top of the wage distribution and that *other specialized* or *medical* knowledge is at the bottom (note that these numbers are derived from the manufacturing and private service sector; the health industry, with predominantly public firms, is excluded).

2.3 Summary statistics of the unmatched sample

The dataset contains a total of 161,186 firm–year observations, including 1209 (3245) MNEs (non-MNEs) in the manufacturing sector and 1340 (3893) MNEs (non-MNEs) in the private service sector. The firms' type of economic activity in terms of industry classification is depicted in Table 2. Within the manufacturing sector, the majority of MNEs belong to the metal, machinery, optics, or electronics industries. Table 3 further reports summary statistics about the firms' characteristics by MNE status and by sector. Two years prior to the FDI event, manufacturing MNEs on average employ 814 workers who perform 21.5 different tasks overall or 5.1 different tasks each. In comparison, the corresponding non-MNEs from our stratified sample are smaller on average (222 workers) but perform a similar number of different tasks per firm (20.3) or per worker (4.8). To sketch the firms' labor input, we study the task intensities in the firms' workforce, that is, a given task's share in all tasks performed in the firm in Table 7 in Appendix A . Manufacturing firms produce by means of the intensive use of tasks such as *organizing the work of others*, *consulting/informing*, *measuring*, *monitoring*, *repairing*, and *producing*. The standardized bias (variance ratio) provides further information about groupwise differences in means (variances) and the balancing of the sample.[20] Relative to non-MNEs, manufacturing MNEs feature high intensities of high-wage tasks such as *research and development*, *training others*, *analysis*, *management*, and *computer engineering*.

Within the service sector, most MNEs belong to the wholesale, retail, storage, or communications industries (Table 2). Notable, however, is the substantial number of MNEs that belong to firms with activities focused on accounting, bookkeeping, legal matters, market research, consulting, or engineering. Another important industry (74.5–8) includes recruitment agencies that may allocate Czech labor to projects in Germany (without Czech workers joining the German social security system). The characteristics of service firms are shown in the last three columns of Table 3. A service MNE employs on average 445 workers who perform 16.1 different tasks or 5.5 different tasks each. The reference group of service firms is smaller on average (143 employees) but performs a similar number of different tasks per firm (15) or per worker (4.9). Service firms' production intensively uses tasks such as *analyzing*, *organizing the work of others*, *consulting/informing*, or *use of software* (see Table 7 in Appendix A). We find that compared to manufacturing firms, service firms devote more resources to *analyzing*, *customer acquisition*, *buying and selling*, *negotiating*, *serving or caring for others*, *marketing*, and the proficient use of the native language (*German*). Across service firms, the standardized bias shows that MNEs again feature higher intensities of high-wage tasks such as *researching*, *analyzing*, *management*, and *giving presentations* and medium-wage tasks such as *organizing the work of others* or the *use of software*.

Overall, the summary statistics show stark sectoral differences, which suggest that separate analyses should be conducted by sector. Since we also observe substantial differences in the task inputs between MNEs and the stratified sample of non-MNEs (the standardized biases systematically exceed |0.1|), any analysis of changes in task intensities is confronted with selectivity. Specifically, if the MNEs' characteristics are typical of more productive firms, the group of all non-MNEs is not suitable for examining the counterfactual evolution of onshore task composition. To address any resulting endogeneity bias, we analyze the relevance of specific task intensities for future FDI decisions in the next section.

[18] Becker et al. (2018) propose an imputation method to map tasks from the BiBB Employment Survey to employment data. Although their approach may be more rigorous, it is motivated by their specific model of heterogeneous task content within occupations and across firms. In our analysis, we do not allow for such variability, and we match treated and control firms on characteristics that would otherwise be used in the imputation method. Consequently, our results are insensitive to the choice of mapping algorithm.

[19] In Appendix A, we also study broad occupational categories that classify jobs by typical education level, earnings, and job activities according to Blossfeld 1985 (see Table 6 for a definition of these categories).

[20] The standardized bias is defined as the mean difference divided by the average standard deviation of the two groups: $(\mu_{treatment} - \mu_{control})/(\frac{\sigma^2_{treatment}+\sigma^2_{control}}{2})^{-\frac{1}{2}}$. The variance ratio is $\frac{\sigma^2_{treatment}}{\sigma^2_{control}}$.

Table 1 Jobs' task and knowledge content

Task content	Avg. wage in euros	Examples
Activities performed		
Researching, developing	243.46	Physicists, chemists, mathematicians
Teaching, training	230.79	Scientists, entrepreneurs, managing directors, instructors
Acquiring customers, PR	225.25	Publicity occupations, insurance specialists, commercial artists
Analyzing, investigating	168.21	Data processing specialists, accountants, chemistry and physics technicians
Buying, selling, procur.	160.97	Salespersons, forwarding business dealers, innkeepers
Organizing others	154.84	Management: consultants, directors, warehouse; specialists: data processing, office; commercial agents; forwarding business dealers; buyers
Informing, consulting	133.79	Specialists: data processing, bank, office; auxiliary office; commercial agents; management consultants
Measuring, checking	131.23	Technicians, assemblers, engineers, warehouse managers
Negotiating	127.86	Buyers; commercial agents; specialists: bank, data-processing, insurance; forwarding business dealers; management; engineers
Serving, caring	119.44	Waiters, telephonists, nursing assistants, nurses
Surveilling, monitoring techn. processes	106.27	Assistants, assemblers, technicians, engineers, nurses, cash collectors, conductors
Repairing	90.56	Chemical plant operatives, drivers, precision mechanics, pipefitters
Producing, manufacturing	73.76	Metal workers, electric motor fitters, carpenters
Associated knowledge		
Management	288.14	Managing directors, management consultants, engineers
Computer engineering	263.46	Data processing specialists, electrical engineers
Giving presentations	258.08	Entrepreneurs, commercial agents, vocational advisers
Foreign languages	255.19	Air transport occupations, translators, scientists
Legal/law	252.61	Legal representatives, vocational advisers
System analysis	221.72	Data processing specialists
Maths	208.24	Accountants, statisticians, engineers
Other technical knowledge	201.09	Electrical fitters, mechanics, printers
Labor legislation	193.86	HR workers, vocational advisers
Design	175.03	Commercial/graphic artists, Designers
Use of softwares	172.76	Managers, foremen, technicians
Marketing, sales	169.61	Commercial agents, publicity occupations
Finance, tax	142.83	Bank specialists, accountants, tax advisers
Native language (German)	124.85	Office specialists, journalists, instructors
Regulation (environ., etc.)[a]	110.43	Chemical plant operatives, tracklayers, generators machinists
Other specialized knowledge	90.77	Food processors, scientific specialists, (telecommunications, chemical, ...) technical specialists
Medical	87.65	Social workers, nursing assistants, nurses, medical receptionists, medical lab assistants

This table describes jobs' tasks and associated knowledge requirements from the BiBB Employment Survey of 1998. Daily wages are drawn from a cross-section in 2010. The reported task intensity corresponds to the intensity 2 years prior to the FDI event. It is defined by the number of workers performing a given task divided by the total number of tasks performed in the firm. Note that most occupations perform more than one task, so the total number of tasks may exceed the total number of employees. PR stands for public relations

[a] The task *regulation* includes knowledge requirements on rules for labor protection such as accident prevention, safety regulations, and occupational health and safety, as well as environmental regulations

3 FDI and facilitating tasks

To account for the selectivity of FDI-conducting firms in our DiD analysis, this section analyzes the task intensities in MNEs that are typically associated with an FDI decision in the near future. We expect to observe high intensities of what we call FDI-facilitating tasks. These are tasks that are observed excessively prior to international expansion and thus are expected to *lower costs* of conducting FDI (e.g., these firms do not need to hire workers for administration). In the context of vertical FDI and production relocation, we can also conjecture that MNEs have high intensities of tasks that are highly offshorable and that thus may induce *greater benefits* from the exploitation of labor cost differences (Helpman et al. 2004; Nocke and Yeaple 2008). Alternatively, market-seeking, horizontal FDI would lead to high intensities of commercial tasks or no relevant differences between MNEs and non-MNEs. In accordance with the work by Yeaple (2003), we consider that a typical FDI event corresponds to complex integration strategies driven by both efficiency-seeking and market-seeking motives.

Table 2 Classifications of MNEs' economic activity

	Number of	
	MNEs	Non-MNEs
Manufacturing sector (ISIC rev. 3)		
Food products, beverages and tobacco (15–16)	37	446
Textiles, leather, and related products (17–19)	66	114
Wood and wood products (20)	34	91
Pulp, paper and paper products; publishing and printing (21–22)	66	322
Coke, refined petroleum products and nuclear fuel (23)	4	8
Chemicals, chemical products and man-made fibers (24)	79	156
Rubber and plastic products (25)	107	193
Other nonmetallic mineral products (26)	59	109
Basic metals and fabricated metal products (27–28)	237	625
Machinery and equipment n.e.c. (29)	204	522
Electrical and optical equipment and machinery (30–33)	226	413
Transport equipment and motor vehicles (34–35)<	53	114
Not elsewhere classified, recycling (36–37)	37	132
Service sector (ISIC rev. 3)		
Sale, repair of motor vehicles; sale of automotive fuel (50)	51	263
Wholesale trade, except motor vehicles (51)	467	704
Retail trade, except motor vehicles; repairs of household goods (52)	127	571
Hotels and restaurants (55)	14	40
Transport (60–62)	35	147
Storage; communications (63–64)	147	260
Financial intermediation (65–67)	29	291
Real estate activities (70)	54	144
Renting of machinery, equipment, vehicles, household goods (71)	13	30
Computer and related activities incl. data processing (72)	70	146
Research and development (73)	6	41
Accounting, bookkeeping, legal; market research; consulting[a] (74.1)	139	360
Technical consulting, testing and analysis; architectural, engineering (74.2–74.3)	95	232
Advertising (74.4)	20	66
Labor recruitment, provision of personnel, cleaning, security, and other (74.5–74.8)	73	598

This table reports frequencies of MNEs and non-MNEs by economic activities denoted in International Standard Industrial Classification codes (ISIC rev. 3)

[a] Specifically, consulting in this industry includes business, management and tax advisory activities

3.1 Empirical strategy—lasso logit regression

The aim of our empirical strategy is to exploratively identify tasks that have predictive power for a firm's future FDI decisions and to determine the specification of a logit model that features the best predictions for those events. Subsequently, we use this model in our matching approach and employ it to predict a firm's propensity to conduct FDI. By using the matched sample, we alleviate selectivity and endogeneity concerns in the DiD analysis.

To identify the task intensities that contribute to the likelihood of a firm's FDI decision, we specify a logit regression and add a least absolute shrinkage and selection operator (lasso) to assess the predictive power of different model specifications for engaging in FDI in the near future (2 years). Without the lasso penalty term, the logit regression has the following form:

$$\ln\left[\frac{\mathbb{P}[\mathrm{FDI}_{f,t+2}=1|\boldsymbol{X_{ft}}]}{\mathbb{P}[\mathrm{FDI}_{f,t+2}=0|\boldsymbol{X_{ft}}]}\right] = \underbrace{\beta_0 + \boldsymbol{\beta_1}'\boldsymbol{\tau_{ft}} + \boldsymbol{\beta_2}'\boldsymbol{c_{ft}} + \delta_i + \gamma_r + \zeta_t}_{\boldsymbol{X_{ft}\beta}} \tag{1}$$

Table 3 Summary statistics—unmatched sample

	Manufacturing			Service		
	MNEs	Non-MNEs	Balancing	MNEs	Non-MNEs	Balancing
	Mean	Mean	Std. bias	Mean	Mean	Std. bias
	Median	*Median*		*Median*	*Median*	
	(Std. dev.)	(Std. dev.)	(Var. ratio)	(Std. dev.)	(Std. dev.)	(Var. ratio)
Plants per firm	2.256	1.594	0.179	11.70	3.093	0.060
	1	*1*	–	*1*	*1*	–
	(4.397)	(2.853)	(2.375)	(203.7)	(12.73)	(255.9)
Size (employees)	814.8	222.2	0.139	443.5	143.0	0.080
	139	*147*	–	*32*	*49*	–
	(6032.7)	(335.8)	(322.8)	(5270.3)	(489.0)	(116.2)
(Daily) wage bill (in thousand euros)	98.791	24.585	0.137	46.865	13.754	0.096
	13.431	*13.049*	–	*36.517*	*41.608*	–
	(761.538)	(60.113)	(160.5)	(484.139)	(48.973)	(97.73)
Number of tasks	21.46	20.26	0.211	16.14	14.97	0.180
	23	*22*	–	*17*	*15*	–
	(5.638)	(5.672)	(0.988)	(6.756)	(6.261)	(1.165)
Tasks per worker	5.144	4.853	0.215	5.499	4.890	0.250
	5.081	*4.816*	–	*5.500*	*4.635*	–
	(1.316)	(1.384)	(0.904)	(2.263)	(2.603)	(0.756)

Table 3 describes the summary statistics for 971 (863) MNEs in the manufacturing (service) sector 2 years prior to the FDI event and the respective statistics of 3320 (3860) manufacturing (service) non-MNEs across all years. For each variable, we report the mean, median and standard deviation. In comparing MNEs and non-MNEs, we also report the standardized bias and the variance ratio between the two groups. The wage bill is denoted in constant 2010 euros.

where f denotes a firm, t is the year of observation and $\boldsymbol{\tau_{ft}}$ is a vector of the firm's intensities of either broad occupational categories or the tasks from the BiBB survey.[21] The coefficients of interest are thus in the vector $\boldsymbol{\beta_1}$, which captures the predictive power of these intensities for FDI. The vector $\boldsymbol{c_{ft}}$ includes firm-level controls such as firm size and other characteristics that we discuss below. Its coefficient $\boldsymbol{\beta_2}$ will not be included in the penalty term of the lasso regression (see Eq. 3). The parameter δ_i denotes industry fixed effects that control for differences in international activities with respect to economic activity. Jointly with firm size, they also control for the non-random stratification of the reference firms. We thus do not interpret their coefficients. Region fixed effects γ_r control for proximity to the Czech Republic and other unobserved heterogeneity related to firm location.[22] Year fixed effects ζ_t account for common time trends, such as the business cycle. According to Helpman et al. (2004), another highly relevant determinant of FDI is a firm's productivity. Hence, in the vector $\boldsymbol{c_{ft}}$, we control for a firm's number of employees, its wage bill, the number of establishments per firm, and the 4-year employment and wage growth rate. In addition to these variables, we refer to insights from Black and Spitz-Oener (2010) and add the share of women to control for gender-specific differences in task profiles within occupations.

Recall that the aim of this exercise is to identify the model with the lowest prediction error. Any causal interpretation of this specification may still suffer from reverse causality or omitted variable bias.[23]

We further solve (1) for $\mathbb{P}[\mathrm{FDI}_{f,t+2} = 1|\boldsymbol{X_{ft}}]$ and employ the derived transformation function

[21] We use the classification of occupation codes by education level, average earnings and activities from Blossfeld (1985). See Appendix A for further details.

[22] We distinguish 4 broad regions: the north (Bremen, Hamburg, Lower Saxony, and Schleswig-Holstein), west (Hesse, North Rhine-Westphalia, Rhineland Palatinate, and Saarland), east (Berlin, Brandenburg, Mecklenburg-Western Pomerania, Saxony, Saxony-Anhalt, and Thuringia), and south (Baden-Wurttemberg and Bavaria).

[23] While we somewhat alleviate concerns about the former by regressing FDI on lagged values of firm characteristics, the estimation could still be biased due to omitted variables correlated with both the FDI decision and the initial task intensities. One such variable could be firm-specific technology or communication costs. If these costs are related to the location or productivity of the firm, the region fixed effects or the vector $\boldsymbol{c_{ft}}$ would mitigate the bias. However, we cannot fully control for all potential confounders and thus refrain from interpreting the estimates as causal and from drawing conclusions on the basis of their absolute magnitudes.

$$\mathbb{P}[\mathrm{FDI}_{f,t+2} = 1|\boldsymbol{X_{ft}}] = \frac{\exp^{X_{ft}\beta}}{1+\exp^{X_{ft}\beta}} = F(\boldsymbol{X_{ft}\beta}) \tag{2}$$

in the maximized log-likelihood with lasso penalization (L1-norm) of $\boldsymbol{\beta_1}$ and standardized regressors in $\boldsymbol{X_{ft}}$:

$$\max_{\beta} \frac{1}{N} \sum_{f} \left[\mathbb{1}[\mathrm{FDI}_{f,t+2} = 1] \ln F(\boldsymbol{X_{ft}\beta}) + \mathbb{1}[\mathrm{FDI}_{f,t+2} = 0] \ln(1 - F(\boldsymbol{X_{ft}\beta})) \right] - \lambda ||\boldsymbol{\beta_1}||_1, \tag{3}$$

The lasso term thereby acts as a model selector that drives the coefficients of task intensities that have low predictive power for FDI to zero. The higher λ is, the higher the penalty imposed on the task intensities in $\boldsymbol{\beta_1}$ and the higher a variable's contribution to the log-likelihood function must be. If the task intensities are weak and/or correlated with other predictors, their coefficients are driven to zero.[24]

We estimate Eq. (3) for the unmatched sample of firms but separately for the manufacturing and service sectors. Moreover, we include only one observation per MNE 2 years prior to the FDI event. For Non-MNEs, we include all observations within the sample period. Therefore, all coefficients in $\boldsymbol{\beta}$ are merely identified by the differences between MNEs prior to investing and the average of non-MNE-observations. This modification avoids undesired attenuation of the estimates due to the autocorrelation in investing firms' observables. To abstract from any difference in the units of measurement, we standardize all variables in $\boldsymbol{X_{ft}}$ to have mean zero and variance one. In the outputs, the estimates are returned to their original scales.

In the first step, we run the lasso logit regressions sequentially on 50 values of λ, which provides us with models of different sparsities.[25] The penalty parameter λ varies from a restrictively high level that contains only nonpenalized coefficients, over so-called knots—where new predictors are successively added—toward a standard logit model in which λ is 0 and the full set of regressors is included in the model. Figures 1 and 2 plot this path of the coefficients in $\boldsymbol{\beta_1}$ for various values of λ to depict how the impact of a given task intensity evolves if others are included or dropped. For instance, this procedure reveals the single best predictor of future FDI and shows whether the direction of the conditional prediction for FDI (the sign of the estimates) changes along the path toward sparser models.

In the second step, we perform a fivefold cross-validation. This means that we repeat the lasso regressions 5 times with each fold using four-fifths of the sample and estimate models with 50 values of λ (these values do not change per fold) to assess their out-of-sample predictions for the omitted fifth of the sample. We stratify the data to include a similar number of random MNEs in each fold.[26] The omitted part is changed for each of the five folds, so we have a total of 250 different regressions. We then identify the value of λ associated with the lowest average of the mean squared prediction error (MSPE) over all five folds. This value of λ identifies the specification of the model that best predicts an FDI decision in the near future. It thus contains a subset of job or task intensities that are correlated with future FDI decisions even after we condition on many other firm characteristics such as size, wages, or industry code.

In the final step, we run a nonpenalized logit model employing only the selected subset of covariates, i.e., a post-lasso regression. We report these coefficients in Tables 4 and 5. The coefficients provide more information on which occupational shares or task intensities are susceptible to generating selection bias in our estimation of the response of onshore employment to firms' FDI decisions. The model specification is subsequently used for the computation of scores on firms' propensity to conduct FDI, which we then use in our matched DiD analysis in Sect. 4.

3.2 Results—occupational sets of tasks

In a first instance, we treat interacting tasks as a fixed set of tasks that need to be performed jointly within broad occupational groups.[27] Starting with the coefficient paths along 50 values of λ, Fig. 1 illustrates the evolution of the coefficients in $\boldsymbol{\beta_1}$ for the manufacturing and service sectors. As λ decreases, the algorithm adds knots or a larger selection of occupation codes for the prediction of future FDI. A positive (negative) coefficient implies that a high (low) occupational share correlates positively with future FDI decisions conditional on all other covariates. We consider iteratively denser models (toward smaller values of λ) and the best-predicting specification, that is, the specification with the lowest MSPE. Notably, the coefficients never change sign (e.g., from positive to negative)

[24] Note that in Eq. (3), the parameter λ acts as the Lagrange multiplier in a constrained maximization problem in which the objective function is the standard logit model and the constraint is a free parameter that determines the regularization.

[25] We used Lassopack (Ahrens et al. 2018) in Stata15.

[26] We apply the random-number seed 12 for the stratification per fold.

[27] In Appendix D, we repeat this exercise for finer (two-digit) occupational categories to disentangle the margins of heterogeneity hidden in the coarse occupation groups.

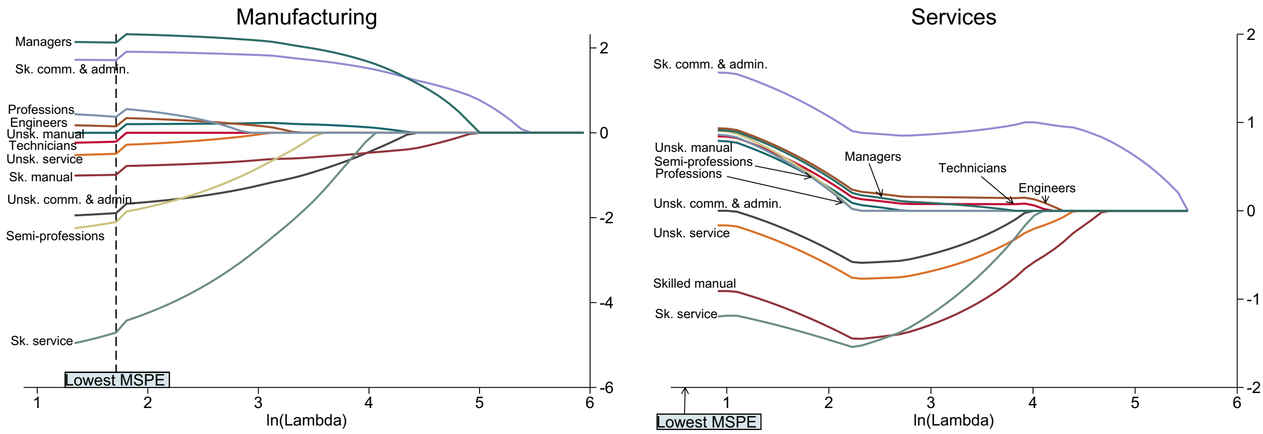


Fig. 1 Coefficient paths of occupational intensities penalized by Lasso. Source: IAB-ReLOC. Fig. 1 displays the coefficient paths of estimates of $\boldsymbol{\beta}_1$ from Eq. (3) with respect to 50 values of the penalty parameter λ. Each line corresponds to the coefficient of an occupational group (see Table 6). The left (right) panel shows the evolution within the manufacturing (service) sector. The dashed line denotes the model with the lowest MSPE (strongest predictive power), which is obtained from a fivefold cross-validation

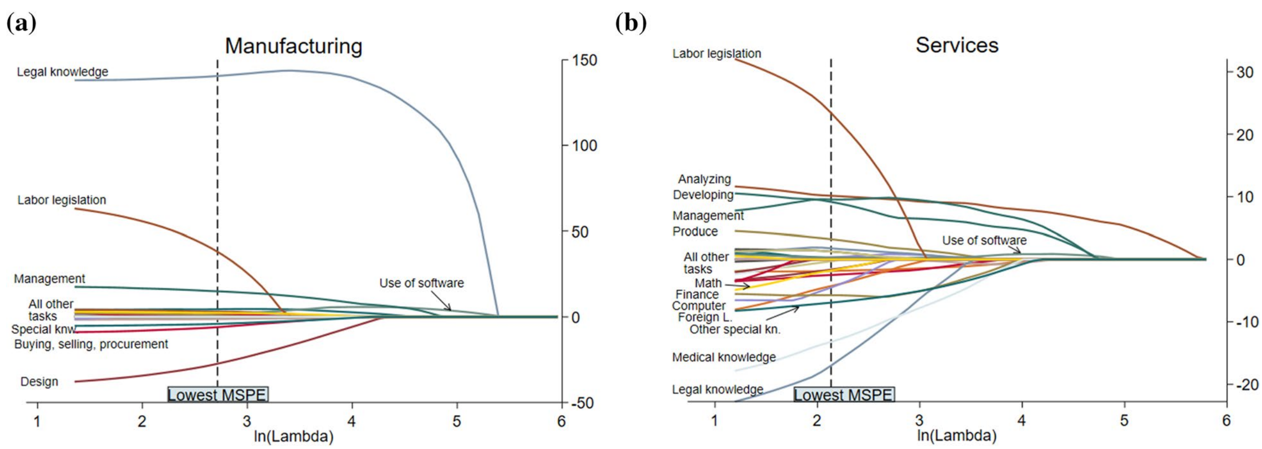


Fig. 2 Predictive power of task intensities for FDI. Source: BiBB Employment Survey and IAB-ReLOC. Fig. 1 displays the coefficient paths of estimates of $\boldsymbol{\beta}_1$ from Eq. (3) with respect to 50 values of the penalty parameter λ. Each line corresponds to the coefficient of task intensity (see Table 1). The left (right) panel shows the evolution within the manufacturing (service) sector. The dashed line denotes the model with the lowest MSPE (strongest predictive power), which is obtained from a fivefold cross-validation

along the path toward sparser models, which increases their plausibility.

The left (right) panel of Fig. 1 presents the results for the manufacturing (service) sector. For both sectors, we find that the share of skilled commercial and administrative employees is the best single predictor of FDI (first knot). Having a high share of employment from this group hence increases the propensity of a firm to engage in FDI. In the manufacturing sector, the second-most important occupational category is managers (second knot). Moreover, in both sectors, high shares of skilled service, unskilled commercial and administrative, and skilled manual occupations are strong negative predictors of FDI in both sectors. Our interpretation of these results follows at the end of this subsection.

If we consider the model with the highest predictive power (lowest MSPE) according to the respective cross-validation exercises, we find that only unskilled manual occupations are excluded in the manufacturing sector and unskilled commercial and administrative occupations excluded in the service sector (marked as '–' in the output tables). For the classification of tasks via broad occupational categories, our preferred specification is hence not very different from a standard logit regression. Using the best-predicting model, we present the respective estimates of a post-lasso logit regression in Table 4.

Table 4 Post-lasso logit results for occupational groups

Dep. variable: FDI in 2 years	Post-lasso logit	
	Manufacturing	Services
	(1)	(2)
Production occupations		
Unskilled manual	–	0.843**
Skilled manual	− 1.044***	− 0.917**
Technicians	− 0.290	0.892**
Engineers	0.232	0.985**
Service occupations		
Unskilled services	− 0.589	− 0.152
Skilled services	− 5.545*	− 1.283
Semiprofessionals	− 2.580	1.019
Professionals	0.565	0.965
Administrative occupations		
Unskilled commercial and admin.	− 2.068***	–
Skilled commercial and admin.	1.742***	1.604***
Managers	2.171***	0.970**
Nonpenalized in lasso		
Log # establishments	0.488***	0.212***
Employment growth	0.0734*	0.172***
Share of women	0.625**	− 0.353*
Log wage bill	0.0157	0.584***
Mean wage growth	0.0432	0.0757*
Log # employees	Yes	Yes
Region fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	57,532	51,519
log λ of min. MSPE	1.71	0.58

This table reports the estimates from a post-lasso logit model. The set of included occupational shares is selected by cross-validating the findings of the model with the lowest MSPE. The covariate employment size and the industry fixed effects control for the stratification of the sample of non-MNEs. Standard errors are clustered at the treatment level, i.e., the firm level, following Abadie et al. (2017)

*$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$

We cluster standard errors at the firm level in accordance with Abadie et al. (2017).

The results show that the coefficients for the occupations with the strongest positive predictive power, such as skilled commercial and administrative occupations and managers, also have the highest statistical significance. Both occupational groups feature relatively high wages (see Table 6), and we conjecture that these tasks are FDI facilitating. This means that they are characteristic features of typically more productive FDI-engaging firms and that they reduce the (fixed) costs of FDI.

The negative predictors correspond to low- or middle-income job categories such as skilled manual or (un)

Table 5 Post-lasso logit results for job tasks

Dep. variable: FDI in 2 years	Post-lasso logit	
	Manufacturing	Services
	(1)	(2)
Job activities		
Researching, developing	–	12.12***
Teaching, training	3.105	–
Acquiring customers, PR	–	− 2.443
Analyzing, investigating	3.136	10.97***
Buying, procurement, selling	− 11.76***	− 3.082**
Organizing/planning for others	0.353	− 0.327
Consulting, informing	–	− 2.483**
Measuring, checking	–	2.820*
Negotiating	2.889	2.831*
Serving, caring	− 2.377	–
Surveilling, monitoring	− 2.095	− 4.322**
Repairing	− 1.929	–
Producing	–	5.604***
Associated knowledge		
Management	19.39***	9.080**
Computer engineering	–	− 10.54**
Giving presentations	–	1.148
Foreign language	–	− 8.301
Legal/law	135.1***	− 31.12***
System analysis	1.013	–
Maths	–	− 4.941*
Other technical knowledge	–	2.431
Labor legislation	88.54	42.12**
Design	− 44.82***	–
Use of software	− 0.312	0.339
Marketing, sales	–	–
Finance, tax	41.853	− 5.075
Native language (German)	–	–
Labor prot., environm. reg.	2.760	–
Other specialized knowledge	− 5.669**	− 10.04*
Medical knowledge	–	− 20.64***
Nonpenalized in lasso		
# of establishments	0.516***	0.299***
Employment growth	0.0795**	0.166***
Share of women	1.163***	0.196
(log) wage bill	− 0.0070	0.585***
Mean wage growth	0.0353	0.071*
(log) employees	Yes	Yes
Region FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	57452	51022
log λ of min. MPSE	2.72	2.13

This table reports the estimates of a post-lasso logit model. The set of included task intensities is selected by cross-validating the findings of the model with the lowest MSPE. The covariate employment size and the industry fixed effects control for the stratification of the sample of non-MNEs. Standard errors are clustered at the treatment level, i.e., the firm level, following Abadie et al. (2017)

*$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$

Table 6 Broad occupational classification (blossfeld)

Broad occupational category	Avg. wage in euros	Examples
Production		
Unskilled manual occupations	68.55	Assembly workers, conveyors, and riveter workers, roadmakers
Skilled manual occupations	84.81	Electricians, mechanics, carpenters, lab assistants, vehicle repairers, carpenters
Technicians	151.02	Mechanical engineers, surveying technicians
Engineers	279.74	Architects, (electro-, ...) engineers, chemists
Service		
Unskilled service occupations	58.67	Janitors, waiters, receptionists, conductors, warehouse managers, packers, cleaners
Skilled service occupations	93.32	Train drivers, hairdressers, pharmacy chemists, judicial officers, administr. and enforcers, medical receptionists, pharmaceutical assistants, property managers, safety testers
Semiprofessions	127.77	Nurses, social workers, teachers, journalists, translators, archivists
Professions	223.31	Doctors, (economic and social) scientists, professors, legal consultants, statisticians
Administration		
Unskilled commercial and admin.	73.95	Cashiers, auxiliary office (secretaries), auxiliary commercial agents (buyers, sellers)
Skilled commercial and admin.	131.91	Bankers, accountants; forwarding, logistics specialists; wholesale traders, data processing, office specialists
Managers	277.71	CEOs, business owners, high-level public servants

This table describes the broad occupational classification by Blossfeld (1985). Each group represents a socioeconomic stratum of the German workforce with similar education levels, average earnings, and types of activities performed. Daily wages are drawn from a cross-section of the IAB-ReLOC sample in 2010

skilled service occupations. While we prefer the interpretation that the correlations simply show the typical task intensities of more productive firms (e.g., management and skilled commercial and administrative occupations), the outcomes also show some consistency with the logic of offshoring in the offshorability literature. That is, firms with high shares of nonoffshorable workers (e.g., (un) skilled service jobs) tend to conduct FDI less frequently.[28]

3.3 Results—specific task intensities

We now turn to directly identifying the tasks that are strong predictors of future FDI to provide more detailed information about the potential selection biases emphasized above. Again, Fig. 2 displays the coefficient paths from $\boldsymbol{\beta_1}$ for varying values of the penalty coefficient λ separately for the manufacturing and service sectors. However, $\boldsymbol{\beta_1}$ now contains the coefficients of the task intensities from the BiBB.

In the manufacturing sector, three tasks stand out in contributing positively to the propensity to engage in FDI: *legal* knowledge, *labor legislation*, and *management*. We interpret these tasks as FDI facilitating and crucial for conducting the due diligence needed to send FDI to a new market and to manage working processes between parents and affiliates. For instance, MNEs need to analyze the legal and tax matters related to international expansion or labor legislation to handle layoff protection and hires in the affiliates' country. The best single predictor is the *use of software*, while *legal* knowledge is added to the second knot and is highly significant in the model with the highest predictive power (lowest MPSE), as column 1 in Table 5 shows. On the other hand, *design*, a task particularly relevant for marketing (e.g., commercial artists), is a strong negative predictor of future FDI in the manufacturing sector, potentially because productive firms outsourced marketing departments earlier than their less productive competitors. Table 5 further reveals negative correlations with FDI for tasks that require local knowledge (networks) or geographic proximity, such as *buying, selling and procurement*, *repairing*, and *other specialized* knowledge.

In the service sector, firms engaging in FDI feature high task intensities in high-wage tasks such as *analyzing, researching and developing* and *management*. In addition to the *use of software*, these tasks appear early in the sequential process (lowest knots), and their contributions remain relatively high even when we use richer models. In higher knots, knowledge of *labor legislation* is added, which also makes a strong positive contribution to the propensity to engage in FDI, while legal expertise shows strong negative correlations with FDI. This may be driven by its ties to codes of law specific to Germany. The

[28] Blinder (2009) provides the example that the tasks of some (skilled) service occupations, such as hairdressers, cannot be offshored while some tasks of (service) professions, such as medical doctors who interpret X-rays, can be performed offshore. Indeed, profession is a weak positive predictor in our sample. We also compare this result to Table 2 in Blinder and Krueger (2013, p. 117). According to the measure preferred by the authors (externally coded), only 0.7% of service occupations are offshorable, while this share amounts to 20.5% for professional occupations and 80.7% for production occupations.

knowledge requirements of medical expertise are also a strong negative predictor of future FDI decisions since this expertise usually requires a physical presence.

Again, we select the model with the lowest MSPE from the cross-validation and run a post-lasso regression , which we cluster at the firm level. The results in column 2 of Table 5 reveal a highly significant correlation for all the abovementioned variables, which, intuitively, are typical of more productive firms (with the exception of *use of software*). In stark contrast with the manufacturing sector, (nonlabor) *legal* expertise has a strong negative correlation with FDI. *Surveilling/monitoring*, *consulting*, *buying, selling, procurement*, *customer acquisition*, *medical*, and *other specialized* knowledge complete the set of negative predictors that we identify. All of these predictors involve some kind of geographic proximity (either to the customer or to local institutions).

Overall, many different tasks have predictive power in the service sector, and they also feature relatively high levels of statistical significance. In contrast, the best predictive model for the manufacturing sector is much sparser. Within the selected tasks from the lasso regression, we observe, on the one hand, sectoral overlap of positive predictors such as *management*, *labor legislation*, and *analyzing/investigating* and negative predictors such as *buying/selling*, *surveillance/monitoring*, and *other specialized* knowledge. Intuitively, the positive predictors are typical of highly productive firms, and they are needed for international expansion and coordination. Therefore, a high fraction of firms employing labor of this type can avoid hiring many new experts who can cope with the international organization and hence increase the benefit–cost ratio of engaging in FDI, as discussed in Helpman et al. (2004).[29] On the other hand, more productive firms could also find it profitable to incur both the costs of FDI and the costs of such managerial activities. Regardless of the causal relationship implied, using the best prediction model for each sector vastly increases the quality of our propensity score matching approach, which we describe in the next section.

4 FDI and task reallocations

The previous results not only revealed the characteristic task intensities of MNEs relative to those of non-MNEs but also provided us with good prediction models for FDI and their propensity scores (by sector). We now turn to our main analysis and estimate changes in firms' onshore task demand in response to FDI.

4.1 Empirical strategy—matched DiD estimation

To weaken potential threats to identification, we control for the selection of firms into FDI by using the propensity scores from the previous section to match each MNE to a similar non-MNE. We then analyze shifts in occupational shares or task intensities using a DiD estimator and verify that our findings are not driven by differential pretrends.

4.1.1 Propensity score matching

Using our propensity scores, we match each MNE to exactly one non-MNE to control for selection into FDI engagement.[30] This step mitigates confounding trends in the DiD analysis that stem from initial differences in firm characteristics and not causally from firms' engagement in FDI. Our design thus relies on the identifying assumption that, conditional on the matching variables, firms' decision to engage in FDI activities is basically random. The control firms then act as a counterfactual evolution for the matched treatment firms in their virtual state of noninvestment. This implies that the pretrends of the outcome variables between MNEs and non-MNEs must be very similar. After testing the balancing statistics of our matching covariates, we analyze this essential prerequisite for our identifying assumption in the following subsections.

The choice of matching variables anticipates the predictive power of economic activity and the other firm characteristics identified in the previous section. These are firm size in terms of the number of employees, the total wage bill, the number of plants per firm, the share of female workers, employment and mean wage dynamics (the respective 4-year log difference), a series of dummies for finer industry classifications, and the set of task intensities identified as predictors in the post-lasso logits. We capture unobserved heterogeneity from geography using a series of regional dummies for the firm's location. Note that most of the matching covariates are in levels and thus only indirectly control for the pre-trend of later outcome variables (e.g., a pre-trend of a growing management intensity that is related to a certain firm size). Only if we also find common pretrends for those firms can we conclude that non-MNEs are very similar to their matches and feature a suited counterfactual evolution after (virtual) FDI.

The matching algorithm is as follows. First, we retain separate samples for manufacturing and service firms

[29] Conversely, the negative predictors decrease the cost–benefit ratio of FDI, potentially because these tasks require a large network or are costly to recruit or coordinate.

[30] We also consider coarsened exact matching, as suggested by Iacus et al. (2012). However, since the lasso exercise has shown that many different variables are relevant for the prediction of FDI, the coarsened exact matching procedure suffers from dimensionality. It thus excessively prunes the data, resulting in an insufficient number of matches.

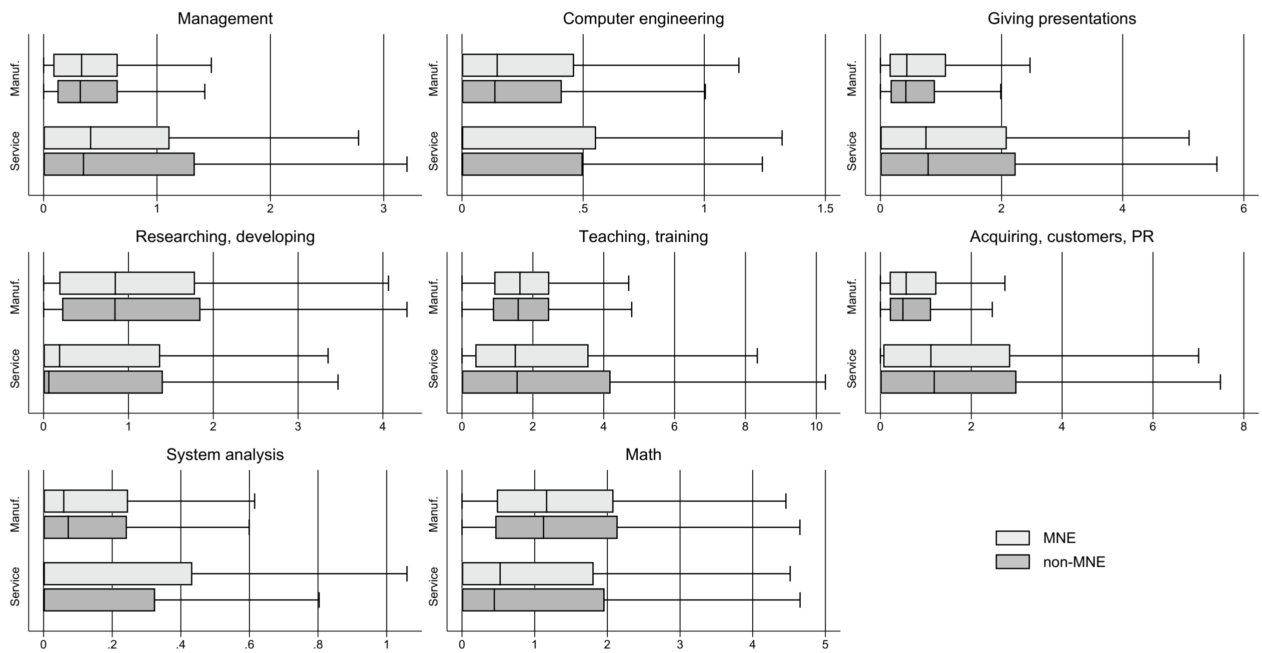


Fig. 3 Sample balancing of task intensities—high-wage tasks. Source: IAB-ReLOC. This figure displays boxplots of the high-wage task intensities used in the matching of MNEs and non-MNEs for manufacturing (service) firms

and consider the respective covariates that are included in the model with the lowest MSPE. We manually prune firm–year observations that feature covariates above or below the respective maximum or minimum value of the comparison group $\pm 0.2\times$standard deviations in each year (of the common support region).[31] Second, we estimate propensity scores using logit models while anticipating the sectoral differences in the selection into FDI. Note that this step is essentially a post-lasso logit regression from Sect. 3, which substantially reduces the predictive error. Third, we match the MNEs with control firms exactly 2 years prior to the FDI event. Our choice of this time span up to the FDI reflects a tradeoff. While some firms anticipate engaging in FDI years before they invest and thus adjust their economic behavior accordingly, other firms are weakly affected until they have already invested. There is heterogeneity in the timing of the FDI effects: Koerner et al. (2022) show that employment responses to FDI accrue from 2 years prior to the FDI event onward. In the fourth step, we perform the iterative matching procedure of Koerner et al. (2023), which ensures that treated units are matched to a unique non-MNE with the most similar propensity to invest. The algorithm proceeds by first matching the logit propensity scores of MNEs to the three nearest neighboring scores of non-MNEs and then marking the score with the closest distance.[32] If the nearest-score match is unique, the two firms are matched. If it is not unique (e.g., one non-MNE score is the nearest for two different MNEs' scores), the algorithm compares the distances of these potential matches and selects the smallest one. As a result, some MNEs do not match with the closest non-MNEs: for these firms, the process iterates by marking the non-MNE with the next smallest distance until each MNE is matched to exactly one unique control unit.

The algorithm returns 738 matches (between 1476 firms) in the manufacturing sector and 540 matches (between 1080 firms) in the service sector. For the distribution of FDI events over time, we refer to Fig. 10 in the Appendix. Compared to propensity score matching without regularization, our matching improves the balancing—measured by the Mahalanobis distance (MD)—by 10.8% in the manufacturing sector and by 20.8% in the service sector. In detail, we compare the pairwise MD of the same set of variables between the matches. In the

[31] The use of the common support region rules out the perfect predictability of FDI from outliers of certain firm characteristics (Caliendo and Kopeinig 2008).

[32] We apply nearest-neighbor matching with replacement and enforce the support region of the logit of the propensity score with a caliper width of $0.2\times$standard deviations (as suggested by Austin 2011b).

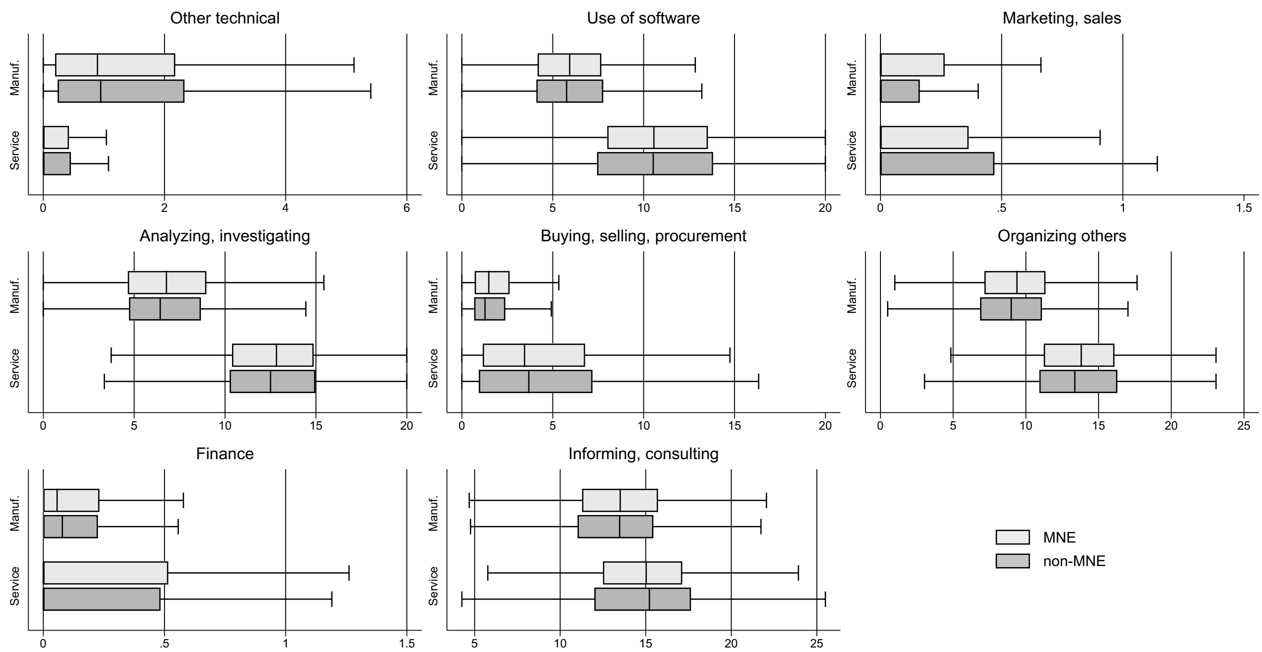


Fig. 4 Sample balancing of task intensities—medium-wage tasks. Source: IAB-ReLOC. This figure displays boxplots of the medium-wage task intensities used in matching MNEs and non-MNEs for manufacturing (service) firms

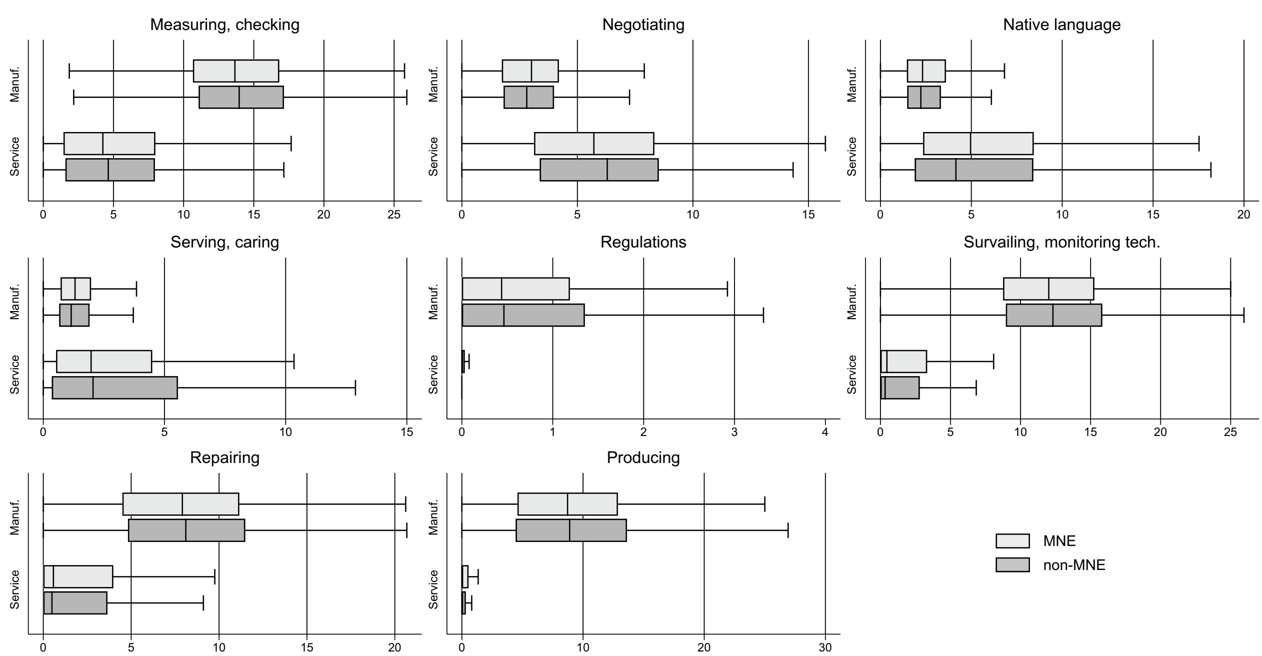


Fig. 5 Sample balancing of task intensities—low-wage tasks. Source: IAB-ReLOC. This figure displays boxplots of the low-wage task intensities used in the matching of MNEs and non-MNEs for manufacturing (service) firms

manufacturing sector, the MD decreases from 0.2485 to 0.2216 after we use lasso. In the service sector, the MD decreases from 0.3494 to 0.2485. In the unmatched sample, the average MD is 6.3949 (9.2028) in the manufacturing (service) sector. We also visually present the success of the matching algorithm in Figs. 3, 4, 5, as it results in a vast harmonization of firm characteristics within the matches.[33] Compared to their counterparts for the unmatched sample, most of the balancing statistics, such as the standardized biases, drop from above |0.1| (Table 7 in Appendix C) to below |0.05| (Table 8 in Appendix B).[34] Additionally, the variance ratios change from above (below) 2 (0.5) to between 0.700 and 1.3 and therefore are much closer to the ideal of 1. We explain the exceptions that fall outside these ranges by the high level of initial heterogeneity and the high number of matching variables. However, since variables untargeted by the matching algorithm also become more balanced (e.g., *marketing/sales* and native language), we consider our strategy successful in the dimension of matching similar firms. Whether these firms also feature similar dynamics in terms of the outcome variables is analyzed in the next subsection.

4.1.2 Difference-in-differences estimation

We use the matched sample to estimate the MNEs' onshore changes in response to FDI events of either the occupational shares or task intensities relative to their pre-FDI levels and to their contemporaneous counterparts for the non-MNEs. The non-MNEs are never-treated units in our overall sample of firms. According to Roth et al. (forthcoming) and Callaway and Sant'Anna (2021), we thus need to fulfill the parallel trends assumption for the staggered setting between treated and never-treated units ($\beta_{PRE} = 0$).

Let L_{oft} denote the standardized share of occupation or task o in firm f in year t. MNE_f is an indicator variable for whether firm f engages in FDI in the Czech Republic during our sample period. For each task o, we estimate the following model:

$$
\begin{aligned}
L_{oft} = {} & \alpha_{PRE}\mathbb{1}(t \in [\tau-6;\tau-3]) + \beta_{PRE}\mathbb{1}(t \in [\tau-6;\tau-3]) \times MNE_f \\
& + \alpha_{-1}\mathbb{1}(t = \tau-1) + \beta_{-1}\mathbb{1}(t = \tau-1) \times MNE_f \\
& + \alpha_{POST}\mathbb{1}(t \in [\tau;\tau+4]) + \beta_{POST}\mathbb{1}(t \in [\tau;\tau+4]) \times MNE_f \\
& + \gamma_f + \delta_t + \varepsilon_{oft}
\end{aligned} \tag{4}
$$

where the coefficients of interest are β_{POST}. They measure the change for MNEs relative to non-MNEs and relative to the baseline period, which is the matching year $\tau-2$, where τ denotes the year of the (virtual) FDI. The coefficients α_{PRE} and α_{POST} capture common trends during the observation window ($\tau-6$ to $\tau-3$ and τ to $\tau+4$) relative to the baseline period and the net of yearly time trends captured by the parameter δ_t. The parameter γ_f denotes firm fixed effects, which capture time-invariant characteristics of the firms. It is necessary to identify changes within MNEs relative to changes within non-MNEs. The standard errors ε_{oft} are clustered at the match level, as suggested by Abadie and Spiess (2021).

We also consider β_{PRE} to explore potential pretrends between the two groups of firms. Note that a negative estimate of this coefficient would reveal a relative *increase* in MNEs' task intensities over the preperiod until the baseline year. We avoid confounding onshore effects from the anticipation of FDI by only a fraction of all firms and exclude observations of $\tau-1$ from the preperiod and postperiod. The results, however, are robust to including the period $\tau-1$ in the average post effect.

A negative estimate of β_{POST} would suggest that the occupational share or task intensity o decreases more strongly in MNEs than in non-MNEs: we label these decreases in onshore demand FDI-*substitutable* tasks. In contrast, a positive estimate would reveal an FDI-*complementary* task.

The next section presents the estimates from the matched DiD model and reveals shifts in the intensity of either broad occupational categories or specific task content in response to FDI activities.[35] Due to the standardization of the dependent variable, the estimates are comparable between groups, regardless of their initial importance for firms.

4.2 Results—occupational sets of tasks

We begin with the analysis of occupational shifts. Figure 6 presents the matched DiD estimates of β_{POST} from Eq. (4) and their 95% confidence intervals (in bold). A possible caveat to the estimates is the prevalence of general trends between the MNE and non-MNE groups. In this case, the trajectory of our control firms would not serve as a good proxy for the counterfactual evolution of treatment firms in the virtual state of noninvestment. To explore prior dissimilar trends between the groups, we report the various β_{PRE} estimates from Eq. (4) and their 95% confidence intervals (in light gray) in Fig. 6. Recall that β_{PRE} captures the deviation in the changes in MNEs relative to those in non-MNEs over the period $\tau-6$ to $\tau-3$ and relative to $\tau-2$. Hence,

[33] Table 8 reports the sample balancing along firm characteristics, task intensities, and untargeted variables such as broad occupational groups and number of tasks per worker.

[34] The metrics are suggested, e.g., by Caliendo and Kopeinig (2008) and Austin (2011a).

[35] We also show matched DiD estimates of Eq. (4) for finer (2-digit) occupational categories in Appendix D.

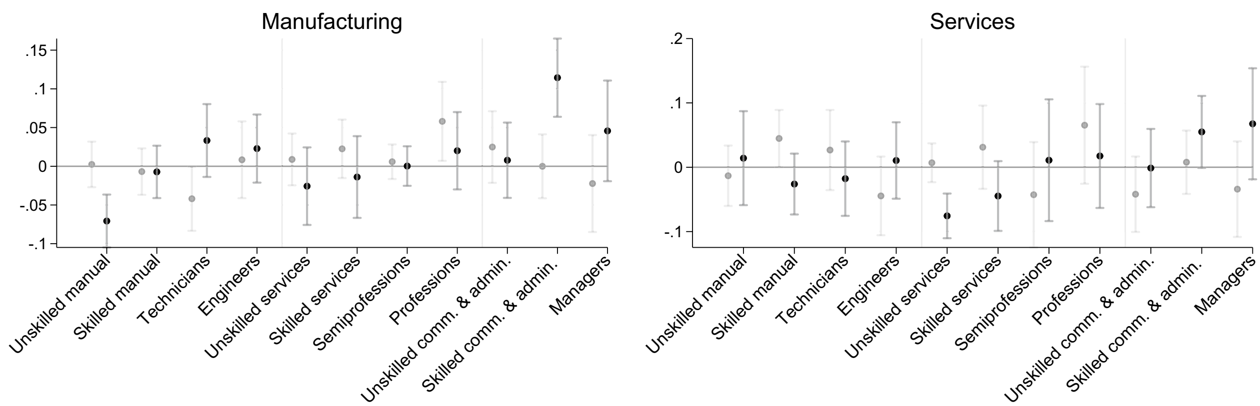


Fig. 6 MNEs' changes in standardized occupational shares relative to non-MNEs'. Source: IAB-ReLOC. This figure displays FDI responses of occupational shares in manufacturing (left panel) or service (right panel) MNEs relative to the shares in non-MNEs (in bold) and their pretrend (in light gray). Formally, the main estimates display the estimates of β_{POST} from Eq. (4), where the outcome is the occupational share o, and the associated 95% confidence intervals. The light estimates display estimates of β_{PRE}

positive estimates of a particular group imply reductions in MNEs relative to non-MNEs over this interval.

Importantly, Fig. 6 does not reveal significant growth differentials for either of the two sectors in the groups affected by FDI (managers, skilled commercial and administrative occupations, unskilled manual occupations, unskilled services and skilled services). The relative share of managers even tends to decrease in MNEs prior to the FDI event (i.e., the estimate is positive).

In manufacturing MNEs (left panel of Fig. 6), FDI particularly affects two groups of workers. On the one hand, the shares of skilled commercial and administrative occupations and of managers increase relative to those in non-MNEs by about 11.4 and 4.6 percentage points (pp), suggesting that these jobs are complementary to offshore production and/or FDI facilitating. Note that these groups were also identified as the strongest predictors of FDI in Sect. 3.[36] On the other hand, the share of unskilled manual occupations features the largest downturn relative to the share in non-MNEs, by about 7.1 pp. This decrease is in line with the findings of previous papers (e.g., Ebenstein et al. 2014; Ottaviano et al. 2013) that unskilled manual jobs are the most prone to substitution with low-wage offshore production. Interestingly, Sect. 3 demonstrates that the share of these jobs has no predictive power for future FDI decisions, implying that prior to the FDI, its direct costs (including the costs of managers and administrative staff) seem to be the more relevant determinant of the investment, not the specific cost–benefit analysis on whether to substitute (manual) workers with offshore labor.[37]

Across manufacturing firms, we find significant and dissimilar pretrends for technicians and professions. Since these groups have only a small impact on the propensity to engage in FDI (see Sect. 3) and since the differential behavior of these groups disappears following the FDI event, we do not suspect that another source of firm heterogeneity is driving the effects in the manufacturing sector.

After FDI, service MNEs (right panel of Fig. 6) see more heterogeneous changes in the various occupational shares. We again observe positive effects for the shares of managers and skilled commercial and administrative occupations relative to the shares in non-MNEs (5.5 and 6.8 pp). These jobs seem to be FDI facilitating and/or complementary to the activities performed in Czech affiliates (e.g., organizations of multisite MNEs). We also estimate negative effects for unskilled services and weaker (significant at 10%) negative effects for skilled services, which exhibit substitutability with low-wage foreign labor.[38] Strikingly, these groups were identified as negative predictors of FDI in Sect. 3, suggesting that service firms' cost–benefit considerations were primarily concerned about the costs and availability of FDI-facilitating tasks and not the share of substitutable workers (similar to the findings in the manufacturing sector).

[36] Figure 12 in Appendix D reveals that this increase is driven by *managers and management consultants*, as well as *accountants* and *data processing* or *office* specialists.

[37] The results for the manufacturing sector are also robust to matching on coarse occupational groups rather than on task intensities, but matching on task intensities is crucial for the results in the service sector.

[38] If these jobs were not offshored, we would obtain similar negative estimates for all other shares. Figure 13 suggests that surface transport jobs or health occupations are driving forces behind this decrease.

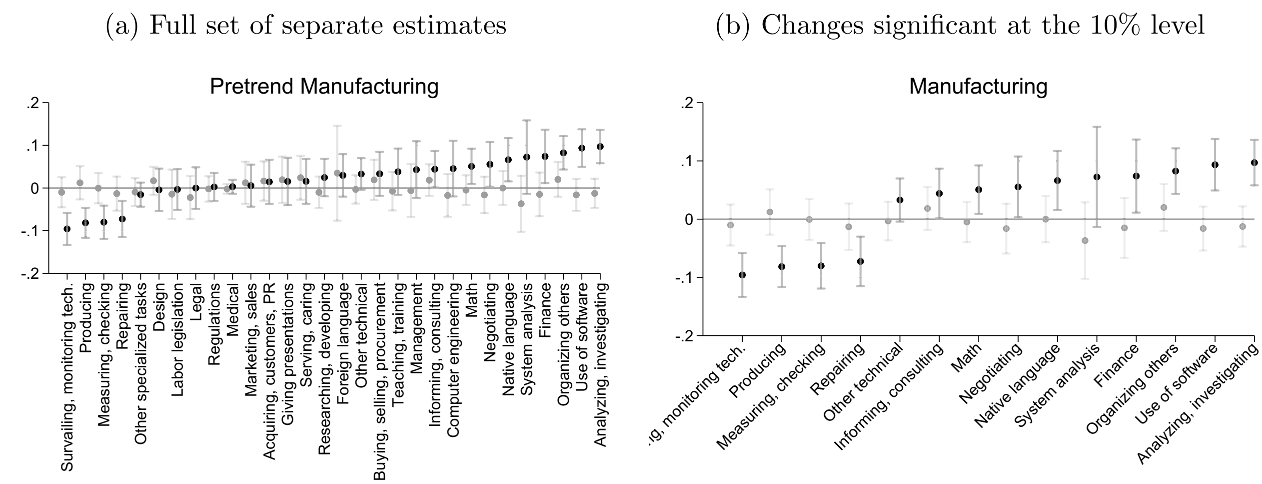


Fig. 7 Changes in standardized task intensities—manufacturing sector. Source: BiBB Employment Survey and IAB-ReLOC. This figure displays the FDI responses of task intensities in manufacturing MNEs relative to the intensities in non-MNEs. Formally, it displays the estimates of β_{POST} from Eq. (4), where the outcome is the intensity of task *o* and the associated 95% confidence intervals. **a** Reports the estimates of each regression, while **b** reports the selection of estimates that are significant at the 10% level

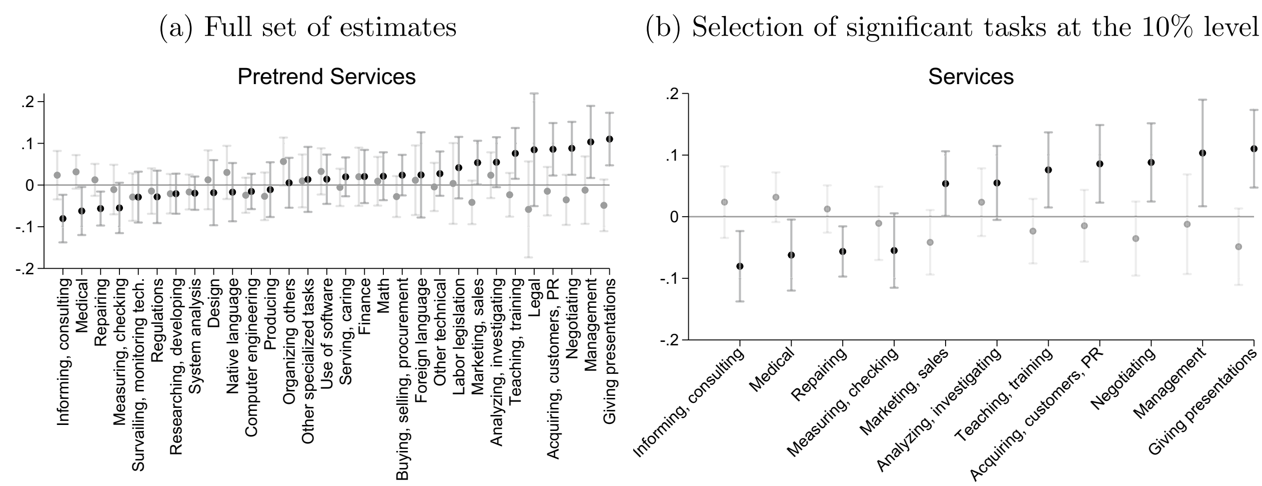


Fig. 8 Changes in standardized task intensities—service sector. Source: BiBB Employment Survey and IAB-ReLOC. This figure displays the responses of task intensities to FDI in manufacturing MNEs relative to the intensities in non-MNEs. Formally, it displays the estimates of β_{POST} from Eq. (4) in bold, where the outcome is the intensity of task *o*, and the associated 95% confidence intervals. The light gray estimates report the respective pretrends. **a** Reports the estimates for each regression, while **b** reports the selection of estimates that are significant at the 10% level

4.3 Results—specific task intensities

Regarding the estimation of nuanced task demand changes, we repeat our analysis with task intensities and present the estimates of β_{POST} from Eq. (4) (in bold) in Fig. 7 for the manufacturing sector and in Fig. 8 for the service sector. In both figures, we also report the estimates of β_{PRE} from Eq. (4) (in light gray) and their 95% confidence intervals. Panel (a) of the respective figures shows the results for each task regression, while Panel (b) presents the subset of estimates that are significant at least at the 10% level to facilitate interpretation. According to the task trade theory of Grossman and Rossi-Hansberg (2008), we would expect negative shifts in all tasks with relative offshorability costs below a threshold and positive shifts in the other tasks.[39] Usually, these

[39] Our empirical strategy allows us to identify only relative employment changes, whereas the shifts suggested by Grossman and Rossi-Hansberg (2008) are general equilibrium effects. We use their insights to guide our interpretation while acknowledging this difference.

offshorability costs are measured by codifiability or routineness (e.g., Baumgarten et al. 2013; Becker et al. 2013). If we, instead, interpret the ranking of offshorability costs as a ranking of tasks with respect to their wage compensation (rather than by any subjective classification), we find empirical evidence of this phenomenon for manufacturing MNEs.

In particular, in the manufacturing sector, we find positive shifts in favor of organizational tasks and tasks that likely pertain to market analysis: *investigating or analyzing* (+ 9.7 pp), *organizing the work of others* (+ 8.2 pp), *system analysis* (+ 7.2 pp), and *negotiating* (+ 5.5 pp). All of these tasks align with the set of FDI-facilitating tasks, confirming the hypothesis that firms face additional challenges in managing and coordinating onshore and offshore activities. Other tasks overlap with typical headquarters activities: the *use of software* (+ 9.3 pp), *finance* (+ 7.4 pp), *math* (+ 5.1 pp), or the native language of the parent company (*German* + 6.6 pp). We also find positive effects of *management* (+ 4.3 pp) and *training* activities (+ 3.8 pp) and commercial tasks such as *negotiating* and *buying and selling* (+ 3.3 pp), presumably to cope with a more geographically distributed value chain.

We also find negative effects for a set of highly related tasks, such as *monitoring* (− 9.6 pp), *producing* (− 8.1 pp), *checking/measuring* (− 8.0 pp), or *repairing* (− 7.3 pp). This shift away from production tasks suggests efficiency-seeking FDI, in which production is relocated to offshore locations. Note also that all of these tasks are low paid (Table 1) and are related to routine and/or noninteractive manual work. This suggests that MNEs source relatively simple tasks from their offshore affiliates and expand their range of well-paid tasks, such as management and sales-related tasks, onshore.

After service firms' FDI, these MNEs also increase the intensity of some headquarters tasks, such as *management* (+ 10.3 pp), *training* (+ 7.6 pp), and *investigating and analyzing* (+ 5.5 pp). Moreover, positive effects become apparent for marketing and sales-related tasks, such as *giving presentations* (+ 11.0 pp), *negotiating* (+ 8.8 pp), *customer acquisition* (+ 8.6 pp), *marketing* (+ 5.4 pp), and *public relations*. These seem to be complementary to production in offshore affiliates and are likely to be associated with market-seeking FDI. There is also a tendency toward increases in legal activities, which appeared as the best single predictor of future FDI in our analysis in Sect. 3. However, we do not find substantial positive effects for some sophisticated tasks that we would expect to be associated with a skill-upgrading process such as *maths*, *computer engineering* and *R&D*. On the one hand, this absence may be due to the many MNEs in the low-tech service sector, including the wholesale, retail, and logistics industries (see Table 2). On the other hand, the sample also includes firms in industries such as data processing, accounting, (technical) consulting, and engineering that may offshore such activities.[40] In summary, the matched service firms could still exhibit high heterogeneity between very dissimilar service industries. We find significant negative estimates for relatively high-skilled service tasks, namely, *consulting and informing* (− 8.0 pp) and *medical* tasks (− 6.2 pp), in line with potential service offshoring. A large fraction of the decreases in medical tasks is driven by Czech nursing assistants who live with and care for people in need of care in Germany (see Appendix A1). Although working in Germany, these workers are employed by a Czech company and pay taxes and social security there.[41] We also find negative shifts for production-related tasks such as *repairing* (− 5.6 pp) and *measuring/checking* (− 5.5 pp).[42] These counterintuitive results contrast with those of studies such as that by Blinder and Krueger (2013, p. 117), who posit an offshorability share of 1.3% of all workers in "installation, maintenance, and repair occupations" (using their preferred measure by external coders).[43] It seems that—instead of offshorability—these negative shifts are driven by the comparative advantage of the Czech Republic in associated economic activities (see also Muñoz 2021).

In both sectors, all pretrend estimates are insignificantly different from zero, affirming that our algorithm matches firms with the same task trajectories prior to the FDI decision (in $\tau - 2$). One notable exception is *organizing the work of others* in the service sector, which tends to increase in the preperiod (negative estimate and significant at 10%). Since FDI does not affect this task category ex post, we conclude that the potential biases from general trends among FDI-engaging firms are rather small in our other estimates.[44]

[40] Marin (2004, p. 23) mentions that many (German) R &D departments are offshored to Eastern European countries. She explicitly notes, for example, that Siemens "plans to centralize and outsource some of its headquarters activities like accounting and management to Siemens subsidiaries in the Czech Republic."

[41] This special working arrangement is possible due to the EU's *Posting of Workers Directive*: employees may be sent to another EU member state to carry out a service on a temporary basis. Some Czech commercial providers directly offer nursing assistant services to people in need of care in Germany.

[42] Other production-related tasks are monitoring activities and hazardous or polluting tasks associated with knowledge of respective regulations in Germany.

[43] Note, however, that the share of workers who self-classify as offshorable in this group is already approximately 17 times higher, at 22% (Blinder and Krueger 2013, p. 117). We also refer to Storm (2020), who highlights the advantages of surveyed task measures over classifications by experts.

[44] The estimate of β_{POST} in the regression of *organizing the work of others* could be severely biased through its pretrend, however.

Table 7 Summary statistics—unmatched sample

	Manufacturing			Service		
	MNEs	**Non-MNEs**	**Balancing**	**MNEs**	**Non-MNEs**	**Balancing**
	Mean	**Mean**	**Std. bias**	**Mean**	**Mean**	**Std. bias**
	Median	***Median***		***Median***	***Median***	
	(Std. dev.)	**(Std. dev.)**	**(Var. ratio)**	**(Std. dev.)**	**(Std. dev.)**	**(Var. ratio)**
Plants per firm	2.256	1.594	0.179	11.70	3.093	0.060
	1	*1*	–	*1*	*1*	–
	(4.397)	(2.853)	(2.375)	(203.7)	(12.73)	(255.9)
Size (employees)	814.8	222.2	0.139	443.5	143.0	0.080
	139	*147*	–	*32*	*49*	–
	(6032.7)	(335.8)	(322.8)	(5270.3)	(489.0)	(116.2)
(Daily) wage bill (in thousand euros)	98.791	24.585	0.137	46.865	13.754	0.096
	13.431	*13.049*	–	*36.517*	*41.608*	–
	(761.538)	(60.113)	(160.5)	(484.139)	(48.973)	(97.73)
Number of tasks	21.46	20.26	0.211	16.14	14.97	0.180
	23	*22*	–	*17*	*15*	–
	(5.638)	(5.672)	(0.988)	(6.756)	(6.261)	(1.165)
Tasks per worker	5.144	4.853	0.215	5.499	4.890	0.250
	5.081	*4.816*	–	*5.500*	*4.635*	–
	(1.316)	(1.384)	(0.904)	(2.263)	(2.603)	(0.756)
Broad occupations (shares in %)						
Production						
Unskilled manual	36.45	32.12	0.171	5.050	5.337	− 0.0194
	37.30	*30.08*	–	*0*	*0*	–
	(25.26)	(25.49)	(0.982)	(14.35)	(15.20)	(0.891)
Skilled manual	19.70	25.53	− 0.276	5.031	7.766	− 0.180
	13.41	*19.21*	–	*0*	*0*	–
	(19.59)	(22.58)	(0.753)	(13.19)	(16.91)	(0.608)
Technicians	8.835	7.756	0.104	4.935	4.051	0.0706
	6.885	*5.263*	–	*0*	*0*	–
	(9.912)	(10.87)	(0.831)	(12.37)	(12.67)	(0.953)
Engineers	3.716	2.853	0.137	4.225	2.825	0.118
	1.681	*0.611*	–	*0*	*0*	–
	(6.306)	(6.317)	(0.996)	(12.64)	(10.96)	(1.329)
Services						
Unskilled service	6.048	7.129	− 0.116	16.89	24.67	− 0.268
	4.100	*4.244*	–	*3.846*	*8.861*	–
	(7.722)	(10.71)	(0.520)	(25.58)	(32.06)	(0.636)
Skilled service	0.341	0.504	− 0.0591	0.818	1.801	− 0.142
	0	*0*	–	*0*	*0*	–
	(2.484)	(3.000)	(0.686)	(4.683)	(8.640)	(0.294)
Semiprofessions	0.201	0.401	− 0.0853	0.497	0.315	0.0492
	0	*0*	–	*0*	*0*	–
	(1.508)	(2.940)	(0.263)	(4.126)	(3.209)	(1.653)
Professions	0.328	0.240	0.0529	0.808	0.847	− 0.00791
	0	*0*	–	*0*	*0*	–
	(1.459)	(1.842)	(0.628)	(4.868)	(5.182)	(0.883)
Administration						
Unskilled commercial and admin.	3.763	6.559	− 0.242	11.06	12.96	− 0.0890

Table 7 (continued)

	Manufacturing			Service		
	MNEs	**Non-MNEs**	**Balancing**	**MNEs**	**Non-MNEs**	**Balancing**
	Mean	**Mean**	**Std. bias**	**Mean**	**Mean**	**Std. bias**
	Median	***Median***		***Median***	***Median***	
	(Std. dev.)	**(Std. dev.)**	**(Var. ratio)**	**(Std. dev.)**	**(Std. dev.)**	**(Var. ratio)**
	1.626	*1.429*	–	*2.439*	*1.961*	–
	(7.080)	(14.72)	(0.231)	(19.70)	(22.86)	(0.743)
Skilled commercial and admin.	17.45	14.57	0.219	43.17	34.23	0.285
	14.29	*12*	–	*38.46*	*23.81*	–
	(13.56)	(12.60)	(1.157)	(30.84)	(31.96)	(0.931)
Managers	2.999	2.203	0.155	7.281	4.782	0.177
	1.660	*1.214*	–	*1.961*	*0.410*	–
	(5.712)	(4.457)	(1.642)	(15.32)	(12.86)	(1.418)
Activities performed						
Researching, developing	1.198	0.963	0.185	1.174	0.723	0.222
	0.842	*0.556*	–	*0*	*0*	–
	(1.317)	(1.223)	(1.159)	(2.202)	(1.838)	(1.435)
Teaching, training	1.878	1.550	0.223	2.442	2.206	0.080
	1.644	*1.299*	–	*1.429*	*0.769*	–
	(1.476)	(1.456)	(1.028)	(2.790)	(3.092)	(0.814)
Acquiring customers, PR	0.998	0.942	0.041	1.958	1.520	0.175
	0.582	*0.451*	–	*0.986*	*0.465*	–
	(1.287)	(1.478)	(0.758)	(2.581)	(2.439)	(1.120)
Analyzing, investigating	7.166	6.201	0.273	12.03	10.18	0.380
	6.874	*5.818*	–	*12.50*	*10.34*	–
	(3.500)	(3.571)	(0.960)	(4.506)	(5.191)	(0.753)
Buying, selling	1.908	2.790	−0.256	4.689	5.618	−0.146
	1.540	*1.365*	–	*3.286*	*2.852*	–
	(1.763)	(4.547)	(0.150)	(5.157)	(7.407)	(0.485)
Organizing others	9.328	8.523	0.207	13.24	11.80	0.300
	9.414	*8.551*	–	*13.64*	*11.84*	–
	(3.684)	(4.070)	(0.819)	(4.420)	(5.157)	(0.735)
Consulting, informing	13.43	14.00	−0.128	15.23	16.93	−0.232
	13.45	*13.83*	–	*15.13*	*15.85*	–
	(3.874)	(4.930)	(0.618)	(5.017)	(9.057)	(0.307)
Measuring, checking	13.51	13.58	−0.0133	5.437	5.617	−0.033
	13.56	*13.82*	–	*4.255*	*4.206*	–
	(5.473)	(5.471)	(1.000)	(5.321)	(5.744)	(0.858)
Negotiating	3.156	2.792	0.178	5.504	4.772	0.187
	3.086	*2.500*	–	*5.508*	*4.094*	–
	(1.956)	(2.145)	(0.832)	(3.811)	(4.019)	(0.899)
Serving, caring	1.641	2.613	−0.279	3.834	5.973	−0.326
	1.334	*1.199*	–	*2*	*2.958*	–
	(1.729)	(4.618)	(0.140)	(5.219)	(7.661)	(0.464)
Monitoring, surveilling	11.84	12.41	−0.095	2.808	3.796	−0.168
	11.91	*12.50*	–	*0.358*	*0.416*	–
	(5.906)	(6.098)	(0.938)	(5.053)	(6.584)	(0.589)
Repairing	8.015	8.612	−0.103	6.183	6.838	−0.042
	7.565	*8.303*	–	*0.308*	*0.635*	–

Table 7 (continued)

	Manufacturing			Service		
	MNEs	**Non-MNEs**	**Balancing**	**MNEs**	**Non-MNEs**	**Balancing**
	Mean	**Mean**	**Std. bias**	**Mean**	**Mean**	**Std. bias**
	Median	***Median***		***Median***	***Median***	
	(Std. dev.)	**(Std. dev.)**	**(Var. ratio)**	**(Std. dev.)**	**(Std. dev.)**	**(Var. ratio)**
	(5.500)	(6.060)	(0.824)	(15.88)	(15.21)	(1.089)
Manufacturing	8.879	9.533	−0.102	1.300	1.805	−0.110
	8.434	*9.259*	–	*0*	*0*	–
	(6.373)	(6.448)	(0.977)	(3.893)	(5.192)	(0.562)
Associated knowledge						
Management	0.539	0.432	0.152	0.965	0.631	0.231
	0.339	*0.264*	–	*0.342*	*0*	–
	(0.762)	(0.635)	(1.443)	(1.629)	(1.249)	(1.702)
Computer engineering	0.376	0.275	0.158	0.698	0.419	0.174
	0.151	*0.053*	–	*0*	*0*	–
	(0.689)	(0.591)	(1.355)	(1.757)	(1.425)	(1.520)
Giving presentations	0.841	0.734	0.0943	1.471	0.990	0.245
	0.435	*0.350*	–	*0.662*	*0.158*	–
	(1.115)	(1.160)	(0.925)	(2.133)	(1.768)	(1.456)
Foreign language	0.062	0.046	0.066	0.031	0.044	−0.033
	0	*0*	–	*0*	*0*	–
	(0.226)	(0.235)	(0.924)	(0.178)	(0.548)	(0.105)
Legal/law	0.018	0.008	0.097	0.017	0.032	−0.054
	0	*0*	–	*0*	*0*	–
	(0.132)	(0.041)	(10.40)	(0.115)	(0.378)	(0.092)
System analysis	0.204	0.161	0.101	0.601	0.368	0.153
	0.066	*0*	–	*0*	*0*	–
	(0.452)	(0.384)	(1.390)	(1.685)	(1.358)	(1.540)
Maths	1.431	1.186	0.178	1.462	2.009	−0.180
	1.155	*0.804*	–	*0.357*	*0.263*	–
	(1.336)	(1.417)	(0.890)	(2.470)	(3.520)	(0.492)
Other technical	1.584	1.445	0.0683	0.750	0.597	0.088
	0.881	*0.709*	–	*0*	*0*	–
	(2.036)	(2.048)	(0.988)	(1.810)	(1.668)	(1.177)
Labor legislation	0.008	0.006	0.086	0.006	0.005	0.012
	0	*0*	–	*0*	*0*	–
	(0.027)	(0.022)	(1.420)	(0.093)	(0.110)	(0.705)
Design	0.069	0.215	−0.182	0.0904	0.101	−0.018
	0	*0*	–	*0*	*0*	–
	(0.404)	(1.051)	(0.148)	(0.549)	(0.658)	(0.696)
Use of software	6.453	5.373	0.281	10.30	8.725	0.292
	5.988	*5.089*	–	*10.34*	*8.929*	–
	(4.413)	(3.174)	(1.933)	(4.994)	(5.728)	(0.760)
Marketing, sales	0.335	0.293	0.051	0.615	0.423	0.125
	0	*0*	–	*0*	*0*	–
	(0.795)	(0.841)	(0.894)	(1.685)	(1.372)	(1.508)
Finance, taxes	0.203	0.186	0.034	0.554	1.242	−0.285
	0.057	*0.044*	–	*0*	*0*	–
	(0.465)	(0.527)	(0.779)	(1.606)	(3.015)	(0.284)

Table 7 (continued)

	Manufacturing			Service		
	MNEs	**Non-MNEs**	**Balancing**	**MNEs**	**Non-MNEs**	**Balancing**
	Mean	**Mean**	**Std. bias**	**Mean**	**Mean**	**Std. bias**
	Median	***Median***		***Median***	***Median***	
	(Std. dev.)	**(Std. dev.)**	**(Var. ratio)**	**(Std. dev.)**	**(Std. dev.)**	**(Var. ratio)**
Native language (German)	3.111	2.713	0.142	5.950	5.440	0.094
	2.361	*2.007*	–	*4.376*	*3.704*	–
	(2.876)	(2.756)	(1.089)	(5.435)	(5.407)	(1.011)
Regulations[a]	1.198	1.093	0.048	0.354	0.487	−0.073
	0.424	*0.277*	–	*0*	*0*	–
	(2.185)	(2.224)	(0.965)	(1.402)	(2.163)	(0.420)
Other specialized	0.546	1.203	−0.258	0.275	0.552	−0.140
	0	*0*	–	*0*	*0*	–
	(1.895)	(3.053)	(0.385)	(1.730)	(2.191)	(0.624)
Medical knowledge	0.074	0.121	−0.047	0.038	0.155	−0.131
	0	*0*	–	*0*	*0*	–
	(0.865)	(1.081)	(0.639)	(0.337)	(1.216)	(0.077)

Table 7 describes the summary statistics for 971 (863) MNEs in the manufacturing (service) sector 2 years prior to the FDI event and the respective statistics of 3320 (3860) manufacturing (service) non-MNEs across all years. For each variable, we report the mean, median and standard deviation. In comparing MNEs and non-MNEs, we also report the standardized bias and the variance ratio between the two groups. The wage bill is denoted in constant 2010 euros. Employment and wage growth are measured as the 4-year log difference

[a] The task *Regulations* includes knowledge requirements on rules for labor protection, such as accident prevention, safety regulations, occupational health and safety, as well as environmental regulations

5 Conclusion

Although the effects of international activities on onshore labor are a well-studied topic, little is known about the *actual* effects of FDI on specific tasks, especially in the service sector (in contrast to offshorability as a measure of a *potential* response). In this paper, we analyze the effect of FDI in a low-wage country on the onshore task recomposition of firms in a country with substantially higher labor costs.

We develop a matching procedure that vastly mitigates the selection bias to which the DiD analysis would otherwise be susceptible. By exploring the selection of firms into FDI, we also investigate the task intensities that are relevant for firms' expansion into the Czech Republic. Lasso logit models reveal positive correlations of FDI events with the shares of management and skilled commercial and administrative occupations or with the intensities of headquarters tasks pertaining to the organization and coordination of international activities. We interpret these correlations as suggestive evidence that such tasks constitute parts of the fixed costs of FDI as described by Helpman et al. (2004).

Using propensity scores from post-lasso logit regressions, we then match each MNE to a non-MNE and estimate a DiD in task intensities after an FDI decision. It shows that relative to non-MNEs, German manufacturing MNEs expand their employment in skilled commercial and administrative occupations while they decrease it in unskilled manual occupations. In terms of tasks, MNEs decrease the intensity of production-related tasks associated with the lowest wage compensation (such as *surveilling/monitoring* −9.6 pp, *producing* −8.1 pp, *measuring* −8.0 pp, and *repairing* −7.3 pp) and increase high-wage headquarters activities (such as *analyzing* +9.7 pp, *organizing the work of others* +8.2 pp, the *use of software* +9.3 pp, *negotiating* +5.5 pp, *informing/consulting* +4.4 pp, tasks involving the native language of the MNE +6.6 pp, *sales* +3.3 pp, and *system analysis* +7.2 pp). For service MNEs, we find relative decreases in employment of (un)skilled service workers—presumably service providers—and relative increases in the share of managers and skilled commercial and administrative occupations. Associated changes in the task composition are systematic increases for high-wage managerial (*management* +10.3 pp, *negotiating* +8.8 pp, and *teaching/training* +7.6 pp) and marketing (*giving presentations* +11.0 pp and *public relations* +8.6 pp) tasks. While management tasks are needed to cope with fragmented production, marketing tasks may become more essential because of higher sales from efficiency gains and/or increased market access due to FDI. Turning to the negative effects in service MNEs, we do not find systematic decreases in any group of tasks but rather nuanced decreases in specific intensities of relatively low-wage service-providing tasks such as *consulting/informing* (− 8.0 pp), *medical* tasks (− 6.2 pp, e.g., of nursing assistants) and *repairing* (− 5.6 pp). It is striking that the latter tasks are explicitly considered nonoffshorable by external experts in BK's study.[45]

Several other aspects would be interesting to investigate in further research. Now that we have observed the typical task intensities in firms that invest in a low-wage country and the changes in task intensities due to this FDI, it is essential to repeat the analysis for FDI to another high-wage country. The motives of FDI (efficiency seeking vs. market seeking) could have a different focus in this case. While we would expect similar initial intensities in FDI-facilitating tasks, differences in the comparative advantage of specific (clusters of) tasks (as in Grossman and Rossi-Hansberg 2012) may change very different task intensities following FDI events. Additionally, it would be interesting to explore whether there are substantial differences in initial task intensities between new FDI-engaging firms and incumbent MNEs (e.g., the tasks of management and HR legal experts could be more intensive in incumbent MNEs, as new MNEs are more similar to non-MNEs) and to explore their subsequent reallocation effects (we would expect higher increases in management task intensities in new MNEs). Finally, in light of the COVID-19 crisis, a relevant avenue for future research would be to analyze the comparability of internationally tradable tasks with tasks that can easily be performed from home.

Appendix

A Descriptive statistics

A1 Broad occupational classification (blossfeld)

Table 1 reports the tasks in the 1998 BiBB survey, the average wages of all workers who perform them, and examples of representative jobs. The best-paid task is *developing and researching*, while *producing* is the worst paid. Regarding the associated knowledge, we observe that *management* skills are at the top of the wage distribution and that *other specialized* or *medical* knowledge is at the bottom. Note that these numbers are derived from the manufacturing and private service sector. The German health industry, which predominantly consists of public firms, is excluded. In the manufacturing sector, 5.32% of workers perform medical tasks. They are mainly in industries such as the manufacture of motor vehicles (25%), (pharmaceuticals, medicinal) chemicals (20%), and the manufacture of electrical machinery such as electric motors, generators, and transformers (14%). The majority of these workers are medical receptionists (16%), nursing assistants (15%), physicians (15%), medical lab assistants (12%), or pharmacists (12%). In the service sector, we observe 3.65% of the workers performing medical tasks. They are mainly in the following industries: labor recruitment and provision of personnel (39%), research and experimental development on natural sciences and engineering (12%), and wholesale of household goods (14%), including pharmaceutical and medical goods. The largest shares of these workers are social workers (20%), nursing assistants (18%), or medical lab assistants (13%).

We also analyze the onshore recompositions of sets of tasks using broad occupational categories according to Blossfeld (1985). These groups represent socioeconomic strata of the German workforce mapping (three-digit) occupation titles according to similar education levels, earnings, and job activities. Table 6 presents an overview of the groups, including the average daily wage in 2010 and examples of typical occupational titles at the three-digit level.

A2 Unmatched sample

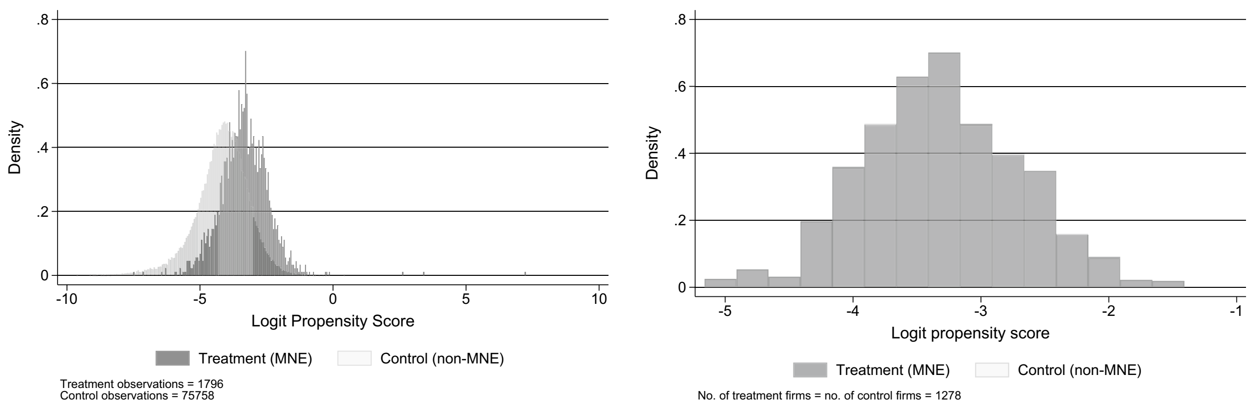
Adding to Tables 3, 7 reports further summary statistics of our sample, such as the task intensities and employment shares of broad occupational groups. As expected, in manufacturing firms, we observe high shares in manual occupations that are predominantly unskilled (e.g., assembly workers). Moreover, MNEs feature a higher share of skilled commercial and administrative staff (e.g., accountants), presumably for headquarters activities. In the service sector, (un)skilled commercial and administrative jobs comprise 40% of the median firm's employment (while nonbusiness services represent approximately 20% of the workforce). The share of skilled commercial and administrative occupations and of managers is particularly higher in MNEs than in non-MNEs.

B Propensity score matching

B1 Balancing statistics

Using the selected variables from the regularized regressions, we rerun a nonpenalized logit regression to estimate propensity scores separately by sector. Corresponding to Sect. 4, Fig. 9 illustrates the pooled distribution of these propensity scores in the treated MNEs (dark gray) and the control units, which are the non-MNEs (light gray). The prematching distributions (left) display the differences between MNEs and non-MNEs in the propensity to invest in the Czech Republic. This difference vastly diminishes in both sectors after matching, as shown by the almost congruent bars in the right panel.

[45] We also complement the analysis by drawing a direct link from our outcomes to BK and other literature on offshorable jobs in Appendix C1.



(a) Full (initial) sample (b) Matched firms two years prior to (virtual) FDI

Fig. 9 Distributions of propensity scores pre- and postmatching. Source: BiBB Employment Survey and IAB-ReLOC. This figure presents the distributions of the estimated propensity scores for MNEs and non-MNEs with respect to sending FDI to the Czech Republic in 2 years. **a** Illustrates the distribution before matching and for all observations of non-MNEs. **b** Shows the distributions for matched treatment and control firms in the year of matching, which are almost perfectly congruent. Propensity scores are derived from a logit model as described in Sect. 4.1

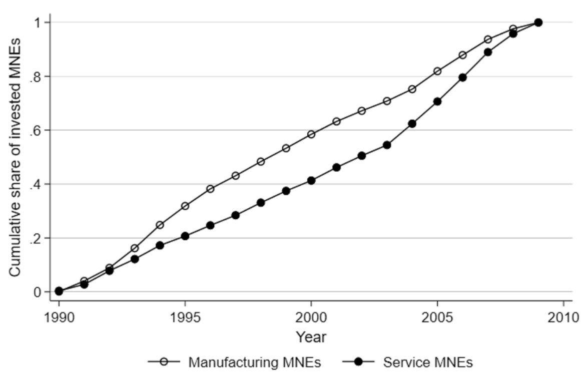


Fig. 10 Timing of FDI events by sector (matched sample). Source: IAB-ReLOC. This figure presents the cumulative share of invested MNEs by sector. It covers all MNEs from the matched sample and shows that the manufacturing firms tended to expand to the Czech Republic earlier than service firms

The two-step matching procedure improves the balancing statistics not only of the matching covariates but also of untargeted variables. In both sectors, the distributions of the observable variables overlap, which we report in terms of the standardized bias (ideally below 0.05) or the variance ratio (close to 1). Table 8 thus shows that our matching procedure selects similar firms even when they are evaluated on untargeted variables such as the broad occupational categories. Although the matching of firms in the service sector greatly improves the balancing of firms, it is still weaker than the balancing in the manufacturing sector because the former firms are more heterogeneous from the beginning. The greatest differences within the matches persist even for the matching covariates size and wage bill, while untargeted variables become fairly similar across the groups. After accounting for the many different and detailed variables, we conclude that in sum, the resulting firms are sufficiently similar in an array of economic activities and task performance to allow us to infer a causal relationship under our DiD approach.

C Additional results: FDI, task profiles, and offshorability

Thus far, we have identified (sets of) task intensities that either expand or contract after FDI events. Since the literature has already attempted to group the occupational task profiles that are affected by international activities (e.g., by their offshorability and routineness), in this appendix, we examine whether our estimates of actual responses overlap with the findings of these studies.

C1 Offshorability indices

To compare FDI-substitutable with offshorable jobs, we borrow established indices related to offshorability from four sources in the literature. We report them in Table 9. Our choice of indices relies on both the intent behind the measures' construction (preferably, to capture heterogeneous effects of globalization) and the prominence of their use in subsequent studies. For example, BK intended to gauge the potential of service jobs in particular to supply their output to the onshore market through work offshore. ALM-SO became the main reference for researchers attempting to quantify job routineness or codifiability. Their measures (or variants of them) are regularly applied in studies on substitutability between labor and machines/technology or offshore production. One of

Table 8 Summary statistics—matched sample

	Manufacturing			Service		
	MNEs	**Non-MNEs**	**Balancing**	**MNEs**	**Non-MNEs**	**Balancing**
	Mean	**Mean**	**Std. bias**	**Mean**	**Mean**	**Std. bias**
	Median	***Median***		***Median***	***Median***	
	(Std. dev.)	**(Std. dev.)**	**(Var. ratio)**	**(Std. dev.)**	**(Std. dev.)**	**(Var. ratio)**
(Log) plants per firm	0.309	0.309	0.001	0.464	0.429	0.044
	0	*0*	–	*0*	*0*	–
	(0.540)	(0.549)	(0.968)	(0.850)	(0.741)	(1.313)
(Log) size (employees)	4.895	4.908	−0.009	3.688	3.487	0.122
	4.942	*5.159*	–	*3.714*	*3.526*	–
	(1.525)	(1.332)	(1.310)	(1.712)	(1.603)	(1.140)
(Log) wage bill (in euros)	9.415	9.441	−0.017	8.392	8.166	0.127
	9.487	*9.638*	–	*8.486*	*8.194*	–
	(1.644)	(1.444)	(1.296)	(1.832)	(1.721)	(1.133)
Employment growth	3.064	3.123	−0.055	2.841	2.763	0.069
	2.833	*2.891*	–	*2.736*	*2.721*	–
	(1.187)	(0.954)	(1.548)	(1.224)	(1.031)	(1.410)
Wage growth	2.093	2.071	0.025	2.436	2.416	0.022
	2.161	*2.140*	–	*2.257*	*2.257*	–
	(0.881)	(0.851)	(1.072)	(0.938)	(0.880)	(1.135)
Female employees (%)	32.56	32.45	0.005	39.83	40.93	−0.046
	27.12	*27.71*	–	*36.38*	*36.36*	–
	(21.05)	(21.21)	(0.985)	(23.22)	(24.91)	(0.869)
Task intensities (%)						
Activities performed						
Researching, developing	1.188	1.250	−0.047	1.274	1.356	−0.035
	0.837	*0.840*	–	*0.176*	*0*	–
	(1.301)	(1.379)	(0.890)	(2.295)	(2.373)	(0.935)
Teaching, training	1.858	1.803	0.040	2.400	2.542	−0.053
	1.610	*1.593*	–	*1.491*	*1.516*	–
	(1.449)	(1.345)	(1.162)	(2.567)	(2.759)	(0.866)
Acquiring customers, PR	0.961	0.905	0.046	1.971	2.020	−0.020
	0.565	*0.492*	–	*1.116*	*1.186*	–
	(1.214)	(1.235)	(0.967)	(2.458)	(2.451)	(1.006)
Analyzing, investigating	7.028	7.028	0	12.51	12.39	0.030
	6.778	*6.443*	–	*12.84*	*12.50*	–
	(3.311)	(3.396)	(0.951)	(3.839)	(3.878)	(0.980)
Buying, selling, procurement	1.832	1.747	0.053	4.451	4.700	−0.058
	1.475	*1.267*	–	*3.448*	*3.659*	–
	(1.552)	(1.658)	(0.876)	(4.286)	(4.345)	(0.973)
Organizing others	9.292	9.185	0.031	13.55	13.46	0.024
	9.401	*8.992*	–	*13.87*	*13.35*	–
	(3.609)	(3.340)	(1.168)	(3.859)	(3.927)	(0.966)
Informing, consulting	13.46	13.44	0.007	14.79	14.83	−0.010
	13.54	*13.48*	–	*15.02*	*15.15*	–
	(3.692)	(3.838)	0.925	(4.108)	(3.972)	(1.069)
Measuring, checking	13.72	13.90	−0.035	5.137	5.054	0.019
	13.63	*13.96*	–	*4.208*	*4.632*	–
	(5.283)	(5.135)	(1.059)	(4.532)	(4.189)	(1.170)

Table 8 (continued)

	Manufacturing			Service		
	MNEs	**Non-MNEs**	**Balancing**	**MNEs**	**Non-MNEs**	**Balancing**
	Mean	**Mean**	**Std. bias**	**Mean**	**Mean**	**Std. bias**
	Median	***Median***		***Median***	***Median***	
	(Std. dev.)	**(Std. dev.)**	**(Var. ratio)**	**(Std. dev.)**	**(Std. dev.)**	**(Var. ratio)**
Negotiating	3.083	3.054	0.016	5.791	6.041	−0.071
	2.970	*2.803*	–	*5.687*	*6.208*	–
	(1.863)	(1.926)	(0.936)	(3.509)	(3.553)	(0.975)
Serving, caring	1.581	1.475	0.075	3.355	3.497	−0.034
	1.314	*1.168*	–	*1.983*	*2.060*	–
	(1.514)	(1.340)	(1.276)	(4.243)	(4.069)	(1.087)
Surveilling, monitoring	12.04	12.09	−0.009	2.484	2.440	0.010
	12	*12.30*	–	*0.440*	*0.349*	–
	(5.630)	(5.379)	(1.095)	(4.466)	(4.391)	(1.034)
Repairing	8.259	8.324	−0.013	6.314	5.586	0.050
	7.924	*8.113*	–	*0.563*	*0.540*	–
	(5.309)	(4.823)	(1.212)	(15.35)	(13.85)	(1.229)
Producing, manufacturing	9.063	9.201	−0.025	1.388	1.288	0.025
	8.679	*8.873*	–	*0*	*0*	–
	(6.237)	(6.031)	(1.070)	(4.123)	(3.752)	(1.208)
Associated knowledge						
Management	0.515	0.479	0.055	0.906	0.921	−0.011
	0.332	*0.324*	–	*0.415*	*0.360*	–
	(0.712)	(0.593)	(1.440)	(1.376)	(1.368)	(1.012)
Computer engineering	0.359	0.366	−0.010	0.837	0.881	−0.022
	0.145	*0.135*	–	*0*	*0*	–
	(0.647)	(0.711)	(0.827)	(1.953)	(2.029)	(0.927)
Giving presentations	0.831	0.752	0.073	1.408	1.524	−0.060
	0.434	*0.419*	–	*0.752*	*0.841*	–
	(1.107)	(1.058)	(1.094)	(1.862)	(1.986)	(0.879)
Foreign language	0.054	0.061	−0.034	0.025	0.033	−0.046
	0	*0*	–	*0*	*0*	–
	(0.187)	(0.228)	(0.675)	(0.124)	(0.189)	(0.435)
Legal/law	0.008	0.010	−0.041	0.013	0.011	0.024
	0	*0*	–	*0*	*0*	–
	(0.027)	(0.034)	(0.615)	(0.069)	(0.078)	(0.767)
System analysis	0.188	0.210	−0.047	0.757	0.741	0.008
	0.060	*0.069*	–	*0*	*0*	–
	(0.420)	(0.511)	(0.675)	(1.913)	(1.917)	(0.996)
Maths	1.419	1.492	−0.052	1.388	1.642	−0.103
	1.158	*1.109*	–	*0.518*	*0.456*	–
	(1.293)	(1.512)	(0.731)	(2.241)	(2.675)	(0.702)
Other technical	1.612	1.630	−0.009	0.638	0.772	−0.082
	0.879	*0.931*	–	*0*	*0*	–
	(2.051)	(2.011)	(1.040)	(1.536)	(1.725)	(0.793)
Labor legislation	0.006	0.007	−0.066	0.001	0.0045	−0.099
	0	*0*	–	*0*	*0*	–
	(0.018)	(0.022)	(0.670)	(0.007)	(0.052)	(0.019)
Design	0.052	0.056	−0.013	0.089	0.117	−0.045

Table 8 (continued)

	Manufacturing			Service		
	MNEs	**Non-MNEs**	**Balancing**	**MNEs**	**Non-MNEs**	**Balancing**
	Mean	**Mean**	**Std. bias**	**Mean**	**Mean**	**Std. bias**
	Median	***Median***		***Median***	***Median***	
	(Std. dev.)	**(Std. dev.)**	**(Var. ratio)**	**(Std. dev.)**	**(Std. dev.)**	**(Var. ratio)**
	0	*0*	–	*0*	*0*	–
	(0.266)	(0.274)	(0.943)	(0.533)	(0.681)	(0.612)
Use of software	6.206	6.251	−0.014	10.73	10.59	0.032
	5.930	*5.748*	–	*10.61*	*10.51*	–
	(3.044)	(3.108)	(0.959)	(4.430)	(4.617)	(0.920)
Marketing, sales	0.339	0.303	0.044	0.653	0.643	0.006
	0	*0*	–	*0*	*0*	–
	(0.828)	(0.836)	(0.981)	(1.671)	(1.575)	(1.126)
Finance, taxes	0.184	0.193	−0.022	0.522	0.653	−0.080
	0.061	*0.079*	–	*0*	*0*	–
	(0.331)	(0.494)	(0.451)	(1.370)	(1.861)	(0.542)
Native language (German)	2.982	2.976	0.002	6.132	5.830	0.058
	2.313	*2.237*	–	*4.969*	*4.186*	–
	(2.574)	(2.796)	(0.848)	(5.037)	(5.295)	(0.905)
Regulations	1.289	1.325	−0.016	0.348	0.287	0.051
	0.437	*0.471*	–	*0*	*0*	–
	(2.262)	(2.281)	(0.984)	(1.230)	(1.155)	(1.134)
Other specialized	0.511	0.452	0.037	0.110	0.120	−0.016
	0	*0*	–	*0*	*0*	–
	(1.760)	(1.447)	(1.480)	(0.603)	(0.617)	(0.953)
Medical	0.073	0.038	0.052	0.027	0.026	0.005
	0	*0*	–	*0*	*0*	–
	(0.881)	(0.369)	(5.716)	(0.172)	(0.387)	(0.197)
Untargeted variables						
Tasks per worker	5.145	5.092	0.042	5.457	5.490	−0.014
	5.119	5.024	–	5.491	5.333	–
	1.227	1.300	0.891	2.207	2.410	0.839
Number of different tasks	21.54	21.70	−0.033	17.02	16.22	0.134
	22	23	–	18	17	–
	5.251	4.822	1.186	6.143	5.892	1.087
Broad occupational categories (shares)						
Production						
Unqual. manual occ.	37.06	35.64	0.057	4.801	4.923	−0.009
	37.96	35.46	–	0	0	–
	24.98	24.44	1.044	13.27	14.28	0.864
Qual. manual occ.	20.13	21.87	−0.090	3.794	3.435	0.035
	14.29	16.89	–	0	0	–
	19.39	19.43	0.996	10.20	10.17	1.005
Technicians	9.088	9.228	−0.014	5.632	4.604	0.085
	7.105	7.216	–	0	0	–
	9.767	9.848	0.984	13.20	10.78	1.498
Engineers	3.501	3.688	−0.031	3.721	5.224	−0.114
	1.739	1.462	–	0	0	–
	5.275	6.703	0.619	10.95	15.00	0.533

Table 8 (continued)

	Manufacturing			Service		
	MNEs	**Non-MNEs**	**Balancing**	**MNEs**	**Non-MNEs**	**Balancing**
	Mean	**Mean**	**Std. bias**	**Mean**	**Mean**	**Std. bias**
	Median	***Median***		***Median***	***Median***	
	(Std. dev.)	**(Std. dev.)**	**(Var. ratio)**	**(Std. dev.)**	**(Std. dev.)**	**(Var. ratio)**
Services						
Unqual. service occ.	6.240	6.222	0.002	18.13	19.67	−0.058
	4.054	4.138	–	5.302	5.463	–
	8.357	9.038	0.855	25.57	27.15	0.887
Qual. service occ.	0.243	0.511	−0.120	0.638	1.269	−0.132
	0	0	–	0	0	–
	1.142	2.953	0.150	2.502	6.289	0.158
Semiprof.	0.154	0.123	0.031	0.239	0.247	−0.004
	0	0	–	0	0	–
	1.042	0.902	1.335	1.688	1.978	0.728
Professions	0.255	0.300	−0.039	0.799	0.849	−0.013
	0	0	–	0	0	–
	0.814	1.413	0.332	3.817	3.566	1.146
Administration						
Unqual. admin. occ.	3.538	3.478	0.0102	9.993	9.271	0.045
	1.639	1.566	–	3.125	3.120	–
	5.795	6.125	0.895	16.96	14.80	1.314
Qual. admin. occ.	16.94	16.17	0.061	46.10	43.17	0.101
	14.25	13.18	–	42.60	40.48	–
	12.40	12.89	0.925	29.03	28.93	1.007
Managers	2.812	2.695	0.022	5.891	7.254	−0.110
	1.660	1.515	–	2.395	2.159	–
	5.008	5.658	0.783	10.76	13.86	0.602

Table 8 describes the summary statistics for 738 (540) MNEs in the manufacturing (service) sector and their matched non-MNEs 2 years prior to the FDI event. For each variable, we report the mean, median and standard deviation. In comparing MNEs and non-MNEs, we also report the standardized bias and the variance ratio between the two groups. The wage bill is denoted in constant 2010 euros. Employment or wage growth is measured as the log difference between $t-2$ and $t-6$

Table 9 Selection of offshorability indices

Name	References	Data source
Offshorability *(Ofty)*	Blinder and Krueger (2013)	PDII[a]
Routine manual *(RM)*	Autor et al. (2003), Spitz-Oener (2006)	BiBB 1992, 1998, 2006
Routine nonanalytic *(RnA)*	Autor et al. (2003), Spitz-Oener (2006)	BiBB 1992, 1998, 2006
Routine noninteractive *(RnI)*	Autor et al. (2003) , Spitz-Oener (2006)	BiBB 1992, 1998, 2006
Routine tasks *(Rt)*	Becker et al. (2013)	BiBB 1998
Noninteractive tasks *(NIt)*	Becker et al. (2013)	BiBB 1998
Offshoring potential *(Off. pot.)*	Brändle and Koch (2017)	BiBB 1992–2012
Occupational low-skill share	Own	BiBB 1998

This table displays our choices of established offshorability indices with their associated references and data sources. We order them alphabetically by source. All indices are normalized such that high values imply high offshorability, high routineness, a high share of low-skilled workers, etc.

[a] PDII—Princeton Data Improvement Initiative

these studies is BEM, who develop indices of routine or interactive job profiles using workplace tools in the BiBB Employment Survey. Last, BrKo construct a measure of the offshoring potential of occupations. Specifically, they conduct a principal component analysis on a battery of tasks in the BiBB Employment Survey that supposedly capture the potential to perform a job abroad. We also add an index that ranks occupations in reverse order of the average educational attainment (skill) of their workers. That is, occupations with the highest shares of low-skilled workers are ranked the highest.

To make the measures comparable, we first adjust the ranking of some of the original measures such that high values of the index (e.g., routineness of the task profile) are always associated with high offshorability.[46] We then take the distribution of each index in a 2% random sample of the universe of employees in Germany and mark the top 25% of these workers as offshorable using a binary variable (based on Baumgarten et al. 2020 and Blinder and Krueger 2013).[47] While yielding a comparable measure across the different indices, our normalization comes at the cost of the loss of index-dependent thresholds for identifying offshorable jobs.

Table 10 summarizes this normalization by displaying the distribution of offshorable workers across occupational groups for each index. While the measure by BK suggests a very differentiated possibility of offshoring jobs across the broad categories (and might suffer from the imprecision of the mapping of American occupational codes to the German classification), ALM-SO's measures identify mainly unskilled manual, unskilled service, and skilled manual jobs. The relative frequencies are similar for the measures by BEM. Notably, the noninteractive task profile also categorizes skilled commercial and administrative occupations as offshorable. BrKo even expect the latter group to have the highest potential for offshoring. Together with unskilled commercial and administrative occupations, these workers account for over 80% of offshorable workers. In terms of the lowest average educational attainment, we observe that most offshorable workers perform (un)skilled manual and unskilled service jobs.

C2 FDI and shifts in offshorable jobs

Due to the similarity between offshoring (in terms of importing inputs) and sending FDI to low-wage countries (see Antras and Helpman 2004; Yeaple 2006), we suspect that there is substantial overlap between offshorable and FDI-substitutable jobs. However, before we assess this overlap in the next subsection, we first explore the effects of FDI on offshorable workers and estimate Eq. (4) using the matched sample and the shares of offshorable workers under the various normalized offshorability measures as outcome variables. Figure 11 reports the estimates of β_{POST}.

In manufacturing MNEs, the estimates for most of the measures reveal a significant decrease in the share of offshorable workers after FDI events. In particular, the ALM-SO measures imply that offshorable workers are negatively affected by FDI, where the index of routine manual occupations exhibits the largest employment shift. This result is similar to the estimate for low educational attainment, which underlines the persistent importance of skill levels in explaining the heterogeneity in the labor market effects of globalization. The measures by BK and BrKo do not reveal a negative effect of FDI on offshorable workers, which is not surprising given that we have explored how these workers are associated mainly with commercial and administrative occupations (see Sect. 4.2 and Appendix C1). It would be interesting to examine whether the decrease in this type of labor is absent because sending FDI to a low-wage country requires more administrative resources than offshore outsourcing.

In the service sector, we find fewer or weaker negative effects of FDI on offshorable workers. The highest decreases occur for routine (BEM), low-skill intensive, or routine and nonanalytic jobs (ALM-SO), while the indices of manual or noninteractive tasks are less helpful than they are in the case of the manufacturing sector for identifying onshore substitution by FDI. The share of offshorable workers according to BK's measure even responds positively to FDI. This is particularly surprising since the index is intended to gauge the tradability of tasks in the service sector (considering trade with foreign affiliates and offshore outsourcing). We provide two reasons for this deviation from the outcomes under the other measures. First, the BK measure designates a relatively large number of administrative occupations as offshorable, and this group might react differently to offshore outsourcing than to task trade with foreign affiliates (which might demand higher intensities of intrafirm administration). Second, the measure was created for international integration overall and not explicitly for trade between high- and low-wage countries. Their results might therefore capture workforce recomposition effects of FDI among high-income

[46] Specifically, this reverses the order of the indices of nonroutine or interactive task profiles of BEM and of nonroutine analytic and nonroutine interactive jobs of ALM-SO. We therefore rename these indices routine, noninteractive, routine nonanalytic, and routine noninteractive.

[47] For a detailed description of the replication and normalization of the indices, see Appendix E.

Table 10 Relative frequencies of offshorable workers across broad occupational groups

	BK	ALM-SO			BEM		BrKo	Low-skill
	Ofty	RM	RnA	RnI	Rt	NIt	Off. pot.	
Production								
Unskilled manual	15.92	**42.85**	**39.74**	**40.14**	29.48	26.57	12.30	**47.69**
Skilled manual	8.62	**40.10**	2.92	9.11	15.50	11.54	1.64	27.28
Technicians	14.87	0.88	1.41	0.00	0.02	0.71	3.49	0.02
Engineers	7.98	0.00	0.00	0.00	0.16	0.00	0.00	0.00
Services								
Unskilled services	1.66	13.43	**40.08**	**33.19**	**43.48**	14.46	0.00	17.13
Skilled services	1.86	0.08	9.05	9.10	3.54	2.31	0.20	5.10
Semiprofessions	1.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Professions	4.49	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Administration								
Unskilled commercial and admin.	10.29	0.00	5.08	6.86	3.01	4.75	10.81	2.31
Skilled commercial and admin.	27.91	0.00	0.12	0.00	0.00	**38.38**	**71.58**	0.00
Managers	5.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00

The relative frequencies of offshorable workers under each measure are taken from a 2% random sample of the universe of employees in Germany. Groups for which more than 30% of workers are offshorable are marked in bold. We suppress categories of agricultural occupations and workers who cannot be assigned to any occupational category

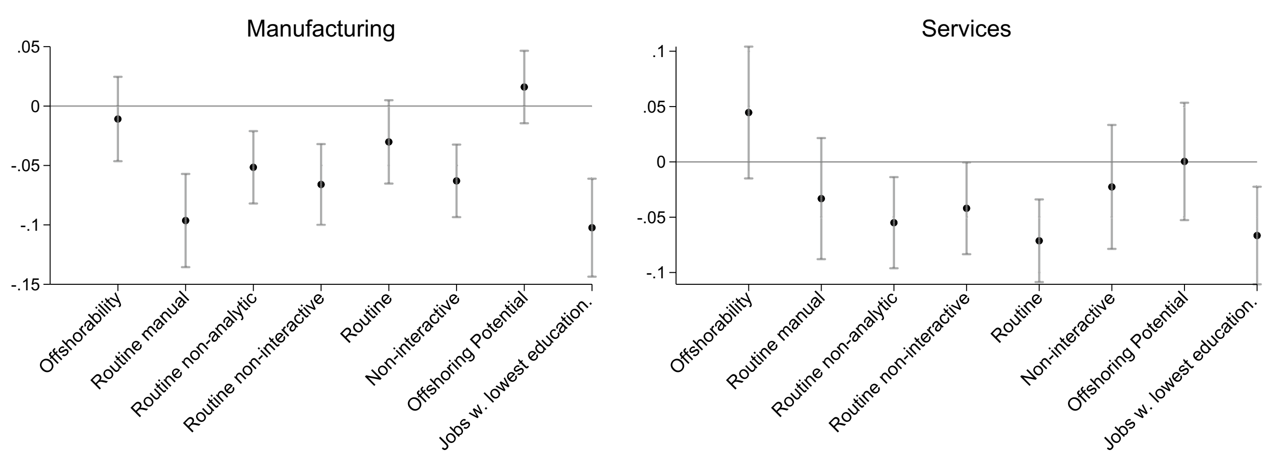


Fig. 11 Matched DiD estimation—standardized share of offshorable workers. Source: Blinder and Krueger (2013); Autor et al. (2003); Becker et al. (2013); Brändle and Koch (2017), and IAB-ReLOC. This figure displays the employment shares in response to FDI events of supposedly offshorable jobs in manufacturing (left panel) and service (right panel) MNEs relative to the shares in non-MNEs. Formally, it displays the estimated coefficient β_{POST} from Eq. (4), where the outcome is the employment share of workers classed as offshorable according to each index in Table 9 and the associated 95% confidence intervals

countries, which are much larger in size than those between countries at different income levels.[48]

Summarizing the outcomes of this exercise, most of the task measures show reductions in the onshore demand for offshorable workers after FDI. However, before drawing stark conclusions about the overlap of FDI-substitutable and offshorable workers, we still need to rule out that these results are driven merely by the normalization of the indices.

C3 Offshorability indices and actual recomposition

We directly compare the existing rankings of occupations from the established indices to our DiD findings on the workforce recomposition effects of FDI. To do

[48] Koerner (2022) shows that occupations with a complex task profile, including many occupations identified as offshorable by the BK index, are more often traded among high-income countries than between high- and low-income countries.

so, we first rerun the DiD analysis for fine occupational categories (2-digit occupation codes) and then rank the occupations according to their FDI substitutability, whereby negative estimates with the largest absolute value are ranked the highest. The explicit estimates are displayed in Figs. 12 and 13. We then directly compare the ranking of FDI-substitutable jobs with the respective ranking of each offshorability index using Spearman's ρ or rank correlation coefficient (to capture any monotone comovement) on the universe of employees in Germany in 2008 (IAB Employment History, BeH). A high positive correlation implies that the offshorability index ranks the occupations according to employment recomposition effects in response to FDI into a low-wage country. Table 11 reports the results.

For both sectors, the data-driven rankings of jobs correlate positively with most of the indices, where the ALM-SO measures feature the highest rankings. While in manufacturing MNEs, FDI affects occupations along the dimension of routine manual tasks (0.79), in the service sector, the effects are strongest along the dimension of routine and noninteractive tasks (0.64). Regarding the distinction between routineness and noninteractivity by BEM, we find that FDI recompositions are driven much more by routineness than by noninteractivity, especially in the service sector, where mere noninteractivity has no correlation with the data-driven ranking of FDI. Additionally, note the high correlation of the education variable, particularly for the manufacturing sector. We suppose that in this sector, the comparative advantage explained by the Heckscher–Ohlin theory is more substantial than that explained by offshorability (Blinder and Krueger 2013). However, this conjecture again raises the question of how offshorable jobs react to globalization. The measures of BK and BrKo, for instance, are directly created to gauge the tradability of task profiles, but they show no or negative correlations with actual FDI effects. One potential reason is given by Baumgarten et al. (2020), who show that demand for the most and least offshorable jobs decreases while demand for other jobs increases in response to offshoring. In addition, considering that the measure identifies many sophisticated jobs as offshorable, we conjecture that these measures are likely better suited to describing offshorability in the context of international integration between high-income countries.

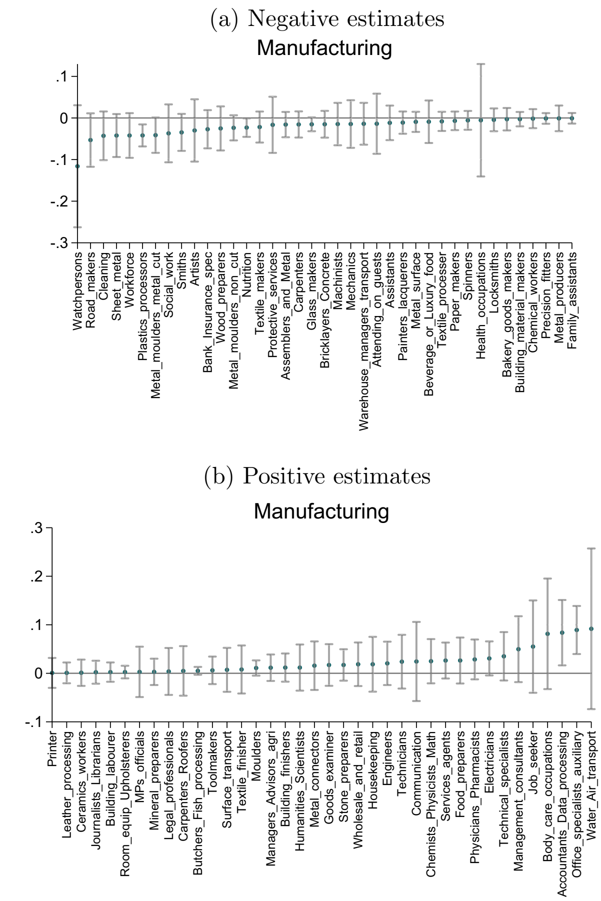


Fig. 12 Matched DiD estimates—fine occupational categories—manufacturing sector. Source: IAB-ReLOC. This figure displays FDI responses of fine occupational shares in manufacturing MNEs relative to the shares in non-MNEs. Formally, it displays the estimates of β_{POST} from Eq. (4), where the outcomes are the employment shares of the two-digit occupation codes o and the associated 95% confidence intervals. Due to the multiplicity of categories, we rank the coefficients by size and report negative results in **a** and positive results in **b**. For a precise description of the methodology, see Sect. 4. Standard errors are clustered at the match level

D Additional results: finer occupational categories

Using the matches from our main analyses, we repeat the estimations of Sects. 3 and 4 for 93 occupational categories (two-digit *KldB88*). This exercise provides interesting insights for two reasons. First, it allows us to underpin our conjectures with detailed occupational information. In addition to the broad occupational group and detailed tasks, we can know more about the finer job category. The estimation tells us, for example, which job shares diminish when service MNEs reduce the share of unskilled service occupations in response to FDI events. Second, the highly disaggregated unit of analysis enables

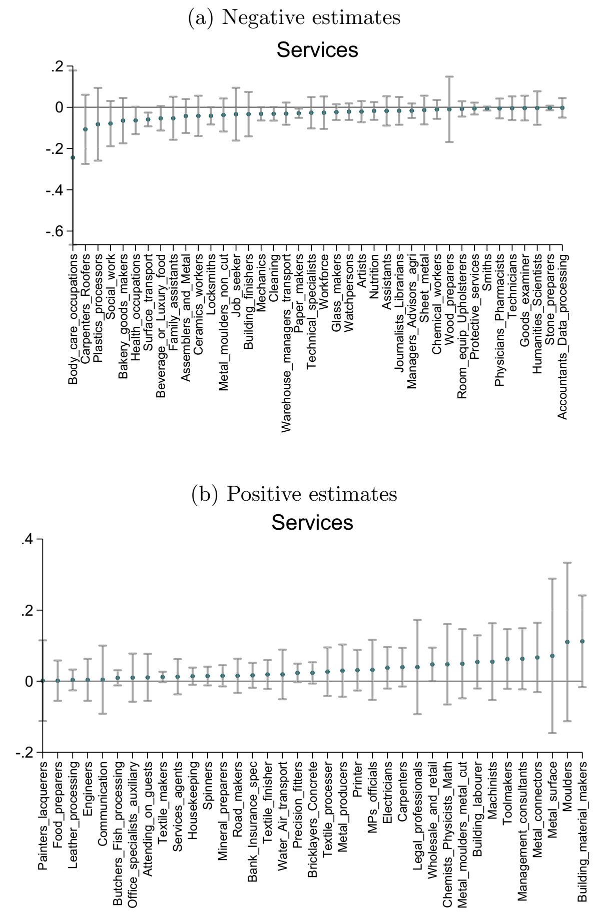


Fig. 13 Matched DiD estimates—fine occupational categories—service sector. Source: IAB-ReLOC. This figure displays FDI responses of fine occupational shares in service MNEs relative to the shares in non-MNEs. Formally, it displays the estimates of β_{POST} from Eq. (4), where the outcomes are the employment shares of the two-digit occupation codes o and the associated 95% confidence intervals. Due to the multiplicity of categories, we rank the estimates by size and report negative results in **a** and positive results in **b**. For a precise description of the methodology, see Sect. 4. Standard errors are clustered at the match level

Table 11 Rank correlations of offshorability indices and FDI-induced employment shifts

	Manufacturing	Services
BK		
Offshorability	−0.06	−0.35
ALM-SO		
Routine manual	**0.79**	**0.55**
Routine nonanalytic	**0.54**	0.43
Routine noninteractive	**0.67**	**0.64**
BEM		
Routine	**0.63**	0.43
Noninteractive	0.42	0.01
BrKo		
Offshoring potential	−0.21	0.01
By education		
Occupational low-skill share	**0.73**	0.45

Rank correlations of offshorability indices and actual employment shifts are obtained from the estimation of Eq. (4) by two-digit occupational category. Correlations are computed for the universe of employees in Germany in 2008. Absolute values above 0.5 are marked in bold

us to create a ranking of fine occupational categories that is comparable to the rankings of established offshorability indices as in Appendix C.

An analysis of very disaggregated units, however, also has its drawbacks. The lower the number of observations per occupation is, the greater the noise, and the less generalizable the result. This is why we still prefer the broader occupational classification as in the main text.

D1 Lasso logit regression

We first explore which job titles feature high predictive power for the firm's FDI decision 2 years later. The reasoning behind this inspection is the conjecture that firms with a high share of either substitutable or complementary workers benefit disproportionately highly from offshore expansions. On the one hand, the costs of FDI could be better compensated for by subsequent benefits from labor cost savings in firms with a high share of substitutable jobs. On the other hand, complementary jobs could lower the relative costs of opening a foreign affiliate since, for example, the firm does not need to hire additional workers to cope with the extra costs of international coordination. The methodological setup is similar to our lasso logit regression in Eq. (3), where we use the employment shares of 93 occupation titles in the vector τ_{ft}.

Due to the multiplicity of groups, we do not show the coefficients' paths along the values of λ as in Figs. 1 and 2. Instead, we show the results for those values of the penalty parameter where the MSPE is minimized using an analogous fivefold cross-validation. Table 12 reports these outcomes for the manufacturing and service sectors.

Of particular interest are occupations that have high predictive power and show statistical significance. These are, among others, (warehouse) managers, assistants, accountants/data specialists, office specialists, legal professionals, and a broad array of manual or production occupations.

Focusing on the predictors of the propensity to engage in FDI in the manufacturing sector, we find that the largest significant predictors are titles identified earlier as skilled administrative occupations: the highest positive predictor is legal professionals, followed by bank and

Table 12 Post-lasso logit results for occupation titles

Dep. variable: FDI in 2 years	Post-logit lasso	
	Manufacturing	Services
	(1)	(2)
Farmers	–	−1.659
Managers_Advisors_agri	8.401	8.409***
Gardeners	7.655	4.671
Forestry_and_Hunting	–	35.82***
Mineral_Oil_gas_quarries	−53.81	−802.7
Stone_preparers	−19.91	8.153**
Building_material_makers	−0.106	4.811
Glass_makers	0.660	–
Chemical_workers	0.514	5.279
Plastics_processors	1.183**	5.085
Paper_makers	1.250*	3.429
Printer	−2.301**	−2.578
Wood_preparers	0.490	8.695**
Metal_producers	−2.051	2.718
Molders	−0.0944	10.89
Metal_molders_non_cut	1.713**	6.417**
Metal_molders_metal_cut	−0.563	6.845**
Metal_surface	−0.938	9.343**
Metal_connectors	–	6.742*
Smiths	−0.126	22.52
Sheet_metal	−1.213	4.570
Locksmiths	−0.679	6.237**
Mechanics	–	1.452
Toolmakers	–	5.917
Precision_fitters	0.0494	1.964
Electricians	1.218**	4.070
Assemblers_and_Metal	0.464	7.806**
Spinners	3.049***	81.25***
Textile_makers	1.329	6.014
Textile_processer	1.164	4.415
Textile_finisher	–	8.741
Leather_processing	1.920	6.967**
Bakery_goods_makers	−0.851	−66.70
Food_preparers	–	7.421**
Beverage_or_Luxury_food	–	−35.40
Butchers_Fish_processing	0.0194	–
Nutrition	1.808**	−97.69
Bricklayers_Concrete	−1.383	−43.54*
Carpenters_Roofers	−1.756	–
Building_laborer	−9.803	−14.81
Building_finishers	–	5.584
Room_equip_Upholsterers	−1.480	5.450
Carpenters	0.544	3.819
Painters_lacquerers	–	5.066*
Goods_examiner	0.858	6.393**
Assistants	0.446	7.493***
Machinists	2.980***	5.982*

Table 12 (continued)

Dep. variable: FDI in 2 years	Post-logit lasso	
	Manufacturing	Services
	(1)	(2)
Engineers	0.716	5.862**
Chemists_Physicists_Math	0.938	3.323
Technicians	0.786	6.277**
Technical_specialists	2.660**	6.270*
Wholesale_and_retail	−0.782	4.660*
Bank_Insurance_spec	8.615*	4.088
Services_agents	−1.967	3.764
Surface_transport	−0.636	2.821
Water_Air_transport	1.147	1.952
Communication	−5.685	6.454**
Warehouse_managers_transport	1.220**	6.318**
Management_consultants	3.296***	6.891**
MPs_officials	−0.103	7.174**
Accountants_Data_processing	1.963**	5.442*
Office_specialists_auxiliary	2.663***	6.797**
Watchpersons	3.318*	5.514
Protective_services	−15.31	7.332
Legal_professionals	31.43***	25.63
Journalists_Librarians	−1.487	18.81**
Artists (e.g., for commercials)	–	7.739**
Health_occupations	−15.47	–
Physicians_Pharmacists	–	2.622
Teachers	3.937	−5.775
Humanities_Scientists	1.140	6.108
Attending_on_guests	–	3.677
Body_care_occupations	7.945	–
Housekeeping	−55.16**	–
Cleaning	−2.209	4.896
Job_seeker	–	8.441*
Workforce	2.287***	4.095
Nonpenalized in lasso		
# of establishments	0.482***	0.222***
Employment growth	0.0689*	0.0367
Share of women	0.535*	−0.193
(Log) wage bill	0.0825	0.552***
Mean wage growth	0.0334	−0.0249
(Log) employees	Yes	Yes
Region FE	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	57,452	51,022
MPSE λ	2.97	2.57

This table reports the estimates from a post-lasso logit model. The set of included occupational shares is selected by cross-validation finding the model with the lowest MSPE. The covariate employment size and the industry fixed effects are needed to capture the effects of the stratified sample of non-MNEs. Standard errors are clustered at the treatment level, i.e., the firm level, following Abadie et al. (2017)

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

insurance specialists, management consultants, office specialists auxiliary and accountants and data processors. These belong to the pool of high-skill occupations, which could be complementary to the firm's expansion and are accompanied by technical manual occupations such as electricians, technician specialists and warehouse managers. We also identify a number of occupations with skill and wage levels that are rather low: spinners, machinists, metal molders or plastic processors. These job titles seem to belong rather to the workforce that could be substituted by production in the offshore affiliates. On the negative side, few occupational titles have a significant negative coefficient in the post-lasso estimation. Very notable are housekeepers and printers. Among the identified titles with a negative although not significant coefficient, we find titles related to raw material handling (e.g., mineral quarry and oil drilling workers, stone preparers, smith and sheet metal workers) and many occupations requiring clear physical interaction with the end user: bakers, carpenters, wholesale and retail traders or service agents.

In the service sector, we find numerous administrative and organizational occupations that overlap with the positive predictors in the manufacturing sector (e.g., office specialists, accountants, warehouse managers, agricultural managers and management consultants). We also find, in line with our analysis at the task level, a substantial set of titles with a manual component: wood preparers, metal molders, and associated workers, assemblers and spinners, machinists, and a set of high-skill production jobs (e.g., engineers, technicians and technical assistants).

This level of analysis captures more nuanced effects that are difficult to generalize without further aggregation. Due to the multiplicity and heterogeneity of fine occupation codes, we thus maintain our choice of broader yet meaningful categories in the main text. Note, however, that management, legal, and organizational jobs remain systematically strong positive predictors of future FDI decisions, a fact that appears robust throughout our analysis. Less clear and robust is the role of both the share of skilled and unskilled manual production tasks for the decision to invest in the Czech Republic. We cannot find strong evidence that they are positive predictors of future FDI decisions.

D2 Difference-in-differences estimation

We now turn to the ranking of occupations, which we compare with the ordinal offshorability indices in Appendix C. We derive the ranking from estimates of a matched DiD analysis, where the dependent variable is the standardized employment share of a given occupation o. For censoring purposes, some occupation codes are dropped, as they represent too few observations. We also exclude agriculture- and mining-related occupation codes. The matching employed in this DiD estimation is identical to that in the main text.

Among the occupations with the largest negative differentials in manufacturing firms (Fig. 12), we identify manual occupations such as metal or plastic workers, precision construction workers, textile-related jobs, and technical specialists. It appears that these occupations drive the outcomes for the broader occupational categories or tasks.

Among the jobs that are FDI complementary, we find headquarters jobs: data specialists, (auxiliary) office specialists and managers.[49] and manual jobs that require in-person performance, such as electricians, transportation workers, and technicians. Intuitively, this makes sense, since MNEs substitute jobs that can be performed in the Czech Republic (seemingly mostly technical or nontechnical manual jobs) but need to expand their management and/or analytic jobs to facilitate coordination and reinforce their local (manual) activities.

Figure 13 reports the outcomes of service MNEs. Again, the picture is qualitatively different from that for the manufacturing sector, with a higher fraction of jobs experiencing positive rather than negative employment shifts.[50] Among FDI-substitutable jobs, we find health-related occupations (from the private sector: body care and other health occupations), janitorial services (surface transport or cleaning), catering occupations and a number of manual jobs (locksmiths, mechanics and paper makers are among the most significant). Among the complementary jobs, we find more nuanced job descriptions of professions and management occupations (such as managing directors, warehouse managers, legal professionals), wholesalers and retailers, and production occupations such as precision fitters or electricians.

Overall, our analysis at the two-digit occupation code level sheds more light on the specific job titles that expand within the broader occupational groups and the jobs that drive the changes at the task level. Another insight at this level of analysis is that jobs with a manual component are identified as being expanded in FDI-engaging firms relative to non-MNEs, whereas these activities are rather negatively affected at the task level.

Most important, we further leverage the ranking of occupations from our matched DiD analysis, which

[49] The management consultant category also includes senior managing staff and entrepreneurs.

[50] Because our sample of matched service firms is relatively small, it includes more occupational titles whose effects are censored if they include an insufficient number of observations.

allows us to compare the data-driven ranking of actual employment shifts from setting up foreign affiliates with the ranking of occupations in offshorability indices as done in Appendix C.

E Data preparation

This section presents the data preparation for the analyses in Appendix C. Specifically, we describe our replications of the established offshorability indices from the literature and how we harmonize them for cross-comparability.

We leverage the particular advantage that many of the offshorability measures are constructed for German occupation codes using the BiBB Employment Survey. We can therefore obtain some measures directly from publications such as Brändle and Koch (2017) and Becker et al. (2013). For the latter, we follow the authors' suggestion and utilize the strict definition of the offshorability index. Adapting measures tailored for American occupational codes, however, is a more involved process.

E1 BK mapping SOC00 to KldB88

The measure of Blinder and Krueger (2013) is compiled by the Princeton Data Improvement Initiative (PDII), which asks questions directly related to the tradability of jobs in the 6-digit American Standard Occupational Classification from the year 2000 (SOC00). Since there is—to the best of our knowledge—no direct possibility of mapping these values to the German KldB88, we follow Baumgarten et al. (2020) and use a series of crosswalks and weightings.[51] We start by obtaining unique offshorability values for each occupation in the PDII using the (min)mode of the entries. We then map the SOC00 to its successor classification SOC10 using 2009 weights from the Occupational Employment Statistics on US labor supply and a crosswalk from the US Bureau of Labor Statistics. In the second step, we map the 6-digit SOC10 to the International Standard Classification of Occupations in 2008 (ISCO08) using 2014 employment weights from the US labor supply and the respective crosswalk from the US Bureau of Labor Statistics. In the third step, we map the 4-digit ISCO08 to the 5-digit KldB10 and then to the 3-digit KldB88 using crosswalks and weights of the German labor supply in 2014 from the German Federal Labor Agency. Note that although the mapping creates considerable distortion, we alleviate much of the related concerns by being interested merely in the ranking of occupations and classing only the top 25% as offshorable.

E2 ALM-SO measures

To avoid the imprecision that comes with such mapping across various classifications, we prefer a different approach for the replication of measures by ALM-SO. Similarly to Spitz-Oener (2006), we prefer to straightforwardly replicate the methodology on similar task data in the BiBB Employment Survey. Our approach is precisely described in the following. Note that ALM's original data are available online for replication purposes. We could have thus taken the indices as directly applied to the census occupations from Autor et al. (2003) and then used several crosswalks and weightings to the German occupation classification. Several construction choices made by ALM convinced us not to pursue this approach: first, the survey used to describe jobs dates to 1970, two decades before the time frame of our analysis. Given the transitory nature of the 3-digit classification of occupations, a 1970 snapshot is outdated for our analysis, which aims to describe jobs in the 1990 s. Second, the indices are extrapolated for subsequent years based on the respective distribution of demographics in the survey and mapped to the demographics of the census data. For German jobs in the KldB88 classification, a weighting by American demographics would create even more noise. Finally, the German Qualification and Employment Survey is relatively similar to the DOT or the O*Net databases and was updated at a higher frequency during our sample period. Similarly to Spitz-Oener (2006), we decide to replicate the ALM measures using the BiBB Employment Survey and do so based on her methodology. However, we still modify the choice of variables used for the aggregation of the indices to stay as close to the original ALM measure as possible.[52]

Baseline rules for selecting underlying task variables

To select the variables for the replication of the ALM-SO measures, we followed a set of constraining rules that make our replication exercise as conservative as possible:

- Use only variables from repeated or very similar questions across survey waves.
- Generate coherent coding: reduce each frequency category into binary variables (dummies), as the answers from some waves are reported on a binary scale only.

[51] We thank Daniel Baumgarten for sharing the crosswalks and ideas on the mapping.

[52] The detailed list of variables available is provided in the following subsection. In essence, we preserve the variable choice of Spitz-Oener (2006) and add additional activity- and knowledge-related variables.

- Use only variables that directly speak to the definitions and examples mentioned in the ALM appendix table.

Exact step-by-step procedure

Each wave's variables can be decomposed into four types of questions:

1. Activities performed,
2. Competencies/knowledge required,
3. Tools used,
4. Working conditions.

The starting point is the translation and assignment of variables along these four categories to select those that are repeatedly covered across waves. We then use the working conditions question in a very specific context: we define a routineness dummy based on the two questions that are repeated almost verbatim in each wave. The first question identifies codifiability, and the second question covers literal routines on the job.

> How often would you say in your job that precise directives and steps are given to you with strict instructions?
> How often would you say in your job that you have to repeat exactly identical tasks in detail?

Then, for each of the three ALM measures, we select the overlapping variables that either are exactly equivalent to the DOT variables (e.g., "use of maths," "eye–hand coordination") or that translate exactly as in the descriptions of the *Handbook for Analyzing Jobs* (e.g., "mixes and bakes ingredients," "drives bus to transport passengers"). We deliberately ignore overlapping variables that pertain to activities, skills, or tools that could apply to many indices at once. In this regard, we follow exactly the methodological choices of Spitz-Oener (2006).

For each ALM measure, we apply the same activities, competences and tools in each of the three survey waves. We obtain one to three dummies per measure (one dummy for activities in that measure, one for tools and one for skills) that we combine in a [0, 1] measure as follows:

$$RI = \frac{(A_I + S_I + T_I)}{3} \times \mathbb{1}[Routine]$$

$$NRI = \frac{(A_I + S_I + T_I)}{3} \times (1 - \mathbb{1}[Routine])$$

Finally, we compound the three waves' measures into one set of five static indices. It is simply the weighted mean of each measure, where the weights are the observations per job in each survey wave.

E3 BEM measures

In Becker et al. (2013), the aggregation method is slightly different. We precisely follow their description: we calculate the average number of nonroutine and interactive tasks involved in a given two-digit occupation (based on their codification). Second, we find the maximum number of nonroutine and interactive tasks required in any two-digit occupation. Third, we measure a given two-digit occupation's degree of nonroutine and interactive tasks as the ratio between the average number of nonroutine and interactive tasks in the occupation and the maximum number in any occupation. We standardize by the maximum and minimum number of tasks in any occupation such that the task shares vary between zero and one across occupations. In her methodology, Spitz-Oener (2006) uses dummies, which justifies the different aggregation choices made for the ALM-SO measures than for the Becker et al. (2013) measures.

E4 Final normalization

A key issue in comparing ordinal offshorability indices is the lack of a common unit to characterize whether a given occupation is offshorable. To alleviate this concern, we follow Blinder and Krueger (2013) and assume that approximately 25% of the total workforce is offshorable regardless of the index. We then define workers as offshorable if they belong to the highest (or if the measure is defined in reverse, lowest) 25 percentiles of a measure's distribution using a cross-section of all workers in 2008. The measure thus takes value 1 if a worker is defined "offshorable" and zero otherwise.

E5 Tasks used for replications of offshorability indices

See Tables 13, 14 and 15.

Table 13 List of variables used for the index of BEM

Nonroutine tasks		Interactive tasks	
Strict	**Lenient**	**Strict**	**Lenient**
v32, v64, v65, v66, v67, v70, v71, v93, v94, v95, v97, v104, v106, v108, v109, v110, v111, v113, v114, v115, v116	v32, v34, v40, v49, v50, v51, v52, v54, v55, v56, v57, v58, v59, v60 v61, v62, v64, v65, v66, v67, v69, v70, v71, v77, v78, v79, v80, v92, v93, v94, v95, v97, v100, v102, v103, v104, v106, v108, v109, v110, v111, v113, v114, v115, v116	v69, v70, v71, v73, v74, v75, v76, v77, v78, v79, v80, v81, v82, v83, v93, v94, v95, v97, v98, v99, v110, v116	v54, v61, v62, v69, v70, v71, v73, v74, v75, v76, v77, v78, v79, v80, v81, v82, v83, v84, v85, v86, v88, v89, v90, v92, v93, v94, v95, v96, v97, v98, v99, v108, v109, v110, v116

This table is replicated from BEM's list of BiBB Employment Survey variables used. All variables are from the 1998/99 survey wave

Table 14 List of variables used for the index of BrKo

Index	1992	1998	2006
COD	v184	v265	f411_02
ROU	v185	v266	f411_03
SUM	v38, v39, v40, v41, v42, v43, v44, v45, v46, v47, v48, v49, v50, v51, v52, v53, v54, v55, v56, v57, v58, v59, v60, v61, v62, v63, v64, v65	v189, v190, v191, v192, v193, v194, v195, v196, v197, v198, v199, v200, v201	f303, f304, f305, f306, f307, f308, f309, f310, f311, f312, f313, f314, f315, f316, f317, f318, f319a
COM	Subset of variables from SUM	Subset of variables from SUM	Subset of variables from SUM
ICT	v140, v141, v160, v161, v162, v163, v164, v166	v53, v54, v55, v56, v57, v59, v60	f320, f324, f1001_02
INT	v189, v190	198	f325_03, f325_06, f325_07
LOC	Use occupation classification	Use occupation classification	Use occupation classification
LAW	v95, v96	v223, v224	f403_04
WRI	Imputed	v124	f403_09
LAN	v274, v275, v276, v277, v278, v279	v726, v727, v728, v729, v730, v731, v732, v733, v734	f406_01, f406_02, f406_03, f406_04, f406_05, f406_06, f406_07, f406_08, f406_09, f406_10
NEW	v186, v187	v267, v268	f411_04, f411_05, f325_01, f325_05

This table lists the replication variables for the strict offshorability measure of Brändle and Koch (2017). The variables are from the BiBB Employment Survey waves from 1991/92, 1998/99, and 2006/07

Table 15 List of variables used for the index of ALM-SO

Wave	NRA	NRI	RM
1992	v186, v187, v77	v190, v64	v38, v39, v50, v130, v134, v135, v136, v137, v138, v139
1998	v267, 268, v213	v195, v198	v112, v113, v31, v33, v34, v35, v36, v37, v38, v39, v40, v44
2006	f411_04, f411_05, f325_01, f325_02, f311, f403_08	f325_03, f325_04, f325_07, f310	f303, f305, f308, f403_02, Tools: 100, 101, 103, 104, 105, 106, 107, 200, 201, 202, 203, 204, 205, 206

Routineness dummy is created with variables v184 and v185 in the 1992 wave, v265 and v266 in the 1998 wave, and f411_02 and f411_03 in the 2006 wave

This table reports a list of the variables from the BiBB Employment Survey that we used for replicating the ALM-SO measures. All variables are from the 1991/92, 1998/99 and 2006/07 survey waves

Acknowledgements

We are particularly thankful to Nikolaus Wolf and Gene Grossman for enabling this research through stays at Princeton University and the Institute for Employment Research. These stays were financially supported by the Society for Economics and Management at Humboldt University of Berlin and the International Economics Section and Industrial Relations Section of Princeton University. Their support is gratefully acknowledged. We are exceptionally appreciative of the constant support from Joachim Möller, who gave extremely valuable feedback and facilitated continuous work on this project through his research group at the Institute for Employment Research and the University of Regensburg. We are indebted to Stephen Redding, who supported the project with valuable comments and knowledge. At a research stay at Dartmouth University, we received valuable feedback from Davin Chor and Teresa Fort, for which we are very thankful. We recognize with appreciation the opportunity to be advised on the notion of offshorability by Alan Krueger, who is no longer with us. We also thank the participants at the EEA-ESEM 2021 virtual congress, the 21st International Economic Relations workshop in Göttingen, Daniel Baumgarten, Rolf Tschernig, Christopher Rust, Charly Porcher, and Adrien Bilal for sharing knowledge and ideas. We also thank Daniel Baumgarten for sharing crosswalks and data for the project. We further express our gratitude to Linda Borrs and Johann Eppelsheimer for support in the data preparation and for fruitful discussions. Proofreading by Christine Zosche from American Journal Experts is highly appreciated.

Author contributions

KK conducted the analyses and created the graphs and tables. Both authors are responsible for discussing the results and approved the final manuscript.

Funding

Not applicable.

Availability of data and materials

Please note that we base our empirical analysis on highly confidential administrative data. We are therefore unable to share the data publicly. It is, however, possible to access our data at the Institute for Employment Research (IAB).

Declarations

Competing interests

There is no known conflict of interest associated with this publication, and there has been no significant financial support for this work that could have influenced its outcome.

Received: 4 January 2023 Accepted: 4 June 2023
Published online: 14 August 2023

References

Abadie, A., Spiess, J.: Robust post-matching inference. J. Am. Stat. Assoc. (2021). https://doi.org/10.1080/01621459.2020.1840383

Abadie, A., Athey, S., Imbens, G. W., Wooldridge, J.: When should you adjust standard errors for clustering? NBER working papers 24003, National Bureau of Economic Research, Cambridge (2017)

Ahrens, A., Hansen, C. B., Schaffer, M. E.: LASSOPACK: stata module for lasso, square-root lasso, elastic net, ridge, adaptive lasso estimation and cross-validation. Statistical Software components, Boston College Department of Economics. https://ideas.repec.org/c/boc/bocode/s458458.html (2018)

Antràs, P.: Incomplete contracts and the product cycle. Am. Econ. Rev. **95**(4), 1054–1073 (2005)

Antras, P., Helpman, E.: Global sourcing. J. Polit. Econ. **112**(3), 552–580 (2004)

Antràs, P., Rossi-Hansberg, E.: Organizations and trade. Annu. Rev. Econ. **1**(1), 43–64 (2009)

Atalay, E., Phongthiengtham, P., Sotelo, S., Tannenbaum, D.: The evolution of work in the United States. Am. Econ. J. Appl. Econ. **12**(2), 1–36 (2020)

Athey, S., Imbens, G.W.: Machine learning methods that economists should know about. Annu. Rev. Econ. **11**(1), 685–725 (2019)

Austin, P.C.: An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivar. Behav. Res. **46**(3), 399–424 (2011a)

Austin, P.C.: Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. Pharm. Stat. **10**(2), 150–161 (2011b)

Autor, D.H.: The "task approach" to labor markets: an overview. J. Labour Market Res. **46**(3), 185–199 (2013)

Autor, D., Salomons, A.: Is automation labor-displacing? Productivity growth, employment, and the labor share, NBER working papers 24871, National Bureau of Economic Research, Cambridge (2018)

Autor, D.H., Levy, F., Murnane, R.J.: The skill content of recent technological change: an empirical exploration. Q. J. Econ. **118**(4), 1279–1333 (2003)

Autor, D.H., Katz, L.F., Kearney, M.S.: The polarization of the US labor market. Am. Econ. Rev. **96**(2), 189–194 (2006)

Baumgarten, D., Geishecker, I., Görg, H.: Offshoring, tasks, and the skill-wage pattern. Eur. Econ. Rev. **61**, 132–152 (2013)

Baumgarten, D., Irlacher, M., Koch, M.: Offshoring and non-monotonic employment effects across industries in general equilibrium. Eur. Econ. Rev. **130**, 103583 (2020)

Becker, S.O., Muendler, M.-A.: Trade and tasks: an exploration over three decades in Germany. Econ. Policy **30**(84), 589–641 (2015)

Becker, S.O., Ekholm, K., Muendler, M.-A.: Offshoring and the onshore composition of tasks and skills. J. Int. Econ. **90**(1), 91–106 (2013)

Becker, S.O., Egger, H.E., Koch, M., Muendler, M.-A.: Tasks, Occupations, and Wage Inequality in an Open Economy. Mimeo, New York (2018)

Bernard, A. B., Fort, T., Smeets, V., Warzynski, F.: Heterogeneous globalization: offshoring and reorganization, NBER working paper 26854, National Bureau of Economic Research, Cambridge (2020)

Bighelli, T., di Mauro, F., Melitz, M., Mertens, M.: Firm concentration and aggregate productivity. Firm productivity report, Competitiveness Research Network (2020)

Black, S.E., Spitz-Oener, A.: Explaining women's success: technological change and the skill content of women's work. Rev. Econ. Stat. **92**(1), 187–194 (2010)

Blinder, A.S.: How many US jobs might be offshorable? World Econ. **10**(2), 41–78 (2009)

Blinder, A.S., Krueger, A.B.: Alternative measures of offshorability: a survey approach. J. Labor Econ. **31**(1), 97–128 (2013)

Blossfeld, H.-P.: Berufseintritt und Berufsverlauf. Mitteilungen aus der Arbeitsmarkt-und Berufsforschung **18**(2), 177–197 (1985)

Boehm, C.E., Flaaen, A., Pandalai-Nayar, N.: Multinationals, offshoring, and the decline of US manufacturing. J. Int. Econ. **127**, 103391 (2020)

Borrs, L., Knauth, F.: Trade, technology, and the channels of wage inequality. Eu. Econ. Rev. **131**, 103607 (2021)

Brändle, T., Koch, A.: Offshoring and outsourcing potentials: evidence from German micro-level data. World Econ. **40**(9), 1775–1806 (2017)

Bundesbank, Deutsche: Bestandserhebung über Direktinvestitionen, Statistische Sonderveröffentlichung 10, Frankfurt a. M. (2014)

Caliendo, M., Kopeinig, S.: Some practical guidance for the implementation of propensity score matching. J. Econ. Surv. **22**(1), 31–72 (2008)

Callaway, B., Sant'Anna, P.H.C.: Difference-in-differences with multiple time periods. J. Econom. **225**(2), 200–230 (2021)

Cortes, G.M.: Where have the middle-wage workers gone? A study of polarization using panel data. J. Labor Econ. **34**(1), 63–105 (2016)

Cortes, G.M., Salvatori, A.: Delving into the demand side: changes in workplace specialization and job polarization. Labour Econ. **57**, 164–174 (2019)

Cortes, G. M., Morris, D. M.: Are routine jobs moving South? Evidence from changes in the occupational structure of employment in the U.S. and Mexico, WIDER working paper 2020/11, World Institute for Development Economics Research, Helsinki (2020)

Cortes, G.M., Jaimovich, N., Siu, H.E.: Disappearing routine jobs: who, how, and why? J. Monetary Econ. **91**, 69–87 (2017)

Cortes, G.M., Jaimovich, N., Nekarda, C.J., Siu, H.E.: The dynamics of disappearing routine jobs: a flows approach. Labour Econ. **65**, 101823 (2020)

Cortes, G.M., Jaimovich, N., Siu, H.E.: The growing importance of social tasks in high-paying occupations: implications for sorting. J. Hum. Resour. (2021). https://doi.org/10.3368/jhr.58.5.0121-11455R1

Crino, R.: Service offshoring and white-collar employment. Rev. Econ. Stud. **77**(2), 595–632 (2010)

Dauth, W., Findeisen, S., Suedekum, J.: The rise of the East and the Far East: German labor markets and trade integration. J. Eur. Econ. Assoc. **12**(6), 1643–1675 (2014)

Dauth, W., Findeisen, S., Suedekum, J., Woessner, N.: The adjustment of labor markets to robots. J. Eur. Econ. Assoc. **19**(6), 3104–3153 (2021)

Ebenstein, A., Harrison, A., McMillan, M., Phillips, S.: Estimating the impact of trade and offshoring on American workers using the current population surveys. Rev. Econ. Stat. **96**(4), 581–595 (2014)

Egger, P., Pfaffermayr, M., Weber, A.: Sectoral adjustment of employment to shifts in outsourcing and trade: evidence from a dynamic fixed effects multinomial logit model. J. Appl. Econom. **22**(3), 559–580 (2007)

Eppinger, P.S.: Service offshoring and firm employment. J. Int. Econ. **117**, 209–228 (2019)

Feenstra, R.C., Hanson, G.H.: Globalization, outsourcing, and wage inequality. Am. Econ. Rev. **86**(2), 240–245 (1996)

Feenstra, R.C., Hanson, G.H.: The impact of outsourcing and high-technology capital on wages: estimates for the United States, 1979–1990. Q. J. Econ. **114**(3), 907–940 (1999)

Geishecker, I.: Does outsourcing to Central and Eastern Europe really threaten manual workers' jobs in Germany? World Econ. **29**(5), 559–583 (2006)

Goos, M., Manning, A., Salomons, A.: Explaining job polarization: routine-biased technological change and offshoring. Am. Econ. Rev. **104**(8), 2509–26 (2014)

Graetz, G., Michaels, G.: Robots at work. Rev. Econ. Stat. **100**(5), 753–768 (2018)

Grossman, G.M., Rossi-Hansberg, E.: Trading tasks: a simple theory of offshoring. Am. Econ. Rev. **98**(5), 1978–1997 (2008)

Grossman, G.M., Rossi-Hansberg, E.: Task trade between similar countries. Econometrica **80**(2), 593–629 (2012)

Hakkala, K.N., Heyman, F., Sjöholm, F.: Multinational firms, acquisitions and job tasks. Eur. Econ. Rev. **66**, 248–265 (2014)

Hecht, V., Hohmeyer, K., Litzel, N., Moritz, M., Müller, J.-A., Phan thi Hong, V., Schäffler, J.: Motive, Strukturen und Auswirkungen deutscher Direktinvestitionen in Tschechien, IAB discussion paper 2013/01. Institute for Employment Research, Nuremberg (2013a)

Hecht, V., Litzel, N., Schäffler, J.: The ReLOC project: method report for implementing a cross-border company survey in Germany and the Czech Republic, IAB discussion paper 2013/04. Institute for Employment Research, Nuremberg (2013b)

Helpman, E., Melitz, M.J., Yeaple, S.R.: Export versus FDI with heterogeneous firms. Am. Econ. Rev. **94**(1), 300–316 (2004)

Helpman, E., Melitz, M., Rubinstein, Y.: Estimating trade flows: trading partners and trading volumes. Q. J. Econ. **123**(2), 441–487 (2008)

Hummels, D., Jørgensen, R., Munch, J., Xiang, C.: The wage effects of offshoring: evidence from Danish matched worker-firm data. Am. Econ. Rev. **104**(6), 1597–1629 (2014)

Hummels, D., Munch, J.R., Xiang, C.: Offshoring and labor markets. J. Econ. Lit. **56**(3), 981–1028 (2018)

Iacus, S.M., King, G., Porro, G.: Causal inference without balance checking: coarsened exact matching. Polit. Anal. **20**(1), 1–24 (2012)

Jensen, J.B., Kletzer, L.G.: Measuring tradable services and the task content of offshorable services jobs. In: Labor in the New Economy, pp. 309–335. University of Chicago Press, Chicago (2010)
Koerner, K.: The wage effects of offshoring to the East and West: evidence from the German labor market. Rev. World Econ. **159**(2), 399–435 (2022)
Koerner, K., Moritz, M., Schäffler, J.: FDI and onshore employment dynamics: evidence from German firms with affiliates in the Czech Republic. World Econ. **45**(6), 1773–1829 (2022)
Koerner, K., Borrs, L., Eppelsheimer, J.: FDI and onshore job stability: upgrades, downgrades, and separations in multinationals. Eur. Econ. Rev. **152**, 104332 (2023). https://doi.org/10.1016/j.euroecorev.2022.104332
Kovak, B.K., Oldenski, L., Sly, N.: The labor market effects of offshoring by US multinational firms. Rev. Econ. Stat. **103**(2), 1–16 (2021)
Liu, R., Trefler, D.: A sorted tale of globalization: white collar jobs and the rise of service offshoring. J. Int. Econ. **118**, 105–122 (2019)
Marin, D.: 'A nation of poets and thinkers'—less so with Eastern Enlargement? Austria and Germany, CEPR discussion paper 4358. Centre for Economic Policy Research, London (2004)
Marin, D.: A new international division of labor in Europe: outsourcing and offshoring to Eastern Europe. J. Eur. Econ. Assoc. **4**(2–3), 612–622 (2006)
Marin, D., Schymik, J., Tarasov, A.: Trade in tasks and the organization of firms. Eur. Econ. Rev. **107**, 99–132 (2018)
Melitz, M.: Firm concentration and aggregate productivity, European Central Bank, CompNet annual conference—keynote speech. https://www.ecb.europa.eu/pub/conferences/shared/pdf/20200922_compnet/Presentation_Keynote_speech_Marc_Melitz.pdf (2020). Accessed 12 Feb 2021
Michaels, G., Natraj, A., Van Reenen, J.: Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. Rev. Econ. Stat. **96**(1), 60–77 (2014)
Moritz, M., Hecht, V., Noska, P., Schäffler, J.: Types of FDI and determinants of affiliate size: the classification makes the difference. Czech J. Econ. Finance **70**(4), 312–331 (2020)
Mullainathan, S., Spiess, J.: Machine learning: an applied econometric approach. J. Econ. Perspect. **31**(2), 87–106 (2017)
Munch, J.R.: Whose job goes abroad? International outsourcing and individual job separations. Scand. J. Econ. **112**(2), 339–360 (2010)
Muñoz, M.: Trading Non-tradables: The Implications of Europe's Job Posting Policy. Mimeo, New York (2021)
Nocke, V., Yeaple, S.: An assignment theory of foreign direct investment. Rev. Econ. Stud. **75**(2), 529–557 (2008)
OCDE, européenne, U., Unies, N., mondiale du commerce, O., des Nations Unies sur le commerce et le développement, C., monétaire international, F.: Manual on statistics of international trade in services 2010. https://www.oecd-ilibrary.org/content/publication/9789264034778-en (2010)
OECD: OECD economic outlook, vol. 2021/1. OECD Publishing, Paris. https://www.oecd-ilibrary.org/content/publication/edfbca02-en (2021)
Ottaviano, G.I.P., Peri, G., Wright, G.C.: Immigration, offshoring, and American jobs. Am. Econ. Rev. **103**(5), 1925–59 (2013)
Roth, J., Sant'Anna, P. H. C., Bilinski, A., Poe, J.: What's trending in difference-in-differences? A synthesis of the recent econometrics literature. J. Econom. (forthcoming)
Schäffler, J.: ReLOC linkage: a new method for linking firm-level data with the establishment-level data of the IAB, FDZ Methodenreport 2014/5. Institute for Employment Research, Nuremberg (2014)
Sethupathy, G.: Offshoring, wages, and employment: theory and evidence. Eur. Econ. Rev. **62**, 73–97 (2013)
Spitz-Oener, A.: Technical change, job tasks, and rising educational demands: looking outside the wage structure. J. Labor Econ. **24**(2), 235–270 (2006)
Storm, E.: Skills, tasks, and wages in labor markets, PhD thesis, The University of Wisconsin-Milwaukee (2020)
Van Welsum, D., Vickery, G.: Potential off-shoring of ICT-intensive occupations. In: Enhancing the Performance of the Services Sector, pp. 179–204. OECD Publishing, Paris (2005)
Verme, P.: Which model for poverty predictions?, GLO discussion paper 468. Global Labor Organization, Essen (2020)
Yeaple, S.R.: The complex integration strategies of multinationals and cross country dependencies in the structure of foreign direct investment. J. Int. Econ. **60**(2), 293–314 (2003)
Yeaple, S.R.: Offshoring, foreign direct investment, and the structure of U.S. trade. J. Eur. Econ. Assoc. **4**(2/3), 602–611 (2006)

Publisher's Note