IWH
Halle Institute for Economic Research
Member of the Leibniz Association

Discussion Papers
No. 14
May 2022

Offshoring, Domestic Employment and Production. Evidence from the German International Sourcing Survey

Wolfhard Kaus, Markus Zimmermann

Authors

Wolfhard Kaus
Federal Statistical Office of Germany
E-mail: wolfhard.kaus@destatis.de

Markus Zimmermann
Federal Statistical Office of Germany
E-mail: markus.zimmermann2@destatis.de

Editor

Halle Institute for Economic Research (IWH) – Member of the Leibniz Association

Address: Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany
Postal Address: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

ISSN 2194-2188

Offshoring, Domestic Employment and Production. Evidence from the German International Sourcing Survey*

Abstract

This paper analyses the effect of offshoring (i.e., the relocation of activities previously performed in-house to foreign countries) on various firm outcomes (domestic employment, production, and productivity). It uses data from the International Sourcing Survey (ISS) 2017 for Germany, linked to other firm level data such as business register and ITGS data. First, we find that offshoring is a rare event: In the sample of firms with 50 or more persons employed, only about 3% of manufacturing firms and 1% of business service firms have performed offshoring in the period 2014-2016. Second, difference-in-differences propensity score matching estimates reveal a negative effect of offshoring on domestic employment and production. Most of this negative effect is not because the offshoring firms shrink, but rather because they don't grow as fast as the non-offshoring firms. We further decompose the underlying employment dynamics by using direct survey evidence on how many jobs the firms destroyed/created due to offshoring. Moreover, we do not find an effect on labour productivity, since the negative effect on domestic employment and production are more or less of the same size. Third, the German data confirm previous findings for Denmark that offshoring is associated with an increase in the share of 'produced goods imports', i.e. offshoring firms increase their imports for the same goods they continue to produce domestically. In contrast, it is not the case that offshoring firms increase the share of intermediate goods imports (a commonly used proxy for offshoring), as defined by the BEC Rev. 5 classification.

Keywords: international sourcing, offshoring, productivity

JEL classification: D24, L60, O30

* This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 822390 (MICROPROD). The views expressed in this paper are those of the authors and do not necessarily reflect those of the Federal Statistical Office of Germany.

1. Introduction

Recent decades have seen an increasing fragmentation of global value chains, with production stages of many products being spread across several countries (Baldwin 2016, Johnson 2018). One form of participation in global value chains is offshoring, i.e. firms relocating economic activities that were previously performed in-house to foreign countries.[1] The possible consequences of these developments for domestic employment and wages are subject of an ongoing public debate. While offshoring is often equated with domestic job losses, the net effect on the offshoring firm's domestic employment is ambiguous in theory (Grossman and Rossi-Hansberg 2008). On the one hand, the 'downsizing effect' reflects a substitution of domestic with foreign tasks, leading to a loss in domestic employment. On the other hand, the 'productivity effect' means that firms may save costs (by sourcing cheaper inputs) and increase productivity, possibly creating new domestic jobs. Moreover, offshoring firms may shift domestic activities towards more knowledge-intensive production stages (such as R&D or marketing), also possibly creating new domestic jobs in these areas (Andersen 2019). Overall, the *net* effect of these changes is unclear.

Moreover, the empirical estimates in the literature also differ widely. Some studies have found negative effects of offshoring on domestic employment (Geishecker 2008, Biscourp and Kramarz 2007), small negative or insignificant effects (Wagner 2011), while others even find positive effects (Moser et al. 2015, Eppinger 2019). However, the measurement of offshoring, the data sources, as well as the empirical setup and identification strategies in these papers varies considerably.[2]

[1] We use the term 'offshoring' in contrast to 'outsourcing', with the latter meaning relocation from firms in-house to other firms (which could be both domestically and internationally).

[2] On top of the average effects, the literature has investigated also distributional effects as low-skilled workers seem to be more negatively affected than high-skilled workers (Hummels et al. 2014, 2018; Baumgarten et al. 2013, Egger and Egger 2003).

In this paper, we study the effects of offshoring on firm outcomes (domestic employment, production, and labour productivity) in Germany. We use data from the 2017 International Sourcing Survey (ISS), a sample of firms with 50 or more persons employed which were asked whether they have offshored during the period 2014-16. It also contains information on the destination country of the relocation, which business functions were affected, and how many domestic jobs were lost/created at the firm due to offshoring. The ISS data are matched to other official firm-level data, in particular the Statistical Business Register (SBR), the International Trade in Goods Statistics (ITGS), and the Prodcom survey.

We make two contributions to the literature. First, the ISS survey allows to identify offshoring firms directly in a clean manner, in contrast to many previous papers which had to use indirect proxies for offshoring (see the literature review in Section 2). The survey question states explicitly that offshoring is defined as the relocation of business functions to foreign countries that were previously performed domestically at the firm. This allows us to separate 'true' cases of offshoring from cases where a firm expands its production abroad and/or increases its imports, but the production never took place domestically. Moreover, the data contain unique direct evidence on how many jobs the firm lost/created due offshoring, allowing us to uncover the underlying employment dynamics.

A second contribution is that the data allow to better understand how the mix of firms' import products changes when they start offshoring. By matching ITGS data on the firm*product level, we can consider different classifications that have been used previously in the literature. We check whether offshoring firms really see an increase in these measures and thus whether these measures are suitable proxies for offshoring. In particular, we consider i) the share of intermediate goods imports over total imports (using the Broad Economic Categories (BEC) classification) and ii) the measure of 'produced goods imports' (imports that are also produced domestically by the firm) as a share of total imports (proposed by Bernard et al. 2020).

On the other hand, we acknowledge that the data also come with some limitations. First, the effective sample size is not large. The survey includes about 8,000 firms, but offshoring is a rare event and only 151 firms in the sample actually offshored during the reference period (2014-16). Data linking further reduces the effective sample size, depending on which data are linked (see Section 3.2). While our sample still is representative of the target firm population in the Statistical Business Register (as shown below), the small sample size precludes more detailed subgroup or heterogeneity analyses. Another limitation is that the survey only includes firms that 'survived' until 2016 (when the sample was drawn). Cases where the firm was shut down completely after offshoring will not be included in the data anymore.[3]

The results can be summarized as follows. First, offshoring is a rare event and the firms that engage in it are a selective group. Even when considering the already selective sample of firms with 50 or more persons employed, only about 3% of manufacturing firms and 1% of trade/business service firms have relocated abroad in the period 2014-2016. These low shares might (partly) be explained by the fact that most of the offshoring has already happened in the past (during the 1990s and 2000s). Regarding the nature of offshoring, we show the important role of Eastern Europe as a destination region, and that most offshoring takes place within the same enterprise group (rather than to firms outside the own group). Considering the factors that determine selection, offshoring firms are larger, more productive, have higher import/export shares relative to revenue, and more often belong to a foreign enterprise group than non-offshoring firms. This confirms both the empirical literature and theoretical models that show that more productive firms self-select into global sourcing because they can bear the fixed costs (Antrás and Helpman 2004).

[3] However, this issue is to some extent mitigated by the fact that our data are on the firm (not plant) level, and we measure total firm employment of all plants that belong to the firm. For example, if a firm operates two plants and one plant was shut down after offshoring but the other was not, we would still observe the firm in our sample, and we would correctly measure the total employment reduction at the firm level.

Second, using a difference-in-differences propensity score matching approach, we find a negative effect of offshoring on domestic employment (in the order of about 9-12 ppts.). By additionally utilizing direct survey evidence on how many jobs the firm has destroyed/created due to offshoring, we are also able to further decompose the underlying employment dynamics. Offshoring firms reduce jobs due to offshoring, but at the same time, they also increase their employment for non-offshoring related reasons, resulting in an overall more or less constant employment level. Thus, on average it is not the case that the offshoring firms shrink, but rather that they don't grow as fast as the non-offshoring firms. This latter result might be driven by the particular time period we study, in which the German economy experienced strong economic growth and falling unemployment. This seemed to allow also the offshoring firms to participate in the dynamic economic environment. Finally, our matching estimates show negative effects on domestic output (revenue and production). Since the negative effects on domestic employment and output are roughly of the same size, there is no effect on labour productivity (the ratio of output over employment).

Third, our results shed some light on the question how the mix of import products changes once a firm starts offshoring. We first consider classifying import products into generic/specific intermediates, capital goods, and consumer goods based on the final use categories in the Broad Economic Categories (BEC) scheme. It emerges that offshoring firms decreased the share of imports which are generic intermediates, but increased the share of specific intermediates and capital goods. This suggests that the measure 'share of intermediate goods imports in total imports' (which is used in the literature as a 'broad' offshoring measure) is too 'broad' to describe offshoring firms' activities. This measure likely reflects all kinds of deepening global integration, not just offshoring. Another possible explanation is that most of the offshoring of simple (generic) intermediate inputs likely has already happened in the past, and in the late time period considered here (2014-16), offshoring firms seems to import more complex goods, such as specific intermediates or capital goods.

Moreover, we consider the classification of imports based on whether the import good is also produced domestically by the firm (a 'narrow' offshoring measure following Bernard et al. 2020 or Hummels et al. 2014). Offshoring firms significantly increased the share of imports of products they also produce domestically. This may point to a fragmentation of global value chains in which the same good is partly produced domestically, partly internationally. However, the measure 'share of produced goods imports in total imports' also has limitations in the sense that not all offshoring firms show an increase in this measure, and, in turn, the measure also increases for some non-offshoring firms. Taken together, our results thus highlight the difficulty of capturing offshoring firms' import behaviour with one single measure. Rather, firms' import patterns seem to be more complex and heterogeneous.

The paper is structured as follows. Section 2 gives a brief summary of different offshoring measures used in the empirical literature. Section 3 outlines the data. Section 4 explains the econometric methods. Section 5 presents the empirical results on the effects on employment, revenue, and productivity. Section 6 discusses how imports change for offshoring vs. non-offshoring firms. Section 7 concludes.

2. Offshoring Measures in the Literature

One challenge for the empirical literature is that offshoring is not observed directly in most data. Rather, proxy variables are constructed based on international trade data, either at the industry-level or the firm-level. Hummels et al. (2018, p. 981) argue that a proper measurement of offshoring should reflect three aspects of the phenomenon: *'that it involves intermediate inputs for production (versus final goods for consumption); that it involves imported inputs* *(versus domestically produced ones); and that the inputs involved could have been produced internally within the same firm'*. We now provide a brief overview of these proxies.[4]

The earliest empirical studies are based on industry-level data. Feenstra and Hanson (1996, 1999) distinguish between 'broad' and 'narrow' offshoring. The former is defined as the industry's share of imported intermediate inputs over total inputs. However, they also note that this measure is likely too broad as not all imported intermediates are offshored in the sense that the firm would or could never have produced these goods itself. That is, an increasing share of intermediate imports over total inputs could as well be a measure for a deepening of global integration, rather than offshoring. Feenstra and Hanson (1996, 1999) therefore also develop a 'narrow' offshoring measure considering only imports of intermediates from the same 2-digit industry, which aims to better capture the idea that the domestic industry could have produced the same good itself. This industry-level 'narrow' offshoring measure (derived based on Input-Output-Tables) has been used in various subsequent papers.[5]

Since industry-level measures will miss the arguably substantial heterogeneity of firms within industries, a more recent strand of the literature has used firm-level data. Some papers have used the firm-level imports of intermediates (either in absolute value, or normalized by total intermediates or total imports) as a proxy for offshoring.[6] In the Feenstra/Hanson-terminology, this corresponds to a 'broad' firm-level offshoring measure. In contrast, Hummels et al. (2014) construct a 'narrow' firm-level measure by matching Danish production and trade

[4] For a more extensive literature review, see Hummels et al. (2018), Crinó (2009), or Moser et al. (2015).

[5] See e.g. Hijzen et al. (2005) for the UK. Many studies use individual-level data in which the outcome variables (e.g., employment, wages) are measured on the worker level, but the treatment variable (offshoring intensity) is still measured on the industry level (depending on the industry the worker belongs to). Examples are Munch and Skaksen (2009) for Denmark, Egger et al. (2009) for Austria, as well as Geishecker and Görg (2008), Geishecker (2008), or Baumgarten et al. (2013) for Germany.

[6] Moser et al. (2015) use German data and define offshoring as the share of imported intermediate inputs over total intermediate inputs (based on survey responses). Baum et al. (2020), using Swedish ITGS data, define offshoring as the total value of imported intermediate goods, and goods are classified as intermediates according to the Broad Economic Categories (BEC) classification (see Section 6.1 below).

data. They proxy offshoring as the total imports of goods in the same HS4 product category as the goods sold (either domestically or exported) by the firm. Hummels et al. (2014) do not distinguish between intermediate vs. final goods imports, but they argue that because their sample only includes manufacturing (not wholesale/retail) firms, it can be assumed that all of the firms' imports are used as intermediate inputs in production, not as final consumption goods.

Moreover, while offshoring is traditionally equated with imports of intermediate inputs (i.e., sourcing of more 'upstream' production stages which are then further processed domestically), this may not always be the case. As emphasized by Johnson (2018), an offshoring firm might as well relocate more 'downstream' production stages abroad (i.e., have the good be assembled abroad), and then re-import the final good. That is, offshoring might as well show itself in the data as an increasing import of final (rather than intermediate) goods.

A final complication is that an increase in firm-level imports (both in the 'broad' and the 'narrow' form) may not only reflect foreign inputs replacing inputs that were previously produced in-house at the firm (offshoring). Rather, the firm may also increase foreign inputs to replace inputs previously sourced from other domestic suppliers (Moser et al. 2015 call this the 'supplier-substitution effect'). In this case, the employment losses do not occur among those firms that perform the importing, but among the previous domestic suppliers that lose their market share. This is a channel which is hard to investigate directly as data sets typically do not have information on the domestic suppliers.

Overall, this discussion has highlighted some of the challenges when capturing all aspects of the offshoring phenomenon with one single proxy variable. While many studies have relied on these proxies, there are actually a few papers in which offshoring is measured directly on the firm level. The International Sourcing Surveys (ISS) have been interesting data sources in this context, as firms are surveyed on whether they have started to source production or service activities from abroad that were previously performed in-house at the firm (see Section 3.1). This arguably is the cleanest measure of offshoring on the 'extensive' margin and most closely corresponds to the theoretical concept of interest.[7] Wagner (2011) uses data from the German ISS 2006, which is similar to the German ISS 2017 we use in the present paper. Kaus (2019) uses data from the German ISS 2017, and we extended these analyses here.

Bernard et al. (2020) use data from the Danish ISS 2006 linked to Prodcom and ITGS data (at the firm*product level). They show that offshoring firms increase the imports of those goods they also produce domestically. An additional twist in this analysis is that the offshoring firms actually *continue* to produce the same goods domestically they offshore. The authors' proposed offshoring measure thus is the share of 'produced goods imports' over total imports. While this measure does not cover all forms of offshoring, the results suggest that offshoring need not be equated with imports of intermediate goods only, but that it could also involve imports of the same (even final) goods which are partly produced abroad, partly domestically. It also emerges that offshoring firms reorganize their domestic workforce by increasing the share of high-tech workers, and that they increase the unit prices of the domestically produced varieties. The authors argue that this is consistent with a quality-upgrading mechanism as domestic production is shifted toward high-skill stages of the value chains of a good (such as R&D, marketing, etc.), while the low-skill stages of the value chain of the good are offshored.

3. Data

3.1. International Sourcing Survey (ISS)

The International Sourcing Surveys (ISS) have been carried out by some National Statistical Offices of EU member states. This paper uses German data from the most recent 2017 wave

[7] Fritsch and Görg (2015) use firm-level surveys from emerging economies which distinguish between two measures: outsourcing (whether the firm has contracted out activities that were previously performed in-house, i.e. a mix of domestic and foreign outsourcing) and a 'broad' offshoring measure (the share of imported intermediates over total intermediates).

(see Destatis 2019 and Kaus 2019).[8] The survey asked firms whether they have offshored at some time between 2014 and 2016, with offshoring being explicitly defined as the relocation of business functions abroad that were previously performed domestically at the firm. This corresponds to a measure of offshoring on the extensive margin. The questionnaires also ask about the destination region of the offshoring, and about which business functions (production and up to seven types of services) were affected. Finally, firms are directly asked about how many jobs were lost and how many jobs were created due to offshoring.

The target population consists of firms with 50 or more persons employed in the non-financial business economy (NACE Rev. 2 B-N, without K). A sample of about 55,000 firms was drawn from the population in the Statistical Business Register (SBR, see Appendix A1), with stratification based on industry and employment size classes. Eventually, data from ca. 7,800 firms are available (an effective response rate of about 14%), among which 151 have performed offshoring during the reference period 2014-16. Survey weights are used, but response was relatively balanced across the different strata. In our analysis, we drop firms from industries in which there was almost no offshoring (dropping the NACE Rev. 2 sections B, D, E, F). We distinguish between the broad industry categories *manufacturing* (NACE Rev. 2, Section C) and *trade/services* (NACE Rev. 2, Sections G-N without K).

To check the representativeness of the data, Appendix Table A1 compares the (unweighted and weighted) ISS sample to the total target population of firms with 50 or more persons employed in the Statistical Business Register. A reassuring result is that the ISS sample is reasonably representative of the target population when considering the variables employment, revenue, and foreign ownership.

[8] The surveys are so far carried out by the National Statistical Offices on a voluntary basis. Germany participated in 2007 and 2017, and again participates in 2021. The compulsory Global Value Chain (GVC) survey will replace the former voluntary ISS surveys in all EU member states from 2024 (reference years 2021-2023) onwards.

3.2. Matching to Other Firm-Level Data and Sample Selection

The data from the ISS survey are matched to various other firm-level data sources in official statistics. Linkage between these data is possible via unique firm IDs. Further details on the data are discussed in Appendix A. In particular, we match:

- Statistical Business Register (SBR) data which include information on the firm's employment, revenue, and membership in an enterprise group with a foreign 'head'.
- Production survey (Prodcom) data include the firm's domestic production values (also broken down by the 8-digit product level). Importantly for the present analysis, the survey only includes production performed *domestically*, but not production sourced from abroad. Goods for resale and repackaged goods are excluded as well.
- International Trade in Goods Statistics (ITGS) include information on firm-level imports and exports. The ITGS data have some methodological issues (regarding import/export thresholds and the treatment of tax groups) which are further discussed in Appendix A2. Moreover, they contain a detailed product-level dimension which we use to classify imports/export products according to the Broad Economic Categories (BEC) scheme (by matching the BEC categories at the HS6 level). Finally, matching of ITGS and Prodcom data at the firm*year*product level allows to calculate whether an import good was also produced domestically by the firm during the year (see Appendix A4).

Further details on sample construction are given in Appendix Table A2, and descriptive statistics of all variables are shown in Table A3. Regarding data matching, one limitation is that we are only able to study labour productivity (based on revenue and employment in the SBR), but not other productivity measures such as TFP. This is because information on value added and intermediates is only available in the Structural Business Statistics (SBS) surveys (e.g. the cost structure survey in manufacturing, see Kaus et al. 2020), and the overlap between these surveys and the ISS is too small.

4. Estimation Approach

To estimate the effects of offshoring on firm outcomes, we use a difference-in-differences matching approach.[9] Define $\mathrm{Y}_{\mathrm{i,t}}^{1}$ as the potential outcome (say, employment) of firm *i* in period *t* if the firm gets the treatment, and $\mathrm{Y}_{\mathrm{i,t}}^{0}$ as the potential outcome if the firm does not get the treatment. In our setting, where the treatment is the offshoring during the years in 2014-16, we consider two time periods, *t0=2013* (before treatment), and *t1=2017* (after treatment). The parameter of interest is the *Average Treatment Effect on the Treated (ATT):*

$$\mathrm{ATT} = \mathrm{E}(\Delta \mathrm{Y}_{\mathrm{i}}^{1} - \Delta Y_{i}^{0} | T_{i} = 1)$$

where the dummy variable T_i denotes whether the firm has offshored, and the first differences are $\Delta \mathrm{Y}_{\mathrm{i}}^{1} = Y_{i,2017}^{1} - Y_{i,2013}^{1}$ and $\Delta \mathrm{Y}_{\mathrm{i}}^{0} = Y_{i,2017}^{0} - Y_{i,2013}^{0}$. Thus, we consider the offshoring firms' actual employment growth between 2013-2017, and compare that to the counterfactual employment growth the offshoring firms would have experienced if they had not offshored.

To proxy this unobserved counterfactual, each treated firm is matched to one or more 'similar' control firms (in terms of observable pre-treatment characteristics). In particular, the assumption is that $\mathrm{E}(\Delta \mathrm{Y}_{\mathrm{i}}^{0} | T_{i} = 1, X_{i}) = \mathrm{E}(\Delta \mathrm{Y}_{\mathrm{i}}^{0} | T_{i} = 0, X_{i})$, i.e. if the offshoring firms would not have performed the offshoring, they would have faced on average the same employment growth as non-offshoring firms with similar observed pre-treatment characteristics X_i. As described further below, we estimate the propensity score $\Pr(T_i = 1 | X_i)$ using a Probit model to reduce the multi-dimensional vector of covariates into a single scalar. Then, matching of treated and controls is based on the estimated propensity score.

Given these assumptions, the ATT can be estimated as:

$$\widehat{ATT} = \frac{1}{N_T} \cdot \sum_{i \in N_T} \left\{ \Delta Y_i - \sum_{j \in N_C} w_{i,j} \cdot \Delta Y_j \right\}$$

---

[9] This also used in e.g. Baum et al. (2020), Eppinger (2019), Moser et al. (2015), or Wagner (2011).

where $\mathrm{N_T}, N_C$ denote the total number of treated and control observations in the sample. ΔY_i and ΔY_j denote the observed outcomes (e.g., employment growth) for treated observation i and control observation j. For each treated observation i, we calculate a weighted average of the outcomes of the matched control observations (i.e., summed over all j). When doing so, $w_{i,j}$ denotes a weight that will be the larger the more similar both observations i and j are (in terms of the estimated propensity score), and the weights sum up to one. Our baseline method to determine the weights is a 5-neighrest neighbour matching.[10]

A key advantage of combining matching and difference-in-differences is that one can account for time-constant selection on unobservables. The assumption underlying the diff-in-diff matching is that if the offshoring firms would not have performed the offshoring, they would have faced on average the same employment *trend* as non-offshoring firms with similar characteristics. To increase the plausibility of this assumption, our empirical implementation uses a large number of pre-treatment characteristics (measured in 2013) as matching variables. This includes employment, industry, labour productivity, membership in a foreign enterprise group, and the share of imports over revenue. Moreover, we also match on lagged employment growth before the treatment (2011-13).[11]

Finally, some papers in the literature use an instrumental variables approach to instrument for firm-level imports using aggregate trade shocks. For example, Hummels et al. (2014) have instrumented imports of a Danish firm from a certain country by using that country's aggregate exports to the rest of the world (except to Denmark). We do not pursue this here for two reasons. First, from a more practical standpoint, the sample used in our analysis is small, which would possibly lead to very imprecise IV coefficients. Second, and more

---

[10]That is, $w_{i,j} = 1/5$ for the five control observations which are closest in terms of the estimated propensity score, and zero for all other control observations.

[11] The programme evaluation literature found that balancing pre-programme employment histories of participants and non-participants is very important to reduce matching bias (see e.g. Biewen et al. 2014).

fundamentally, the assumption of instrument exogeneity requires, among others, that the instrument (in our case, aggregate exports of the respective partner country to all other countries except Germany) is not itself affected by demand shocks arising from Germany. While this assumption is plausible for a relatively small country like Denmark, we think it is more problematic in the case of Germany. Most of the offshoring takes place to Eastern Europe (EU13), and exports to Germany constitute a large part of EU13 countries' aggregate exports. It thus seems unlikely that German-specific demand conditions are orthogonal to EU13 countries' trade activity.

5. Effects of Offshoring on Employment and Production

5.1. Characteristics of Offshoring Firms

Figure 1 shows that in all sectors, only a small share of firms performed offshoring in the reference period 2014-2016: ca. 3% in manufacturing, and 1% in trade/ services. Since these firms are much larger on average, ca. 14% of all persons employed in the manufacturing sector (in the base year 2013) work at offshoring firms, and 4% of all persons employed in the trade/services sector.

Table 1, Panel A shows that among the sample of offshoring firms, production and service activities were relocated more or less to the same extent (about 56% and 58%).[12] Considering the destination region of offshoring (Panel B), the important role of Central/Eastern Europe stands out. Ca. 47% of all offshoring firms have the EU13 as their destination region, and this share is higher than for other regions (EU-15/Other Europe: 43%, China/India: 31%). Panel C shows that offshoring to firms within the own enterprise group

[12] The survey also distinguishes between different service categories (management/administration, marketing/customer support, R&D, etc.), but the number of observations is too small to plot them here.

occurs much more often (75%) than to firms outside the own enterprise group (33%), confirming the importance of 'intra-firm trade'.

Table 2 analyzes the selection into offshoring by considering various 'pre-treatment' variables measured in 2013. Regarding the industry affiliation, offshoring firms are disproportionately coming from high-technology manufacturing (as compared to low-technology manufacturing and to services). Offshoring firms on average are larger (in terms of employment), and they have about (exp(0.644)-1)*100%=90% higher labour productivity. They are more likely to be part of a foreign enterprise group (44% vs. 11%) and they have higher import/export shares relative to revenue. Thus, our results confirm the selection patterns that were found in various other empirical studies. We also find that offshoring and non-offshoring firms had very similar 'pre-treatment' employment growth (in the period 2011-13).

Appendix Table A4 shows results from a Probit regression that controls for the above-mentioned characteristics simultaneously. We then use the Probit estimations to calculate the propensity scores for each firm (the predicted probabilities that a firm offshores, based on its observable characteristics). As shown in Appendix Table A5, the propensity scores are relatively low for both 'treated' (6.2% on average) and 'control' (1.8% on average). This reflects the fact that offshoring is a rare event even in narrowly defined cells. The table also shows the number of treated and control firms in different intervals of the estimated propensity score. Within each interval, there is a sufficient number of control firms with a similar propensity score. For the matching analysis, this suggests that the assumption of common support of the propensity score is fulfilled, i.e. for each treated firm we are able to find a control firm with similar characteristics.

5.2. Offshoring and Employment Dynamics

We now consider employment outcomes. Table 3 shows average log employment in 2013 and 2017 for offshoring and non-offshoring firms (in 2014-16), and the employment growth for both groups. When pooling all sectors (Panel A), non-offshoring firms show on average large employment growth (by 13.5%), while offshoring firms show a slight employment decline (by -1.5 %). The 'double-difference' is a -15.0 percentage points (ppts.) negative effect for offshoring firms. These patterns are similar in the manufacturing sector (Panel B) and the trade/service sector (Panel C). Thus, most of the negative employment effect is not because the offshoring firms shrink, but because they don't grow as fast as the non-offshoring firms.

The finding that the offshoring firms did not reduce their employment much on average may seem surprising, but that only measures the *net* job change and does not mean that no jobs were lost due to the offshoring. To better understand these dynamics, we perform in Table 4 the following simple decomposition:

$$\begin{gathered} Total\ net\ job\ change\ rate_i \\ = \underbrace{Job\ loss\ rate\ due\ to\ OS_i + Job\ creation\ rate\ due\ to\ OS_i}_{Net\ job\ change\ rate\ due\ to\ OS_i} \\ + Net\ job\ change\ rate\ due\ to\ nonOS_i \end{gathered}$$

That is, for firm i the total net job change rate between 2013 and 2017 is decomposed into i) the net change rate due to offshoring, and ii) the net change rate due to non-offshoring reasons. This is possible because in the ISS survey, firms were directly asked how many jobs were created, and how many were lost, due to offshoring.[13] The survey asked firms to report job gains due to offshoring, for example, if the relocation allows the firm to save costs and hire new workers. Moreover, the same worker might be transferred within the firm from an offshored business function A to another business function B of the firm. In this case, the survey asks firms to report both a job loss in business function A *and* a job gain in business function B.

[13] However, note that we don't observe the variable 'net job change rate due to non-offshoring reasons' directly in the data. Instead, we take the 'net job change rate due to offshoring' in the ISS survey and the 'total net job change rate' in the Statistical Business Register, and then calculate 'net job change due to non-offshoring reasons' as the residual. Thus, it is also not possible to decompose the variable 'net job change due to non-offshoring reasons' into job loss and job creation.

Table 4 shows that, on average, offshoring firms lost 15.2% jobs (column 1, row 1) and generated 3.9% new jobs (row 2) due to offshoring, resulting in a net job loss rate due to offshoring of -15.2%+3.9%=-11.3% (row 3). At the same time, however, these firms generated 9.8% new jobs for reasons not related to offshoring (row 4), resulting in a net job loss rate of only -11.3%+9.8%=-1.5% overall (row 5). The patterns are similar for manufacturing and services. Thus, on the one hand, offshoring firms have net job losses due to offshoring, but on the other hand, these job losses are to a large part compensated by new jobs created for other reasons than offshoring. The latter suggests that also the offshoring firms participated in the rather dynamic economic environment in Germany during the 2010s with strong economic growth and falling unemployment.

These employment dynamics may at the same time reflect compositional changes if less-skilled workers were laid off and high-skilled workers were hired. Figure 2 shows job loss/creation rates due to offshoring separately by skill group.[14] It confirms the expected pattern that most of the jobs that are lost come from less-skilled workers. Among the 0.152 total job loss rate overall, 0.115 come from less-skilled workers, and 0.037 come from high-skilled workers. Among newly created jobs (0.039 job creation rate overall), both skill groups make up about half (ca. 0.020). For both skill groups the total job creation rate due to offshoring is too small to outweigh the losses.

5.3. OLS and Matching Results

While the previous descriptive analysis compared average employment trends of the two groups, the strong selection effects we have shown earlier also require to condition on further characteristics. Table 5 shows results from a basic OLS regression where we regress the employment growth rate 2013-2017 on an offshoring dummy and then control for further 'pre-

---

[14] The survey does not include the baseline level of low-skill/high-skill workers in 2013. Rather, the absolute change in low-skill/high-skill workers is divided by the level of all workers in the firm in 2013.

treatment' covariates (all measured in 2013).[15] The 'raw' effect of offshoring declines in magnitude when controlling for selection (from -14.5% to -10.2%), but the effects remain economically and statistically highly significant. The decrease in magnitude mainly reflects the fact that offshoring firms are on average larger, and larger firms on average have lower employment growth.[16] The latter is shown by the strongly negative coefficients of the dummies for large firms (100-249 and 250+ persons employed) compared to the baseline group of smaller firms (<100 persons employed).

Other control variables also have the expected signs. Service sector firms (especially in high-technology services) have higher growth rates than manufacturing firms. Foreign-owned firms have lower growth rates (in manufacturing), everything else equal. There is also evidence for productivity-enhancing reallocation, i.e. firms with higher labour productivity have higher growth rates, conditional on firm size.

In the next step, we turn to difference-in-differences matching to estimate the effect of offshoring more systematically. A key advantage of matching compared to OLS is that the former allows to account for effect heterogeneity and allows to explicitly consider the common support of the control variables. We compare in Appendix Table A6 the characteristics of the treatment group and the matched control group, to assess whether both groups are sufficiently comparable in terms of observable characteristics. Both groups are indeed well balanced, with the standardized biases of all variables lying below 10%.[17] Moreover, t-tests indicate that none of the differences is statistically significant after matching.

[15] In the following analyses, and in line with Table 4, the dependent variable is the 'DHS' growth rate (of employment, revenue, or productivity) defined as: $\mathrm{g} = (y_{2017} - y_{2013})/(0.5 \cdot (y_{2017} + y_{2013}))$. This formulation follows Davis, Haltiwanger, and Schuh (1996) and is more robust to outliers than e.g. using log changes.

[16] In regressions where we only include offshoring and employment (not shown here), the offshoring coefficient is almost identical to the regressions where we also control for the other characteristics.

[17] The standardized bias after matching is a common metric to assess how well the characteristics are balanced in the two samples. For a variable X, it is calculated as: $\mathrm{sb(X)} = 100 \cdot (\overline{X_T} - \overline{X_{C*}})/(\sqrt{0.5 \cdot (\mathrm{Var(X_T)} + \mathrm{Var(X_{C*})}})$, where T denotes the treated sample, C* the matched control

Table 6 then shows the results of the diff-in-diff matching estimation. It shows, for each outcome variable, the average among the treated firms, the average among the matched control firms, and the ATT as the difference between the two. Panel A confirms a robust negative effect of offshoring on the employment growth rate, with an estimated ATT of -0.092 for manufacturing and -0.134 for trade/services. Moreover, the magnitudes of the employment ATTs are very similar to the numbers for 'net job change rate due to OS' (in Table 4, row 3) which are based on direct responses by firms about how many jobs they lost/created. This supports the conjecture that the ATTs actually estimate the 'causal' effects of offshoring.

Moreover, Panel B shows a negative effect on revenue growth (-0.098 for manufacturing and -0.110 for trade/services). Again, the negative effect on revenue mainly reflects the fact that the offshoring firms' revenues do not grow as fast as those of the non-offshoring firms. Moreover, Panel C show that there is no effect on labour productivity growth (with productivity being measured as the ratio of revenue to employment). This is driven by the fact that the negative employment and revenue effects are more or less of the same size, and thus cancel each other out. Finally, for the manufacturing sector, we can consider as outcome variable the growth in domestic production value (in Panel D, merged from the Prodcom survey). There is a negative effect on domestic production (-0.118) which is slightly more pronounced than that for revenue. When measuring labour productivity as production over employment (in Panel E), we again find no effect.

We also show in Appendix Table A7 several robustness checks for the sample of manufacturing firms. In particular, we compare all manufacturing firms (columns 1 and 2) and the subsample of 'Prodcom+ITGS' manufacturing firms (columns 3 and 4). The latter subsample requires that firms have positive imports in 2013 and 2017, and that they are matched

sample, and $\bar{X}$ and $Var(X)$ denote the mean and variance. Most empirical studies view a standardized bias of below 5% or 10% as sufficient.

in the Prodcom survey in both years. Overall, the estimated ATTs are similar in this subsample compared to the full sample. This subsample is interesting for two reasons. First, offshoring and non-offshoring firms may be are more comparable when considering only firms that are active in international trade. Second, the 'Prodcom+ITGS' subsample will be used later on when classifying import goods (in Section 6). Finally, we compare matching results with two types of treatments: any type of offshoring (columns 1 and 3), and only production offshoring (columns 2 and 4). There is no clear tendency as to which of the two is larger, possibly also due to the small samples.

6. Classifying import goods of offshoring firms

We now analyse how the mix of import goods changes for offshoring vs. non-offshoring firms. In doing so, we can not only better understand the import dynamics taking place, but we can also check the performance of various offshoring proxies developed in the literature. We consider two possible classifications of import goods: i) the end-use categories in the Broad Economic Categories (BEC) scheme, and ii) the measure of 'produced-goods imports' developed by Bernard et al. (2020). Note that the following analyses only refer to the subsample of manufacturing firms which have positive imports in both 2013 and 2017. Only for these firms the import share measures have a non-zero denominator.

6.1. BEC Classification

Import products are often classified according to the Broad Economic Categories (BEC) scheme that is developed by the U.N. Statistical Commission and is frequently applied in trade statistics (see UNSD 2016 for a discussion of the most recent BEC Rev. 5). Products are classified by the end-use categories *intermediates*, *gross fixed capital formation*, and *final consumption*. Intermediates can be further split up to *primary intermediates* (raw products from farming, fishery etc.), *generic processed intermediates* (inputs which are used by many different industries) and *specific processed intermediates* (inputs which are used by only a few industries or even only a few buyers).[18]

We utilize a UNSD concordance table between HS6 products (used in our ITGS data) and BEC categories, to classify the firm's import goods in the ITGS data.[19] [20] For illustration, Appendix Table A8 shows the 10 most important HS6 import goods (measured by aggregate import value) per BEC category, considering the sample of ITGS+Prodcom manufacturing firms pooled across 2012-16.

In principle, one can also use the BEC to derive a measure of offshoring (the increase in the share of imported generic/specific intermediates over total imports). This would correspond to the 'broad' offshoring measure in Feenstra and Hanson (1996, 1999) discussed in Section 2. Table 7 shows the share of each BEC category over total imports. In the base year 2013, generic intermediates goods (ca. 26-32%) and specific intermediate goods (34-38%) constitute the largest share of imports, followed by consumer goods (13-15%) and capital goods (14-21%), with only a minor role of primary and other goods (2-5%).[21] Offshoring firms have a considerably higher share of imports in specific intermediates and capital goods, and a lower share of generic intermediates. This could be a by-product of the fact that offshoring firms are

---

[18] Dividing processed intermediates into generic vs. specific has been newly introduced in the BEC Rev. 5. This aims to better characterize global value chains which often involve highly differentiated products or very specific buyer-supplier relationships (UNSD 2016, Sturgeon and Memedovic 2010).

[19] The concordance table is available at Eurostat's RAMON server: https://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL

[20] The classification is not always clear-cut. For example, computers or vehicles may be used either as capital goods (if the firm uses them in its own production) or as consumer goods (if the firm trades them). We use the priority assigned in the UNSD concordance table, i.e. the category "CONS/CAP" is classified as "consumption", while the category "CAP/CONS" is classified as "capital good".

[21] Note that the sample consists of manufacturing firms only, whose imports by construction are less likely to be consumer goods than e.g. for wholesale firms.

larger and more productive (see Table 2), and thus use more 'sophisticated' imports, such as specific intermediates or capital goods.

Besides these pre-treatment differences, the more relevant question is about the changes over time (during 2013-17). It emerges that offshoring firms *decrease* their import share of generic intermediates compared to non-offshoring firms (the 'double difference' is -5.5 ppts.), while they increase the share of specific intermediates (+1.2 ppts.). Taken together, the total share of intermediates (generic plus specific) thus *decreases* (-5.5+1.2=-4.3 ppts.). Correspondingly, there is an increase in the share of imports which are consumer goods (+1.7 ppts.) and capital goods (+2.9 ppts.).[22]

Overall, these findings may seem surprising as offshoring has traditionally been equated with an increasing import of intermediate goods. Instead, the patterns seem to be more complex, at least with the BEC classification and with the present data. One possible explanation is that the total imports of intermediates only is a 'broad' offshoring measure (in the Feenstra/Hanson terminology), and it likely captures all kinds of global integration, not only offshoring (see also Section 2). For example, imported intermediates may involve imports of goods that the firm never could have produced in-house, and/or imports of goods that the firm previously sourced from domestic suppliers. Moreover, the distinction between generic vs. specific intermediates seems to be important as well. Offshoring firms decrease the share of generic intermediates imports, but increase the share of imports which are specific intermediates or capital goods. It is possible that during the time period we study (2014-16), most of the offshoring involving 'simple' (generic) intermediate goods has already happened in the past (during the 1990s and 2000s), and that firms that offshore during this relatively late time period might import more 'sophisticated' goods, such as specific intermediates or capital goods.

[22] In Appendix Table A9, we also show very similar results when using propensity score matching.

In that context, one also has to consider that the BEC classification only refers to the *final* use of products. But whether a product is, for example, an intermediate or a capital good in a firm's production process likely differs across firms. For some of the offshoring firms, goods that are classified as capital goods in the BEC according to their final use may actually resemble intermediate goods in these firms' own production process (if the firm produces the capital good and then sells it on the market).

6.2. Produced-goods imports

The next offshoring measure we consider is the share of 'produced goods imports' over total imports. As discussed in Section 3 and in Appendix A4, we match ITGS and Prodcom data at the firm*year*product level and define a good as 'produced-good import' if a firm both imports it and produces it.

Table 8 shows that in the base year 2013 offshoring firms already had higher levels of produced-goods imports as a share of total imports (27.3% vs. 18.7% for non-offshoring firms). These pre-treatment differences might be driven by e.g. offshoring episodes that happened in the past. Moreover, offshoring firms significantly increased their share of produced-good imports by 6.4 ppts. between 2013 and 2017 (from 27.3% to 33.9%), while the share stayed flat for non-offshoring firms (-0.5 ppts.). The 'double-difference' is an increase of +7.1 ppts. which is also statistically significant. This confirms that offshoring is associated with an increase in the imports of goods that are also produced domestically.[23]

In the baseline analysis, we consider all goods a firm produces in the 'pre-treatment' year 2013, and track imports of these goods until 2017 (that is, a product that is produced in 2013, but is no longer produced in 2017, would still be classified as a 'produced-good' import

[23] These levels and changes are smaller in magnitude compared to Bernard et al. (2020) for Denmark. They show that offshoring firms have an increase in the produced goods import share from 40% to 57% (by ca. 17 ppts., compared to a ca. 6 ppts. increase in our analysis). Besides the country differences, also the different time periods and durations under analysis might play a role (the 2001-06 period vs. the 2014-16 period in our analysis).

if it its imported in 2017). An alternative is to require that the product is produced in the same year as it is imported. The results are similar with this alternative definition, with a double-difference of +5.3 ppts. (compared to +7.1 ppts. when using the goods produced in 2013 as reference). This reflects the pattern that offshoring firms do rarely stop the domestic production of a good.

However, while the expected pattern does hold on average, there is at the same time a lot of heterogeneity in the response. Table 9 shows various percentiles of the indicator, separately for both types of firms. On the one hand, regarding the 'sensitivity' of the indicator, not *all* offshoring firms increase their share of 'produced good imports' (about one third actually see a decrease). This means that the indicator does only capture one possible aspect of offshoring. Offshoring may as well be associated with increasing imports of goods which the firm does not produce domestically. This could be the case if, for example, the firm offshores production of a good it used to produce domestically, but the foreign production is in the form of specific components/intermediate inputs which are used to produce that good. Then, the imports might be classified as a different product (in the ITGS data) than the production that happens domestically (in Prodcom). On the other hand, regarding the 'specificity' of the indicator, Table 9 shows there are also many non-offshoring firms which increase the share of 'produced good imports'. For these firms, increasing the imports of goods they also produce domestically may not necessarily reflect a replacement of domestic production, but rather an expansion of foreign activity which is complementary to domestic production.

In Table 10, we go one step further and also consider the interaction of produced-good status and BEC category (giving 2*5 possible combinations). The most visible increase for offshoring firms is for the share of imports of self-produced capital goods (+3.9 ppts.), while there is a strong decrease of non-self-produced generic intermediates (-6.9 ppts.).

7. Conclusion

This paper has used German data from the International Sourcing Surveys (ISS) 2017 linked to various other firm-level data to provide a fresh perspective on the nature and consequence of offshoring.

To estimate the effect of offshoring on firm outcomes, we have used a difference-in-difference propensity score matching to account for time-constant unobservable selection. The results show, firstly, a negative effect of offshoring on the growth in domestic employment and domestic revenue/production. An interesting finding is that although offshoring firms reduce jobs due to offshoring, on average their employment does not fall due to employment increases for non-offshoring reasons. This means that on average, the offshoring firms do not grow as fast as the non-offshoring firms. This may be explained by the fact that during the time period we consider, Germany experienced high economic growth and falling unemployment, and also the offshoring firms seemed to participate in these dynamics. The results may not hold in other time periods or in countries with a less favourable economic environment. Finally, we do not find any effect of offshoring on labour productivity, perhaps in contrast to expectations. Possible explanations are that productivity may only slowly respond to organizational changes, e.g. as the retraining of workers takes time, and that the effect will only materialize in subsequent years. At the same time, we acknowledge that our data only allow to consider labour productivity, and it would be interesting to repeat the analysis using more elaborate productivity measures (such as TFP).[24]

Finally, when considering how the type of import goods changes for offshorers vs. non-offshorers, a perhaps surprising result is that offshoring firms do not increase the share of

[24] On the other hand, the literature has found rather mixed results regarding the productivity effects. For example, Baum et al. (2020) find no effect of offshoring on TFP once firm fixed effects are included (which is similar to our diff-in-diff strategy) and conclude that most of the correlation is due to selection.

intermediate goods imports (measured by the BEC classification). In fact, the share of imports which are intermediate goods falls, while the share of capital goods imports increases. It is possible that during the relatively late time period we consider (2014-16), most of the offshoring firms of 'simple' intermediates has already happened in the past. Firms that offshore during this late period seem to increase their imports of more 'sophisticated' goods, such as capital goods.

Moreover, we confirm that offshoring is associated with an increase in the share of 'produced goods imports', i.e. goods which the firm both imports and produces domestically. This holds especially for self-produced capital goods. Nevertheless, while this pattern holds on average, it does not hold for all offshoring firms. Vice versa, there are also many non-offshoring firms that see an increase in the share of 'produced goods imports'.

Overall, our results suggest that there is no single measure that captures all forms of offshoring and that firms' import patterns are more complex and heterogeneous. This demonstrates the need for micro data that contain more precise information on firms' sourcing strategies (including offshoring). The ISS data used in this paper can serve as an important starting point, but of course there are limitations given the small sample sizes and the fact that not all aspects of offshoring are covered in great depth. Thus, future research might built upon this, e.g., by using larger samples, or more detailed information on firms' sourcing strategies.

Literature

Andersen, S. (2019): Offshoring Brains? Evidence on the Complementarity between Manufacturing and R&D in Danish Firms, *Scandinavian Journal of Economics*, 122(4), 1315-1342.

Antràs, P. and E. Helpman (2004): Global Sourcing, *Journal of Political Economy*, 2004, 112(3), 552–580.

Baldwin, R. (2016): *The Great Convergence. Information Technology and the New Globalization*, Harvard University Press.

Baum, C., H. Lööf, A. Stephan, and I. Viklund-Ros (2020): The impact of offshoring on innovation and productivity: Evidence from Swedish manufacturing firms, mimeo.

Baumgarten, D., I. Geishecker, and H. Görg (2013): Offshoring, tasks, and the skill-wage pattern, *European Economic Review*, 61(1), 132 ff.

Bernard, A., T. Fort, V. Smeets, and F. Warzynski (2020): Heterogeneous globalization: Offshoring and reorganization, NBER Discussion Paper No. 26854.

Biscourp, P. and F. Kramarz (2007): Employment, Skill Structure and International Trade: Firm-Level Evidence for France, *Journal of International Economics*, 72(1), 22-51.

Crino, R. (2009): Offshoring, Multinationals, and the Labour Market: A Review of the Empirical Literature, *Journal of Economic Surveys*, 23, 197-249.

Davis, S. J., J. Haltiwanger, and S. Schuh (1996): *Job Creation and Destruction*. Cambridge, MA: MIT Press.

Destatis [Statistisches Bundesamt] (2019): Organisation und Verlagerung wirtschaftlicher Aktivitäten – Methodische Erläuterungen und Ergebnisse 2016. Available at: https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Unternehmen/Publikationen/Downloads-Wirtschaftliche-Aktivitaeten/verlagerung-aktivitaeten-5529301169004.html

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

Egger, P. and H. Egger (2003): Outsourcing and Skill-Specific Employment in a Small Economy: Austria after the Fall of the Iron Curtain, *Oxford Economic Papers*, 55(4), 625-643.

Eppinger, P. (2019): Service Offshoring and Firm Employment, *Journal of International Economics*, 117, 209-228.

Feenstra, R. and G. Hanson (1996): Globalization, Outsourcing, and Wage Inequality, *American Economic Review*, 86, 240-245.

Feenstra, R. and G. Hanson (1999): The Impact of Outsourcing and High-Technology Capital on Wages: Estimates for the United States, 1979-1990, *Quarterly Journal of Economics*, 114(3), 907-940.

Fritsch, U. and H. Görg (2015): Outsourcing, Importing and Innovation: Evidence from Firm-level Data for Emerging Economies, *Review of International Economics*, 23(4), 687-714.

Geishecker, I. (2008): The Impact of International Outsourcing on Individual Employment Security: A Micro-level Analysis, *Labour Economics*, 15(3), 291-314.

Geishecker, I. and H. Görg (2008): Winners and Losers: A Micro-Level Analysis of International Outsourcing and Wages, *Canadian Journal of Economics*, 41, 243-270.

Grossman, G. and E. Rossi-Hansberg (2008): Trading Tasks: A Simple Theory of Offshoring, *American Economic Review*, 98(5), 1978-97.

Hijzen, A., H. Görg, and R. Hine (2005): International Outsourcing and the Skill Structure of Labor Demand in the United Kingdom, *The Economic Journal*, 115(506), 860-878.

Hummels, D., J. Munch, and C. Xiang (2018): Offshoring and Labor Markets, *Journal of Economic Literature*, 56, 981-1028.

Hummels, D., R. Jorgensen, J. Munch, and C. Xiang (2014): The Wage Effects of Offshoring: Evidence from Danish Matched Worker-Firm Data, *American Economic Review*, 104, 1597-1629.

Johnson, R. (2018): Measuring Global Value Chains, *Annual Review of Economics*, 10, 207-236.

Jung, S. and S. Käuser (2016): Challenge and Potential of Linking Microdata in Business Statistics, *Wirtschaft und Statistik*, 2-2016, 1-11.

Kaus, W., V. Slavtchev, and M. Zimmermann (2020): Intangible Capital and Productivity. Firm-level Evidence from German Manufacturing, IWH Discussion Papers 1/2020.

Kaus, W. (2019): Auslandsverlagerung wirtschaftlicher Aktivitäten: Unternehmens-charakteristika und Beschäftigungswirkung, *Wirtschaft und Statistik* 3-2019, 11-24.

Leppert, P. (2020): The Micro Data Linking Panel: A Combined Firm Dataset, *Jahrbücher für Nationalökonomie und Statistik*, 240(4), 525-535.

Moser, C., D. Urban, and B. Weder di Mauro (2015): On the heterogeneous employment effects of offshoring: Identifying productivity and downsizing channels, *Economic Inquiry*, 53(1), 220-239.

Munch, J. and J. Skaksen (2009): Specialization, Outsourcing and Wages, *Review of World Economics (Weltwirtschaftliches Archiv)*, 145(1), 57-73.

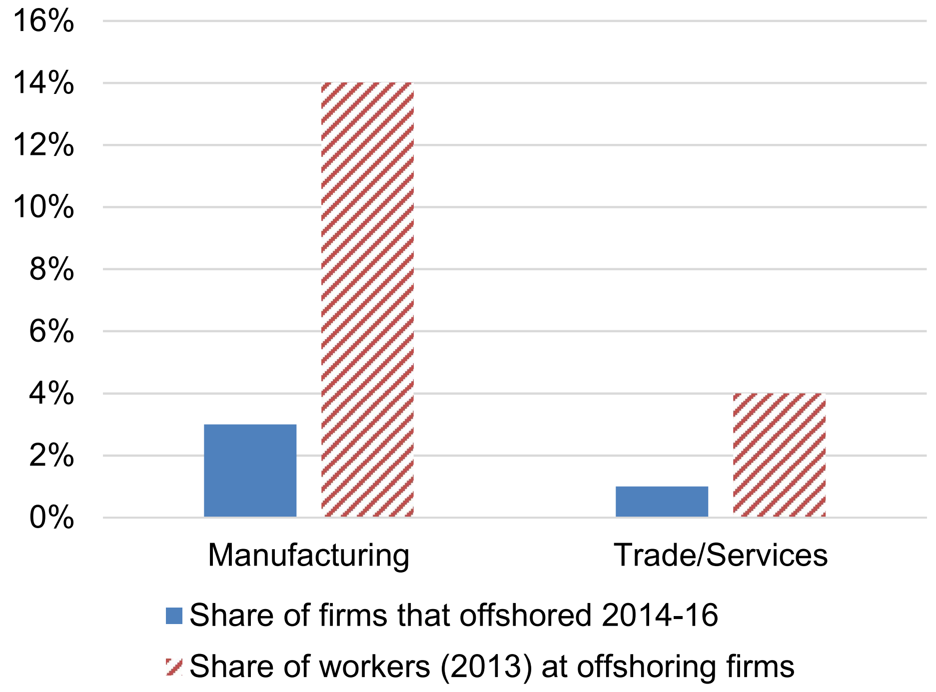
Sturgeon, T. and O. Memedovic (2010): Mapping Global Value Chains. Intermediate Goods Trade and Structural Change in the World Economy, UNIDO Working Paper 05/2010.

United Nations Statistics Division [UNSD] (2016): Classification by Broad Economic Categories Rev. 5, Department of Economic and Social Affairs, Statistics Division, Statistical Papers Series M, No. 53, Rev. 5.

Van Beveren, I., A. B. Bernard, and H. Vandenbussche. (2012): Concording EU Trade and Production Data over Time, Tuck School of Business mimeo.

Wagner, J. (2011): Offshoring and firm performance: self-selection, effects on performance, or both?, *Review of World Economics (Weltwirtschaftliches Archiv),* 147(2), 217-247.

Figure 1: Offshoring and industry



Note: The sample includes N=6,570 firms with 50 or more persons employed in the ISS 2017. Survey weights used. Manufacturing refers to NACE Rev. 2, Section C, and trade/services refers to NACE Rev. 2, Sections G-N (without K).

Table 1: Offshoring by business function, destination region and group status

	All offshoring firms 2014-16
A. By business function:	
Production	56%
Services	58%
B. By destination region:	
EU13	47%
EU15/Other Europe	43%
China, India	31%
Other countries	*
C. By group status:	
Within own group	74%
Outside own group	33%
N	135

Note: Multiple answers possible within each category. * = unreliable due to the small sample size. The sample includes firms with 50 or more persons employed in the ISS 2017. Survey weights used.

Table 2: Selection into offshoring (variables measured in 2013)

	(1) Offshoring firms 2014-16	**(2) Non-offshoring firms 2014-16**	**Difference (1)-(2)**
Industry:			
Low-tech manufacturing 0/1	0.245	0.225	0.020 (0.040)
High-tech manufacturing 0/1	0.344	0.132	0.211*** (0.041)
Low-tech trade/ services 0/1	0.267	0.457	-0.190*** (0.046)
High-tech trade/ services 0/1	0.145	0.186	-0.041 (0.032)
Log employment	5.520	4.719	0.801*** (0.117)
Log labour productivity	12.352	11.708	0.644*** (0.107)
Member of a foreign enterprise group 0/1	0.436	0.110	0.326*** (0.046)
Imports per revenue	0.184	0.076	0.109*** (0.018)
Exports per revenue	0.280	0.122	0.158*** (0.024)
Employment growth rate 2013-11	0.066	0.093	-0.027 (0.028)
N	135	6435	

Note: Manufacturing refers to NACE Rev. 2, Section C, and trade/services refers to NACE Rev. 2, Sections G-N (without K). 'High-tech manufacturing' refers to 2-digit industries 20, 21, 26-32, and 'low-tech manufacturing' to all other manufacturing industries. 'High-tech trade/services' refers to 2-digit industries 50, 51, 58-63, 69-75, 78, 80; and 'low-tech trade/services' to all other trade/service industries. Heteroskedasticity-robust standard errors in parentheses (based on a univariate regression of the respective variable on an offshoring dummy). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The sample includes firms with 50 or more persons employed in the ISS 2017. Survey weights used.

Table 3: Employment growth 2013-2017

A. All sectors

	(1) Offshoring firms 2014-16	(2) Non-offshoring firms 2014-16	Difference (1)-(2)
Log employment 2013	5.520	4.719	0.801***
			(0.117)
Log employment 2017	5.505	4.855	0.651***
			(0.110)
Delta log employment 2013-2017	-0.015	0.135	-0.150***
			(0.029)
N	135	6435	

B. Manufacturing

	(1) Offshoring firms 2014-16	(2) Non-offshoring firms 2014-16	Difference (1)-(2)
Log employment 2013	5.495	4.823	0.672***
			(0.120)
Log employment 2017	5.481	4.915	0.567***
			(0.118)
Delta log employment 2013-2017	-0.014	0.092	-0.106**
			(0.033)
N	90	2707	

C. Trade/Services

	(1) Offshoring firms 2014-16	(2) Non-offshoring firms 2014-16	Difference (1)-(2)
Log employment 2013	5.557	4.662	0.895***
			(0.222)
Log employment 2017	5.540	4.821	0.719***
			(0.205)
Delta log employment 2013-2017	-0.017	0.160	-0.176***
			(0.052)
N	45	3728	

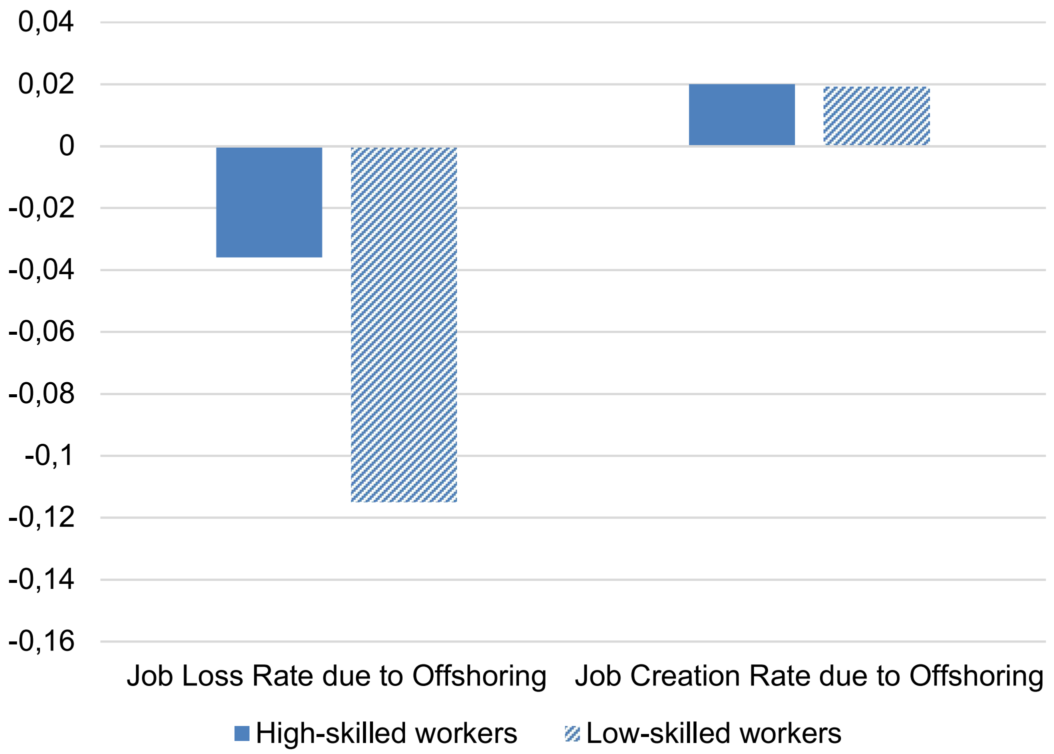
Note: Heteroskedasticity-robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The sample includes firms with 50 or more persons employed in the ISS 2017. Survey weights used. Manufacturing refers to NACE Rev. 2, Section C, and trade/services refers to NACE Rev. 2, Sections G-N (without K).

Table 4: Decomposing job loss rates and job creation rates, 2013-2017

	All sectors			Manufacturing			Trade/Services		
	(1) Offshoring firms	**(2) Non-offshoring firms**	**Difference (1)-(2)**	**(1) Offshoring firms**	**(2) Non-offshoring firms**	**Difference (1)-(2)**	**(1) Offshoring firms**	**(2) Non-offshoring firms**	**Difference (1)-(2)**
(1) Job loss rate due to OS	-0.152	0	-0.152	-0.124	0	-0.124	-0.192	0	-0.192
(2) Job creation rate due to OS	0.039	0	0.039	0.033	0	0.033	0.046	0	0.046
(3) (1)+(2) = Net job change rate due to OS	-0.113	0	-0.113	-0.091	0	-0.091	-0.146	0	-0.146
(4) Net job change rate (non-OS reasons)	0.098	0.130	-0.032	0.077	0.092	-0.015	0.130	0.151	-0.021
(5) (3)+(4) = Total net job change rate	-0.015	0.130	-0.145	-0.014	0.092	-0.106	-0.017	0.151	-0.168
N	135	6435		90	2707		45	3728	

Note: Following Davis et al. (1996), the growth rates are calculated as: $g = (\Delta y)/(0.5 * (y_{17} + y_{13}))$, where Δy denotes the employment change between 2013 and 2017, and y_{17}, y_{13} denote the levels of employment in 2013 and 2017. The variable "jobs loss/creation rate due to OS" (rows 1, 2) is based on firm's responses asked in the ISS survey. The variable "total net job change rate" (row 5) is calculated based on data from the statistical business register in 2013 and 2017. "Net job change rate due to non-OS related reasons" (row 4) is calculated as the residual from row 5 and rows 1,2. The sample includes firms with 50 or more persons employed in the ISS 2017. Survey weights used.

Figure 2: Job loss rates and job creation rates due to offshoring – by skill group (All sectors)



Note: The variable "jobs loss/creation rate due to OS" is based on firm's responses about how many jobs they lost/created due to offshoring (see Table 4). The sample includes firms with 50 or more persons employed in the ISS 2017. Survey weights used.

Table 5: Offshoring and firm employment growth (OLS regressions)

Dependent variable: Employment growth rate 2013-17, independent variables measured in 2013

	All sectors		Manufacturing		Trade/Services	
Offshoring 2014-16	-0.145***	-0.102***	-0.106***	-0.083***	-0.168***	-0.128***
	(0.028)	(0.027)	(0.031)	(0.031)	(0.050)	(0.049)
Low-tech manufacturing		Ref.		Ref.		-
High-tech manufacturing		0.022**		0.020**		-
		(0.010)		(0.010)		
Low-tech business services		0.033***		-		Ref.
		(0.010)				
High-tech business services		0.088***		-		0.054***
		(0.016)				(0.016)
Employment <100		Ref.		Ref.		Ref.
Employment 100-249		-0.120***		-0.079***		-0.142***
		(0.009)		(0.011)		(0.013)
Employment 250+		-0.143***		-0.098***		-0.168***
		(0.013)		(0.018)		(0.018)
Log labour productivity		0.015***		0.018*		0.014**
		(0.005)		(0.009)		(0.006)
Member of a foreign enterprise group		-0.013		-0.039***		0.003
		(0.014)		(0.014)		(0.023)
Imports per revenue		0.021		-0.020		0.042
		(0.025)		(0.035)		(0.035)
Exports per revenue		-0.011		-0.005		-0.046
		(0.018)		(0.020)		(0.037)
Employment growth rate 2011-13		0.133***		0.086		0.140***
		(0.035)		(0.100)		(0.037)
Constant	0.130***	0.071***	0.092***	0.044	0.151***	0.119***
	(0.005)	(0.027)	(0.005)	(0.048)	(0.006)	(0.031)
N	6570	6570	2797	2797	3773	3773
R squared	0.004	0.062	0.006	0.067	0.003	0.059

Note: Following Davis et al. (1996), the growth rates are calculated as: $g = (y_{17} - y_{13})/(0.5 * (y_{17} + y_{13}))$, where y_{17} and y_{13} denote the levels of employment in 2013 and 2017. Heteroskedasticity-robust standard errors in parentheses. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. Survey weights used. The sample includes firms with 50 or more persons employed in the ISS 2017. Manufacturing refers to NACE Rev. 2, Section C, and trade/services refers to NACE Rev. 2, Sections G-N (without K).

Table 6: Effect of offshoring 2014-16 on firm outcomes (Difference-in-differences propensity score matching)

	All sectors			Manufacturing			Trade/Services		
	Offshoring Firms	Matched Non-offshoring Firms	ATT	Offshoring Firms	Matched Non-offshoring Firms	ATT	Offshoring Firms	Matched Non-offshoring Firms	ATT
Outcome Variables:									
A. Employment growth rate 2013-2017	-0.019	0.095	-0.114*** (0.027)	-0.017	0.075	-0.092*** (0.031)	-0.022	0.113	-0.134*** (0.038)
B. Real revenue growth rate 2013-2017	-0.017	0.086	-0.103** (0.041)	0.003	0.102	-0.098* (0.045)	-0.059	0.051	-0.110 (0.099)
C. Real labour productivity growth rate (revenue/ employment) 2013-2017	-0.006	-0.010	0.004 (0.037)	0.015	0.027	-0.012 (0.040)	-0.048	-0.060	0.012 (0.086)
D. Real domestic production value growth rate 2013-2017				-0.029	0.089	-0.118*** (0.040)			
E. Real labour productivity growth rate (domestic production/employment) 2013-2017				-0.006	0.017	-0.024 (0.036)			
N	135	562		90	382		45	197	

Note: The outcome of the matched control firms and the Average Treatment Effect on the Treated (ATT) are estimated based on a propensity score matching with 5 nearest neighbours. Following Davis et al. (1996), the growth rates are calculated as: $g = (y_{17} - y_{13})/(0.5 * (y_{17} + y_{13}))$, where y_{17} and y_{13} denote the levels of employment/revenue/productivity in 2013 and 2017. Revenue and domestic production are deflated using price indices at the 2-digit industry level, with base year 2015. See Appendix Table A4 for a full list of matching variables. Standard errors in parentheses. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$. The sample includes firms with 50 or more persons employed in the ISS 2017. Manufacturing refers to NACE Rev. 2, Section C, and trade/services refers to NACE Rev. 2, Sections G-N (without K).

Table 7: Share of total imports by Broad Economic Category (BEC) classification

(Sample: Manufacturing firms with imports in both 2013 and 2017)

	(1) Offshoring firms 2014-16	**(2) Non-offshoring firms 2014-16**	**Difference (1)-(2)**
Share of imports which are primary intermediate goods			
Share 2013	0.021	0.049	-0.028***
Share 2017	0.016	0.047	-0.031***
Delta Share 2017-2013	-0.005	-0.002	-0.003
Share of imports which are generic processed intermediates			
Share 2013	0.257	0.317	-0.059***
Share 2017	0.204	0.318	-0.114***
Delta Share 2017-2013	-0.053	0.002	-0.055***
Share of imports which are specific processed intermediates			
Share 2013	0.382	0.344	0.038
Share 2017	0.395	0.345	0.049
Delta Share 2017-2013	0.013	0.001	0.012
Share of imports which are consumer goods			
Share 2013	0.131	0.152	-0.021
Share 2017	0.144	0.148	-0.004
Delta Share 2017-2013	0.013	-0.004	0.017
Share of imports which are capital goods			
Share 2013	0.209	0.139	0.070**
Share 2017	0.241	0.142	0.099***
Delta Share 2017-2013	0.032	0.003	0.029
N	75	1568	

Note: The sample includes manufacturing firms with 50 or more persons employed in the ISS 2017 which are matched with Prodcom and ITGS in both 2013 and 2017. BEC categories are merged based on the HS6 product level in the ITGS data.

Table 8: Share of total imports that are "produced good" imports

(Sample: Manufacturing firms with imports in both 2013 and 2017)

	(1) Offshoring firms 2014-16	**(2) No offshoring firms 2014-16**	**Difference (1)-(2)**
Share 2013	0.273	0.187	0.086** (0.036)
Share 2017	0.339	0.182	0.156*** (0.037)
Delta Share 2017-2013	0.064	-0.005	0.071** (0.028)
N	75	1568	

Note: A "produced good import" refers to imports of goods that the firm also produced domestically in the base year 2013. The sample includes manufacturing firms with 50 or more persons employed in the ISS 2017 which are matched with Prodcom and ITGS in both 2013 and 2017.

Table 9: Percentiles of change in the share of "produced good" imports (2013-2017)

(Sample: Manufacturing firms with imports in both 2013 and 2017)

	Mean	**P10**	**P25**	**P50**	**P75**	**P90**
Offshoring 2014-16 (N=75)	0.064	-0.134	-0.020	0	0.135	0.230
No offshoring 2014-16 (N=1568)	-0.006	-0.124	-0.023	0	0.010	0.096

Note: A "produced good import" refers to imports of goods that the firm also produced domestically in the base year 2013. The sample includes manufacturing firms with 50 or more persons employed in the ISS 2017 which are matched with Prodcom and ITGS in both 2013 and 2017.

Table 10: Change in import shares 2013 to 2017 (Interaction of BEC category and "produced-good" status)

Difference between offshoring firms and non-offshoring firms

	Produced goods imports	**Non-produced goods imports**
Delta Share Primary	0.001	-0.004
	(0.001)	(0.004)
Delta Share Intermediates Processed Generic	0.014	-0.069***
	(0.009)	(0.017)
Delta Share Intermediates Processed Specific	0.003	0.008
	(0.012)	(0.025)
Delta Share Consumer	0.013	0.004
	(0.010)	(0.009)
Delta Share Capital	0.039*	-0.010
	(0.023)	(0.020)
Total	0.071**	-0.071**
	(0.028)	(0.028)
N	1643	

Note: A "produced good import" refers to imports of goods that the firm also produced domestically in the base year 2013. BEC categories are merged based on the HS6 product level in the ITGS data. The sample includes manufacturing firms with 50 or more persons employed in the ISS 2017 which are matched with Prodcom and ITGS in both 2013 and 2017.

Appendix

A1. Statistical Business Register (SBR)

The statistical business register (SBR) starts in 2001 and covers the universe of all firms which have an economic activity contributing to GDP and have a seat in Germany. The SBR not only is the backbone on which the sample for the ISS was drawn, but it also includes firm IDs with which to merge other data sets (such as the ITGS or Prodcom data). For the purpose of this paper, we use SBR information on employment (the number of employees covered by social security plus marginal employees), which is one of the main outcome variables. The employment information comes from administrative employment records by the Federal Employment Agency, and thus can be considered as very reliable. Moreover, we merge information on firm revenue, and on whether the firm is member of an enterprise group with a foreign 'head'.

A2. International Trade in Goods Statistics (ITGS)

The ITGS data include imports and exports of goods (values and physical quantities) by 9-digit product level[25] and origin/destination country. Micro data are available since 2009. For intra-EU trade, firms are requested to directly report to the Federal Statistical Office when their trade volumes exceed certain thresholds.[26] For the part of intra-EU trade below the threshold, it is possible to reconstruct firms' aggregate trade volume (but not at the product/country level) using VAT declarations. For extra-EU trade, the information comes from customs authorities and the reporting threshold is 1000 €.

The ITGS data have two limitations that have to be kept in mind. First, one has to consider the treatment of tax groups (German: *steuerliche Organschaften*). Typically, the head unit of a tax group reports imports and exports for all tax group members. However, the head unit is mostly not the same unit where the actual production takes place.[27] We thus redistribute the imports/exports of

[25] This product classification is identical to the classification of the Combined Nomenclature (CN) at the 8-digit level, and identical to the HS6 classification at the 6-digit level.

[26] For intra-EU imports, these thresholds were 400,000 € in 2009-2012, 500,000 € in 2012-2016, and 800,000 € since 2016. For intra-EU exports, the thresholds were 400,000 € in 2009-2012 and 500,000 € since 2012. At the aggregate level, about 97% of the intra-EU export volume and 93% of the intra-EU import volume are above the threshold.

[27] Many tax group head units are holding companies that are based in NACE Rev. 2 industry M70 'Activities of head offices; management consultancy activities'.

a tax group to all tax group members proportional to the individual members' revenues.[28] This approach has been described by e.g. Leppert (2020) or Jung and Käuser (2016) to redistribute firm-level imports/exports. In the present paper, we also redistribute firm*product-level import/export values in this way. However, we acknowledge that this is only an approximation and that the proportionality assumption likely does not hold for all products or all firms.

The second limitation is that there are rather high reporting thresholds in intra EU-trade (see above). While we are able to reconstruct the firm's total values of intra-EU trade below the threshold using VAT declarations, for these values we lack the detailed breakdown by product/country level. This not an issue for the matching estimation (Section 5.1.-5.3.) where only information on the firm's total imports/exports is needed. However, it is relevant for the second part of the analysis (Section 6), where we aim to classify imports by country or product category (BEC classification and 'produced good' status). Thus, for these analyses we drop firms for whom the 'black box' part of imports (intra-EU imports below the threshold without product/country classification) accounts for 20% or more of the firm's total imports.

A3. Production Survey (Prodcom)

The monthly and quarterly production surveys (German: *Produktionserhebungen*) contain information on the production values and physical quantities of actually produced goods (not goods for resale) at the nine-digit-level of the Prodcom classification. These surveys include the full population of producing plants with 20 or more persons employed.[29] Thus, we are able to merge information to almost all manufacturing firms in the ISS sample.[30] We aggregate the plant-level information to the firm level which is the unit of analysis in all other data sources. Importantly for the present analysis, the survey only includes production that the plant performs *domestically*, but not production sourced from abroad. Goods for resale and repackaged goods are excluded as well.

---

[28] Tax groups are identifiable in the SBR by tax group IDs. We then use the SBR to identify all firms which belong to a certain tax group ID, and we also use the SBR to obtain individual firms' revenues.

[29] Note that some of the plants in the Prodcom survey may belong to firms which are classified outside of manufacturing, if these firms have plants with physical production. Nevertheless, our analysis Prodcom sample focuses on manufacturing firms only.

[30] The firm's total production value will be underreported for those firms which have plants with less than 20 persons employed, as these plants (and their production values) are not covered in Prodcom. However, these missing plants will likely only make up a small part of the firm's total production value.

A4. Matching Data Sources

For the firms in the 2017 ISS sample, we create a panel data set spanning the years 2011-2017 to reconstruct each firm's history before, during and after the 'treatment' (=offshoring in 2014-16). Appendix Table A2 shows the sample sizes. From the raw data in the ISS 2017, we first drop a few firms that were not matchable in the Statistical Business Register with a positive number of employees or revenue in either of the years 2011, 2013, or 2017. This gives a sample of 6,570 firms for the baseline analysis in Sections 5. Part of the analysis (on classification of imports, in Section 6) will be conducted on the subsample of manufacturing firms that were matched in both the ISS, the ITGS, and the Prodcom survey in 2013 and 2017 (see Appendix). This subsample is by construction much smaller (1,643 firms).

For the analyses in Section 6, we merge the ITGS and Prodcom data at the firm*year*product level, starting from the 6-digit product level (HS6) in the trade data and the 8-digit product level in the Prodcom data. There is the challenge that not all products of the two classification schemes directly map to each other. We thus use the concordance procedure developed by Van Beveren et al. (2012) which relies on creating 'synthetic' product categories whenever there is no unique match.[31]

After having matched the data in this way, we then follow Bernard et al. (2020) and classify for each firm a certain good as 'produced goods import' if the firm both produces the good domestically (according to the Prodcom data) and imports it (according to the ITGS data).

[31] Out of the 5,074 HS6 products in the ITGS data and the 3,935 8-digit products in the Prodcom data, we create 2,803 'synthetic' products in the matched data. These numbers refer to the total population of firms in the Manufacturing-Prodcom sample in the years 2011-2017. Thus, even though some aggregation of products is necessary, the matched data still contain sufficient across-product variation.

Appendix Tables and Figures

Appendix Table A1. Comparison ISS sample vs. target population in the statistical business register (SBR), 2016

A. Manufacturing

	Target population in SBR (firms with 50+ persons employed)	ISS Sample (unweighted)	ISS Sample (weighted)
N	21,584	2,797	20,257
Employment:			
P10	56	60	59
P25	70	73	73
P50	109	113	112
P75	211	217	207
P90	443	461	429
Revenue (1000 €):			
P10	4,879	5,937	5,512
P25	8,416	9,683	9,068
P50	17,091	19,165	18,300
P75	42,138	44,481	41,671
P90	111,961	117,871	111,158
Foreign ownership 0/1	0.17	0.18	0.17

B. Trade/Services

	Target population in SBR (firms with 50+ persons employed)	ISS Sample (unweighted)	ISS Sample (weighted)
N	39,773	3,773	35,737
Employment:			
P10	54	57	57
P25	64	68	69
P50	91	95	98
P75	167	163	172
P90	359	325	355
Revenue (1000 €):			
P10	1,946	3,166	2,567
P25	4,049	6,137	5,056
P50	9,412	13,710	11,420
P75	25,263	36,114	31,854
P90	71,265	88,380	85,441
Foreign ownership 0/1	0.12	0.12	0.12

Note: The ISS sample refers to the analysis sample used in the regressions (see Table A2). Manufacturing refers to NACE Rev. 2, Section C, and business services refers to NACE Rev. 2, Sections G-N (without K).

Appendix Table A2. Number of observations in the ISS Survey

	All		**Manufacturing**		**Trade/Services**	
	OS	**Non-OS**	**OS**	**Non-OS**	**OS**	**Non-OS**
Analysis sample for employment regressions (Sections 5.1-5.3):						
(1) All firms in the ISS	148	6971	96	2877	52	4094
(2) = (1) minus firms which are not matched with positive employment in the statistical business register 2011-2017, or with missing control variables	135	6435	90	2707	45	3728
Analysis sample for import classification analysis (Section 6):						
(3) = (2) minus firms which are not matched in Prodcom and ITGS data in 2013 and 2017	-	-	81	2419	-	-
(4) = (3) minus firms with non-classifiable import shares of >20%	-	-	75	1568	-	-

Appendix Table A3. Main variables

Variable	Description	Data source	Sample for which the variable is available	N	Mean	Standard deviation
Offshoring indicator	=1 if firm performed offshoring in 2014-16, =0 else	ISS	All	6570	0.018	n/a
Dependent variables:						
Employment growth rate 2013-2017	Growth rate of employment, defined as $g = (y_{17} - y_{13})/(0.5 * (y_{17} + y_{13}))$	BR	All	6570	0.127	0.312
Revenue growth rate 2013-2017	Growth rate of revenue	BR	All	6570	0.129	0.391
Labour productivity growth rate (version 1) 2013-2017	Growth rate of labour productivity (revenue/employment)	BR	All	6570	0.004	0.348
Domestic production growth rate 2013-2017	Growth rate of domestic production	Prodcom	Only Manu-facturing	2694	0.103	0.315
Labour productivity growth rate (version 2) 2013-2017	Growth rate of labour productivity (domestic production/employment)	Prodcom	Only Manu-facturing	2694	0.002	0.028

Variable	Description	Data source	Sample for which the variable is available	N	Mean	Standard deviation
Variables measured in 2013:						
Employment 2013	Number of persons employed	BR	All	6570	207.697	1118.096
Labour productivity (v1) 2013	Revenue in TSD € per number of persons employed	BR	All	6570	265.531	1506.897
Foreign ownership 2013	=1 if firm belongs to a group with a foreign head, =0 else	BR	All	6570	0.116	n/a
Imports over revenue 2013	Import value per revenue (=0 for non-importers)	ITGS, BR	All	6570	0.078	0.154
Exports over revenue 2013	Export value per revenue (=0 for non-exporters)	ITGS, BR	All	6570	0.125	0.218
Lagged employment growth 2011-2013	Employment growth rate 2011-13	BR	All	6570	0.092	0.261

Note: The sample includes firms with 50 or more persons employed in the ISS 2017. Revenue and domestic production are deflated using price indices at the 2-digit industry level, with base year 2015. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A4. Propensity score estimation

Dependent variable: =1 if firm performed offshoring in 2014-16, =0 else

Probit model, Average Partial Effects (APEs)

	(1)
Industry (Ref: Low-tech manufacturing)	
High-tech manufacturing	0.011*
	(0.006)
Low-tech services	-0.007*
	(0.004)
High-tech services	0.004
	(0.006)
Employment class (Ref: <100)	
Employment 100-249	0.004
	(0.003)
Employment 250+	0.030***
	(0.006)
Log labour productivity	0.005***
	(0.002)
Member of a foreign enterprise group	0.020***
	(0.004)
Imports per revenue	0.025***
	(0.008)
Exports per revenue	0.007
	(0.007)
Employment growth rate, 2011-13	-0.002
	(0.009)
N	6570

Note: The sample includes firms with 50 or more persons employed in the ISS 2017. Manufacturing refers to NACE Rev. 2, Section C, and business services refers to NACE Rev. 2, Sections G-N (without K).

Appendix Table A5. Distribution of estimated propensity scores

	Offshoring firms	Non-offshoring firms
Average propensity score	0.062	0.017
Number of firms by interval of propensity score:		
<0.025	44	5151
0.025-0.050	26	615
0.050-0.075	18	144
0.075-0.100	22	329
0.100-0.125	7	71
0.125-0.150	2	25
0.150-0.175	7	33
0.175-0.200	3	25
0.200-0.225	3	27
0.225-0.250	1	6
0.250-0.275	2	6
0.275+	0	3
N	135	6435

Note: The sample includes firms with 50 or more persons employed in the ISS 2017. Manufacturing refers to NACE Rev. 2, Section C, and business services refers to NACE Rev. 2, Sections G-N (without K).

Appendix Table A6. Covariate balance after matching

	Offshoring Firms	**Matched non-offshoring firms**	**Standardized bias after matching (in %)**	**p-value t-test diff.**
Low-tech manufacturing	0.235	0.225	2.4	0.841
High-tech manufacturing	0.426	0.450	5.2	0.697
Low-tech services	0.199	0.160	8.5	0.413
High-tech services	0.140	0.164	-7.0	0.568
Employment <100	0.257	0.240	3.8	0.737
Employment 100-249	0.301	0.302	-0.3	0.979
Employment 250+	0.441	0.457	-3.7	0.790
Log labour productivity	12.308	12.249	5.2	0.661
Member of a foreign enterprise group	0.433	0.411	5.2	0.714
Imports per revenue	0.194	0.179	8.7	0.551
Exports per revenue	0.304	0.324	-8.2	0.555
Delta log employment 2011-13	0.115	0.101	3.2	0.810
N	135	582		

Note: The standardized bias after matching for variable X is calculated as $\mathrm{sb(X)} = 100 \cdot (\overline{X_T} - \overline{X_{C*}})/(\sqrt{0.5 \cdot (\mathrm{Var(X_T)} + \mathrm{Var(X_{C*})})}$, where T denotes the treated sample, C* the matched control sample, and $\bar{X}$ and $Var(X)$ denote the mean and variance. The sample includes firms with 50 or more persons employed in the ISS 2017. Manufacturing refers to NACE Rev. 2, Section C, and business services refers to NACE Rev. 2, Sections G-N (without K).

Appendix Table A7. Robustness checks for manufacturing firms

Average Treatment Effect on the Treated (ATT) from Diff-in-diff propensity score matching

	All manufacturing firms		Only manufacturing firms with ITGS+Prodcom matches in 2013 and 2017	
	Treatment: Any offshoring	Treatment: Production offshoring	Treatment: Any offshoring	Treatment: Production offshoring
A. Employment growth rate 2013-2017	-0.092*** (0.031)	-0.101*** (0.038)	-0.105*** (0.028)	-0.126*** (0.031)
B. Real revenue growth rate 2013-2017	-0.098* (0.045)	-0.065 (0.044)	-0.099** (0.045)	-0.100** (0.044)
C. Real labour productivity growth rate (revenue/employment) 2013-2017	-0.012 (0.040)	0.032 (0.036)	0.002 (0.045)	0.023 (0.035)
D. Real domestic production value growth rate 2013-2017	-0.118*** (0.040)	-0.131*** (0.049)	-0.117** (0.043)	-0.171*** (0.048)
E. Real labour productivity growth rate (domestic production/employment) 2013-2017	-0.002 (0.003)	-0.006 (0.005)	-0.002 (0.004)	-0.005 (0.004)
N Treated	90	74	75	61
N Controls	2797	2797	1643	1643

Note: The Average Treatment Effect on the Treated (ATT) is estimated based on a propensity score matching with 5 nearest neighbours. Revenue and domestic production are deflated using price indices at the 2-digit industry level, with base year 2015. See Appendix Table A4 for a full list of matching variables. Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. The sample includes firms with 50 or more persons employed in the ISS 2017.

Appendix Table A8. The 10 most important HS6 import products by BEC category

(Measured by aggregate import value, sample of manufacturing firms in ITGS+Prodcom, pooled sample 2012-16)

Intermediates Primary

Rank	HS6	Description
1	270900	petroleum oils and oils from bituminous minerals, crude
2	260300	copper ores and concentrates
3	260111	iron ore concentrates (other than roasted iron pyrites) and non-agglomerated iron ores
4	090111	coffee, not roasted, not decaffeinated
5	260112	agglomerated iron ores
6	120510	low erucic acid rape or colza seeds, whether or not broken
7	240120	tobacco, partly or wholly stemmed/stripped
8	270112	bituminous coal, whether or not pulverized, but not agglomerated
9	010392	swine, live, nesoi, weighing 50 kg (110.23 lb.) or more each
10	440320	coniferous wood in the rough, whether or not stripped of bark or sapwood or roughly squared, not treated

Intermediates Generic

Rank	HS6	Description
1	760120	aluminum alloys, unwrought
2	740311	refined copper cathodes and sections of cathodes
3	710812	gold, nonmonetary, unwrought nesoi (other than powder)
4	401110	Rubber; new pneumatic tyres, of a kind used on motor cars (including station wagons and racing cars)
5	760612	aluminum alloy rectangular (including square) plates, sheets and strip, over 0.2 mm thick
6	843149	parts and attachments, nesoi, for derricks, cranes, self-propelled bulldozers, graders etc. and other grading, scraping, etc. machinery
7	711011	platinum, unwrought or in powder form
8	711299	precious metal (other than of gold or platinum) waste and scrap, including metal clad with precious metals, nesoi
9	390110	polyethylene having a specific gravity of less than 0.94, in primary forms
10	470329	chemical woodpulp, soda or sulfate, other than dissolving grades, semibleached or bleached, nonconiferous

Intermediates Specific

Rank	HS6	Description
1	300210	antisera and other blood fractions, and modified immunological products
2	870829	parts and accessories of bodies (including cabs) for motor vehicles, nesoi
3	880330	parts of airplanes or helicopters, nesoi
4	840820	compression-ignition internal combustion piston engines (diesel or semi-diesel), for the propulsion of vehicles except railway or tramway stock
5	300490	medicaments, in measured doses, etc. (excluding vaccines, etc., coated bandages etc. and pharmaceutical goods), nesoi

6	870899	parts and accessories for motor vehicles, nesoi
7	870840	gear boxes and parts thereof, for motor vehicles
8	853710	boards, panels, consoles, etc. with electrical apparatus, for electric control or distribution of electricity, for a voltage not exceeding 1,000 v
9	940190	parts of seats (except parts of medical, dentist', barbers' and similar seats), nesoi
10	840734	spark-ignition reciprocating piston engines for propulsion of vehicles except railway or tramway stock, over 1,000 cc cylinder capacity

Consumer Goods

Rank	HS6	Description
1	271019	petroleum oils & oils (not light) from bituminous minerals or preps nesoi 70%+ by wt. from petroleum oils or bitum. min.
2	870332	passenger motor vehicles with compression-ignition internal combustion piston engine (diesel), cylinder capacity over 1,500 cc but not over 2,500 cc
3	870323	passenger motor vehicles with spark-ignition internal combustion reciprocating piston engine, cylinder capacity over 1,500 cc but not over 3,000 cc
4	271012	light oils and preparations
5	870333	passenger motor vehicles with compression-ignition internal combustion piston engine (diesel), cylinder capacity over 2,500 cc
6	870322	passenger motor vehicles with spark-ignition internal combustion reciprocating piston engine, cylinder capacity over 1,000 cc but not over 1,500 cc
7	870321	passenger motor vehicles with spark-ignition internal combustion reciprocating piston engine, cylinder capacity not over 1,000 cc
8	841480	air pumps and air or other gas compressors, nesoi; ventilating or recycling hoods incorporating a fan, nesoi
9	040690	cheese, nesoi, including cheddar and colby
10	950300	toys, including riding toys o/than bicycles, puzzles, reduced scale models

Capital Goods

Rank	HS6	Description
1	880240	airplanes and other aircraft nesoi, of an unladen weight exceeding 15,000 kg
2	842139	filtering or purifying machinery and apparatus for gases, nesoi
3	850300	parts of electric motors, generators, generating sets and rotaary converters
4	903289	automatic regulating or controlling instruments and apparatus (excluding thermostats, manostats and hydraulic types), nesoi
5	901890	instruments and appliances for medical, surgical or veterinary sciences, nesoi, and parts and accessories thereof
6	870421	motor vehicles for goods transport nesoi, with compression-ignition internal combustion piston engine (diesel), gvw not over 5 metric tons
7	850440	electrical static converters; power supplies for adp machines or units of 8471
8	903180	measuring or checking instruments, appliances and machines, nesoi
9	851762	machines for the reception, conversion and transmission or regeneration of voice, images or other data, including switching and routing apparatus
10	841330	fuel, lubricating or cooling medium pumps for internal combustion piston engines

Appendix Table A9. Change in import shares 2013-2017: Offshoring vs. non-offshoring firms

	BEC categories:					
	Delta Share Primary	Delta Share Intermed Processed Generic	Delta Share Intermed Processed Specific	Delta Share Consumer	Delta Share Capital	Delta Produced goods imports
Average difference (unconditional)	-0.003	-0.055***	0.012	0.017	0.029	0.071**
	(0.005)	(0.019)	(0.026)	(0.013)	(0.022)	(0.028)
ATT	-0.011**	-0.056***	0.015	0.017	0.035*	0.055**
	(0.006)	(0.020)	(0.023)	(0.013)	(0.019)	(0.024)

Note: The Average Treatment Effect on the Treated (ATT) is estimated based on a propensity score matching with 5 nearest neighbours. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. A "produced good import" refers to imports of goods that the firm also produced domestically in the base year 2013. BEC categories are merged based on the HS6 product level in the ITGS data. The sample includes manufacturing firms with 50 or more persons employed in the ISS 2017 which are matched with Prodcom and ITGS in both 2013 and 2017.

Halle Institute for Economic Research –
Member of the Leibniz Association

Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany

Postal Adress: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

ISSN 2194-2188

Leibniz
Association