Online Appendix A: Theoretical Framework

The framework illustrates how changes in the relative use of imported inputs affect labor demand and wages. It builds on Hummels et al. (2014), where the starting point is a Cobb-Douglas-type production function

$$Y_{jt} = A_{jt} K_{jt}^{\alpha} \prod_{q=1}^{Q} C_{qjt}^{\alpha_q}, \tag{8}$$

with $C_{qjt} = (L_{qjt}^{\rho_q} + M_{qjt}^{\rho_q})^{\frac{1}{\rho_q}}$, $\rho_q = (\sigma_q - 1)\sigma_q^{-1}$, $\sum_{q=1}^{Q} \alpha_q = 1 - \alpha$, $\ln L_{jt} = \sum_{q=1}^{Q} \ln L_{qjt}$, $\ln M_{jt} = \sum_{q=1}^{Q} \ln M_{qjt}$, and the indexing of occupations q=1, 2, ..., Q, ordered by increasing job complexity. Y_{jt} denotes output in industry j and year t, A_{jt} is productivity, K_{jt} is capital, and the composite input C_{qjt} is composed of the task-specific labor inputs per occupation q, L_{qjt}, and the tasks M_{qjt} in the imported inputs M_{jt} that substitute the occupational task bundle according to a CES technology with an occupation-specific elasticity $\sigma_q > \frac{1}{1-\alpha_q}$.

If ψ_{jt} is a reduced-form representation of the demand function for the output of industry j, then taking the derivative of equation (8) with respect to the labor of occupation $\bar{q}$ yields the occupation's labor demand by plant j in year t,

$$\psi_{jt} \frac{\partial Y_{jt}}{\partial L_{\bar{q}jt}} = \psi_{jt} \alpha_{\bar{q}} A_{jt} K_{jt}^{\alpha} L_{\bar{q}jt}^{-\frac{1}{\sigma_{\bar{q}}}} C_{\bar{q}jt}^{\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1} \prod_{\substack{q=1 \\ q \neq \bar{q}}}^{Q} C_{qjt}^{\alpha_q}. \tag{9}$$

This equation provides the demand relationship between offshoring and the labor input of workers in occupation $\bar{q}$. As shown in equation (14b), imported tasks $M_{\bar{q}jt}$ lower the demand and wage for labor of type $\bar{q}$ because $\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1 < 0$. The magnitude of the wage effect depends not only on the size of $M_{\bar{q}jt}$ but also on the elasticity of substitution $\sigma_{\bar{q}}$, which is assumed to decrease in q. In contrast, imported complementary tasks $M_{-\bar{q}jt}$ increase the real wage of workers in occupation $\bar{q}$ if workers supply labor in the form of an upward-sloping curve.

Equation (9) also depicts the endogeneity problem concerning the estimation of offshoring on wages. Both an increase in productivity A_{jt} and an increase in the demand for industry j's output ψ_{jt} will increase the labor demand for occupation $\bar{q}$ and the demand for imported inputs. The empirical strategy therefore employs an instrumental variable estimation, which identifies the exogenous variation in offshoring. Given an upward-sloping labor supply, I show in Equations (12)-(21) that the log representation of equations (8) and (9) yields

$$\ln w_{iqjt} = b_{q,M} \ln M_{qjt} + b_{q,M_{-q}} \ln M_{-qjt} + b_{q,D} \ln \psi_{jt} + b_{q,L_{-q}} \ln L_{-qjt} + \\ \ln A_{jt} + b_K K_{jt} + b_x x_{it} + \xi_{ij} + \epsilon_{iqjt}, \tag{10}$$

where w_{iqjt} is the wage rate of worker i in industry j, occupation q and year t, x_{it} denotes a worker's observable characteristics related to productivity in year t, and ξ_{ij} represents unobservable and time-invariant, worker-industry-specific productivity. $b_{q,M}$ is the wage elasticity of occupation q to imported substitutes, and $b_{q,M_{-q}}$ represents this job's wage elasticity of imported complements.

Equation (10) becomes a feasible estimation equation with the following modifications. First, imported inputs relative to gross output by industry OS_{jt} illustrate the importance of offshoring relative to the demand for industry output. This ratio thus captures output demand ψ_{jt} and offshoring, where the respective substitutes M_{qjt} for low-q (high-q) occupations are approximated by components from low- (high-) wage countries. Accordingly, the respective complements M_{-qjt} are approximated by high- (low-) wage countries for low- (high) q, represented by region-specific offshoring from equation (2) Ofs_{jtr}.

The industry variables K_{jt}, A_{jt}, and ψ_{jt} consist of plant outcomes that are available in the dataset. Using such plant-level information has the advantage of controlling for heterogeneity within industries that may not be visible at the aggregate level. The vector $\boldsymbol{v}_{lt}$ adds plant controls to the equation, such as information on the plant's revenue, capital per worker, export share, number of employees, and union status. Including these controls captures K_{jt} and parts of A_{jt}. Other pieces of A_{jt} and ψ_{jt} are taken into account by year fixed effects η_t that capture common time trends. Employee-plant fixed effects γ_{il} consider ξ_{ij} and any time-invariant, match-specific components of A_{jt} and ψ_{jt}.[43,44] The vector $\boldsymbol{x}_{it}$ captures a worker's time-varying characteristics that influence productivity. These include the quadratic value of age and a quadratic polynomial of job tenure.[45]

The task complexity index $CMPLX_q$ orders occupations from low (0) to high (1) complexity. Its interactions with the offshoring terms are of particular interest for this study. It shows the versatile wage impact of offshoring from different regions on heterogeneous labor. These adjustments yield

$$\ln w_{ijqlt} = \sum_r (\beta_r + \beta_{R+r} \times CMPLX_q) Ofs_{jtr} + \delta CMPLX_q + \boldsymbol{x}_{it}\boldsymbol{\lambda} + \boldsymbol{v}_{lt}\boldsymbol{\mu} + \gamma_{il} + \eta_t + \epsilon_{ijqt}, \tag{11}$$

where r indexes the offshoring destination. Equation (11) describes the industry-level regression of offshoring.

Derivations

Deriving the wage of occupation $\bar{q}$ yields

$$\left.\frac{\partial Y_{jt}}{\partial L_{\bar{q}jt}}\right|_{K, L_{-\bar{q}}, M \text{ constant}} = \alpha_{\bar{q}} A_{jt} K_{jt}^{\alpha} L_{\bar{q}jt}^{-\frac{1}{\sigma_{\bar{q}}}} C_{\bar{q}jt}^{\alpha_{\bar{q}}-1} \prod_{\substack{q=1\\ q\neq\bar{q}}}^{Q} C_{qjt}^{\alpha_q} \underbrace{\left(L_{\bar{q}jt}^{\frac{\sigma_{\bar{q}}-1}{\sigma_{\bar{q}}}} + M_{\bar{q}jt}^{\frac{\sigma_{\bar{q}}-1}{\sigma_{\bar{q}}}} \right)^{\frac{\sigma_{\bar{q}}}{\sigma_{\bar{q}}-1}-1}}_{C_{\bar{q}jt}^{\frac{1}{\sigma_{\bar{q}}}}}, \tag{12}$$

which is used for equation (9). The log transformation of equation (12) yields

$$\ln w_{\bar{q}jt} = \ln \left[\alpha_{\bar{q}} A_{jt} K_{jt}^{\alpha} L_{\bar{q}jt}^{-\frac{1}{\sigma_{\bar{q}}}} \right] + \left(\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1 \right) \ln C_{\bar{q}jt} + \sum_{\substack{q=1\\ q\neq\bar{q}}}^{Q} \alpha_q \ln C_{qjt}. \tag{13}$$

Then, after inserting for the composite input C_{kjt}, it becomes

$$\begin{aligned} \ln w_{\bar{q}jt} = \ln \left[\alpha_{\bar{q}} A_{jt} K_{jt}^{\alpha} L_{\bar{q}jt}^{-\frac{1}{\sigma_{\bar{q}}}} \right] + \left(\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1 \right) \left[c_{0\bar{q}} \ln L_{\bar{q}jt} + (1 - c_{0\bar{q}}) \ln M_{\bar{q}jt} \right] + \\ \sum_{\substack{q=1\\ q\neq\bar{q}}}^{Q} \alpha_q \left[c_{0q} \ln L_{qjt} + (1 - c_{0q}) \ln M_{qjt} \right], \end{aligned} \tag{14a}$$

or

$$\begin{aligned} \ln w_{\bar{q}jt} = \ln \left[\alpha_{\bar{q}} A_{jt} K_{jt}^{\alpha} L_{\bar{q}jt}^{-\frac{1}{\sigma_{\bar{q}}}} \right] + \left(\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1 \right) c_{0\bar{q}} \ln L_{\bar{q}jt} + \sum_{\substack{q=1\\ q\neq\bar{q}}}^{Q} \alpha_q c_{0q} \ln L_{qjt} + \\ \left(\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1 \right) (1 - c_{0\bar{q}}) \ln M_{\bar{q}jt} + \sum_{\substack{q=1\\ q\neq\bar{q}}}^{Q} \alpha_q (1 - c_{0q}) \ln M_{qjt}, \end{aligned} \tag{14b}$$

where

$$\ln C_{qjt} \approx c_{0q} \ln L_{qjt} + (1 - c_{0q}) \ln M_{qjt} + c_{1q}. \tag{15}$$

c_{0q} and c_{1q} are constants with codomains between 0 and 1. To obtain equation 15, see the following proof.

PROOF:

[43] Therefore, I account for the endogeneity of worker mobility, i.e., worker mobility is nonrandom, and workers sort into firms that generate a high match productivity (Krishna, Poole and Senses, 2014).

[44] The worker-plant-specific fixed effects also incorporate variation across German regions and render redundant respective fixed effects.

[45] Age is included only as a squared variable, as its linear form would generate perfect collinearity in the presence of fixed effects and time dummies.

Consider $y = \ln(L/M)$ without subscripts. Moreover, $C = (e^{y\frac{\sigma-1}{\sigma}}+1)^{\frac{\sigma}{\sigma-1}}M$ and $\ln C = h(y)+\ln M$, where $h(y) = \frac{\sigma}{\sigma-1}\ln\left(e^{y\frac{\sigma-1}{\sigma}}+1\right)$. Then, the first-order Taylor approximation of $h(y)$ yields $h(y) = h(y_0) + h'(y_0)(y - y_0)$. Note that y_0 denotes a constant and that $h'(y_0) = \frac{e^{y_0\frac{\sigma-1}{\sigma}}}{e^{y_0\frac{\sigma-1}{\sigma}}+1}$ ranges from 0 to 1 $\forall y_0$. Defining $c_0 = h'(y_0)$ and $c_1 = h(y_0) - y_0h'(y_0)$ yields equation (15).

$$\begin{aligned}\ln C &= \underbrace{h'(y_0)}_{c_0}y + \underbrace{h(y_0) - y_0h'(y_0)}_{c_1} + \ln M\\ &= c_0\ln\left(\frac{L}{M}\right) + c_1 + \ln M\\ &= c_0\ln L + (1 - c_0)\ln M + c_1\end{aligned} \tag{16}$$

QED.

To reveal the wage effect of an increase in M_{jt}, consider setting $c_{0\bar{q}} = c_{0q}\forall q$ and using $\sum_{q=1}^{Q}\alpha_q = 1 - \alpha$. Then, the bottom line of equation (14b) becomes

$$\left(\alpha_{\bar{q}} + \frac{1}{\sigma_{\bar{q}}} - 2\right)(1 - c_{0\bar{q}})\ln M_{\bar{q}jt} + (1 - \alpha)(1 - c_{0\bar{q}})\ln M_{jt}. \tag{17}$$

Therefore, an increase in intra-industry imports M_{jt} may increase the occupation's $\bar{q}$ wage if the fraction $M_{\bar{q}jt}$ in M_{jt} is sufficiently low or the elasticity of substitution $\sigma_{\bar{q}}$ is close to 1.

The elasticity of labor demand for type $\bar{q}$ is implied by equations (9) and (14b):

$$\gamma_{\bar{q},D} = \frac{\partial\ln w_{\bar{q}}}{\partial\ln L_{\bar{q}}} = -\left[\frac{1}{\sigma_{\bar{q}}} + \left(1 - \alpha_{\bar{q}} - \frac{1}{\sigma_{\bar{q}}}\right)c_{0\bar{q}}\right] < 0 \tag{18}$$

To derive equation (10) in section 3, assume that industry j faces

$$w_{qjt} = aL_{qjt}^{\gamma_{q,S}}, \tag{19}$$

the labor supply curve for occupation $\bar{q}$. Again, $w_{\bar{q}jt}$ denotes the (daily) real wage of occupation $\bar{q}$ in industry j and year t. $\gamma_{\bar{q},S} = \frac{\partial\ln w_{\bar{q}jt}}{\partial\ln L_{\bar{q}jt}} > 0$ denotes the elasticity of supply for occupation $\bar{q}$. Drawing on equations (9) and (19), the wage elasticity of workers in occupation $\bar{q}$ is

$$b_{\bar{q},M_{\bar{q}}} = \left.\frac{\partial\ln w_{\bar{q}jt}}{\partial\ln M_{\bar{q}jt}}\right|_{K,L,M_{-\bar{q}}\text{ constant}} = \frac{(\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1)c_{0\bar{q}}\gamma_{\bar{q},S}}{\gamma_{\bar{q},S} - \gamma_{\bar{q},D}}, \tag{20}$$

Further assume that each worker i features individual yearly productivity $a_{ijt} = exp(b_1x_{it} + \xi_{ij})$, which includes a vector of coefficients b_1, observable individual characteristics such as age, tenure, and work experience, denoted by x_{it}, and unobservable worker-industry productivities ξ_{ij}. Apart from this productivity definition, the workers in occupation q are identical. Thus, the wage of worker i is composed of

$$w_{iqjt} = w_{iqt}a_{ijt}. \tag{21}$$

Solving equations (9), (19), and (21) for $\ln w_{iqjt}$ yields equation (10).

Online Appendix B: Data Sources and Processing

B.1 LIAB MM 9308

The LIAB itself is composed of various datasets, namely, the Integrated Employment Biographies (IEB), the Establishment History Panel (EHP), and the IAB Establishment Panel (EP). The data on individuals are taken from the IEB, which again combines five sources that originate from the social security notification process, from working processes of the German Federal Employment Agency (BA), or from related agencies.[46] Each employment spell is allocated to a unique plant identifier, which facilitates matching the personnel data with plant-level information from two other sources in the LIAB: the EHP and the annually performed surveys in the IAB EP.

Table B1: Data Processing and Employed Variables

Variable (source)	Description and Modification
Capital per worker (EP)	Prior investments in the plant per employee. This variable is constructed from the retrospectively reported values of investments. I approximate the capital stock of a plant by using the mean of all deflated investments in the three previous years, i.e., t, t-1, and t-2. Then, I divide the capital stock by the reported number of full-time workers in the EP (Schank, Schnabel and Wagner, 2007).
Daily real wage (IEB)	An employee's real wage per day denoted in euros. For each spell, the monthly earnings are divided into daily rates. The measure also considers additional payments such as annual bonus payments and allowances in the context of changes in the employment spell. I obtain real wages by deflating nominal values by using the consumer price index provided by the Federal Statistical Office. The daily real wage is denoted in euros in year 2000-constant prices. The imputation of top-coded wages above the social security contribution ceiling is described in B.1.3 below.
Education (IEB, BIBB-IAB)	The highest educational degree attained by the worker. In the IEB, the education variable contains many missing values and inconsistencies. I apply the imputation procedure described in B.1.2 and subsequently apply the resulting values in the wage imputation. The information on the average educational attainment per occupation (*average skill*) is drawn from the BIBB-IAB.
Employees (EHP)	The number of full-time and part-time employees per plant.
Export (EP)	The retrospectively reported export share of a plant (in the previous year). I forward impute the variable to create current-year values. In some years, the questionnaire distinguishes among export destinations, e.g., 1998-2003 between exports to the Eurozone and the rest of the world and 2004-2007 with an additional group of the new EU member states. For these years, I sum the specific export shares to maintain a consistent measure.
Revenue (EP)	The retrospectively reported sales of a plant (in the previous year). I forward impute the variable to create current-year values. To obtain consistent entries, I deflate the variable to year-2000 values using the consumer price index developed by the Federal Statistical Office.
Tenure (IEB)	The duration of the current job spell in years. This figure is derived from the number of days on the job (*tage_job*).
Union coverage (EP)	The plants' status of labor union coverage, i.e., the level of the wage agreement or collective bargaining. To replace missing entries, I interpolate the union coverage status by using a recursive procedure, i.e., replacing missing values with valid entries of the previous year or if available only in the subsequent year by that value. Other entries are interpolated by using the modal value of reported coverage types. In the case of ties, I use the stricter entry, i.e., industry-level bargaining, firm-level bargaining, and no coverage, in descending order.
Work experience (IEB)	The sum of all job-spell durations in years. This figure is derived from the number of days in employment (*tage_erw*).

The LIAB Mover Model contains two identifiers to match employers and employees. The broader identifier matches the administrative accounts of all workers with social insurance in the EHP. Specifically, these accounts include a plant's number of employees, location, age, and industry. Additional plant information is obtained by linking the second identifier to the EP. For each plant-year

[46] The direct sources for the IEB are employee histories, benefit receipt histories, participants-in-measures histories, jobseeker histories, and unemployment benefit II receipt histories.

record in the EP, the information on all of its workers with social insurance is included from the IEB.[47] The reference date for both entries is June 30 of each year.

One advantage of the LIAB Mover Model over the other longitudinal model of the LIAB is the number of observations per individual and per plant. Therefore, the former data are better suited for models with multidimensional fixed effects. The dataset comprises 3,175,801 to 3,815,061 individuals per year, which results in observations of 4,666,926 individuals in the total sample from 1993 to 2008. These are linked to between 2,361 and 8,879 plants per year in the IAB Establishment panel. Over the full period, the sample includes 24,709 different plants. Other longitudinal datasets, e.g., the LIAB 93-14, comprise between 1,006,028 and 1,533,327 individuals per year and 1,918,086 in total. The number of plants that are not repeatedly reported is also vastly higher, at 2,436 to 11,868 plants per year relative to a total number of 192,323 plants in the overall dataset.

The sampling of the LIAB Mover Model follows a two-step procedure with the EP as the starting point. First, all plants for which the number of employees differs by more than 50 percent from the value in the IEB are excluded. Among the remainder, plants that employ at least one mover are selected. A mover is defined as an employee who worked for at least two plants with valid entries in the EP on different reference dates. Moreover, such employment has to be the main occupation of the individual. Second, up to 500 employees are added to each of the identified plants in the first step. Thus, in the sample, all employees are included for small businesses, while a maximum of 500 employees are included for large businesses. The additional employees either do not change plants or switch to a plant outside of the EP.[48]

IAB Establishment Panel (EP)

The EP is a subsample of businesses of all industries and sizes that include at least one employee with social security in the year prior to the survey. The exact number of recorded plants varies between approximately 4,100 and 16,000 observations per year. The EP is available from 1993 onwards for West Germany and from 1996 onwards for East Germany. The sample design is stratified by plant size (number of employees), industry, and state. Thus, the sampling probability is higher for larger plants.[49]

In the analysis, changes in industry categories constitute a potential problem for longitudinal comparability: From 1993 to 2002, the industry classification WZ73 is used, which is a unique system of the BA and comprises 16 different industries in total. In 1999, classification WZ93 was introduced, which is better suited for international comparison because it is similar to the European NACE or the ISIC classification of the United Nations and comprises 20 different industries. In 2003, records began to use industry classification WZ03 and 17 different industry units. However, this change in industry classification has a relatively small impact on longitudinal comparability because the changes are below the applied level in the EP. This impact is anticipated in the following analysis, which uses a time-consistent imputed and extrapolated WZ93/NACE/ISIC rev. 3 classification at the 2-digit level developed by Eberle et al. (2011).

B.1.1 Occupation and Industry Codes within Employee-Plant Matches

Each job notification in the LIAB is associated with an occupational category ("*Klassifizierung der Berufe 1988*") and an industry classification of the employer. Within job spells, it is possible that the assignment of these variables changes: while the industry code changes in 0.25 percent of all job spells, 7.51 percent of job spells incorporate changes in the occupation classification. Since the latter represent a potentially important channel through which offshoring affects wages, I do not assign a fixed occupation code to any job spell (occupation-spell fixed effects) but separately include occupation fixed effects.

B.1.2 Imputation of Education

Although the education variable does not enter the analytical regressions for offshoring, it is employed for the imputation of top-coded wages. The objective of the data collection is solely for statistical purposes, in contrast to most of the other information on administrative labor processes. Frequently, information is missing from or inconsistent in the plants' reports. To mitigate these deficits, I follow the imputation procedure (version 1) developed by Fitzenberger, Osikominu and Völter (2006). Therefore, I map information on the highest degree attained (*bild*) into five educational groups: 1) missing, not recognized, or no degree; 2) lower secondary education without vocational training; 3) lower secondary education with vocational training or upper secondary

[47] Furthermore, the dataset includes marginal part-time employees (since 1999), recipients of unemployment benefits, and registered jobseekers at the BA (since 2000). Not included are civil servants, military members, the self-employed, family workers, and students.

[48] For a more detailed description of the sampling procedure of the LIAB MM 9308, I refer to Heining et al. (2012, p. 30 f.).

[49] For more information about the sampling of the survey, I refer to Fischer et al. (2008, p.4 ff.).

education without vocational training; 4) upper secondary education with vocational training; and 5) a college or university (of applied science) degree. Then, I forward extrapolate the information and apply the highest entry. The subsequent backward extrapolation anticipates the following age limits: 20 years for vocational training, 27 years for degrees from universities of applied science, and 29 years for university degrees.

B.1.3 Imputation of Wages

The wage information in the IAB employment sample is censored at the social security contribution limit, which amounts to 11-15 percent of the wage data of male, full-time workers in manufacturing. Missing information must be inferred from the available observables. I therefore stochastically impute the upper part of separated cross-sectional wage distributions (by years and educational groups) using a series of Tobit models, akin to Dustmann, Ludsteck and Schönberg (2009) and Card, Heining and Kline (2013). This extends the method developed by Gartner (2005) and adds a two-step procedure.[50] Specifically, it assumes that the error terms are normally distributed and variances vary for the interactions of each of the five educational groups. I fit these 65 Tobit models (13 years $\times$ 5 educational groups) to log daily wages. The controls include a quadratic polynomial for age, a binary variable for workers above the age of 40 and its interactions with the age terms, a quadratic polynomial for tenure, work experience, occupation, and plant information such as the state, a quadratic polynomial for employees, the corresponding industry (3-digit NACE/ISIC rev. 3), and the median wage. Subsequently, I replace the censored wages with uncensored predictions from the estimated parameters and a random component that remedies the correlation between the covariates and the error term. This component is drawn from a truncated normal distribution with a mean zero and the corresponding variance from the standard error of the forecast.

In a second step, I extend the imputation models by including means of the wage information of either workers or plants of all years other than the respective episode of the cross-section (leave-one-out means per worker and per plant). Therefore, I also include imputed wages from the first step. Singleton worker or singleton worker-plant observations are accounted for by the sample mean of (imputed) wages. Thereafter, I repeat the estimation procedure from the first step using a series of Tobit models to fit the log daily wages.

Workers above the social security contribution limit belong to the following occupational groups as a percentage of the full sample (percentage of top-coded entries per occupation): “601 mechanical, motor engineers”, 11.03 percent (59.95); “602 electrical engineers”, 9.59 percent (57.10); “607 other engineers”, 4.92 percent (53.21); “628 other technicians”, 6.96 percent (24.05); “751 entrepreneurs, managing directors, divisional managers”, 10.82 percent (80.63); and “781 office specialists”, 8.96 percent (25.39). When these data are aggregated over two-digit occupation codes, I have the following: “60 engineers”, 28.52 percent (57.53); “62 technicians”, 18.46 percent (25.66); “75 entrepreneurs and management”, 12.94 percent (75.79); “77 accounting professionals, data processing specialists”, 5.92 percent (40.41); and “78 office specialists’, 9.21 percent (24.94).

B.2 Job Complexity Index

The job complexity index comprises waves 1998 and 2006 of the BIBB-IAB work surveys. For each wave, 4 indices are constructed, which ultimately yield a single, static measure of job complexity. First, each worker is assigned a value (see column 4 in Table B2) with respect to the frequency of the performance of the task. Then, for each of the 4 groups (activities, knowledge, performance, and tools or activities), I sum all affirmative responses and take the occupational mean of this sum. By dividing these averages by the highest mean, I normalize and obtain an index for the group and year. Finally, I take the weighted average of all indices using the number of observations per occupation and normalize again to obtain a single measure. Entries based on 5 observations or fewer are eliminated.

B.3 Offshoring Measure

The (industry- or occupation-level) offshoring measures are constructed in several steps. The starting point is the ”narrow” definition of offshoring for manufacturing industries, as in Feenstra and Hanson (1996, 1999). Its construction considers imported inputs that are produced in the same classification of economic activity as the using industry (NACE/ISIC rev. 3). Hence, it contemplates firms’ productivity decisions with respect to either producing those inputs or importing them.

[50] I thank Johann Eppelsheimer and Wolfgang Dauth for sharing their program code.

The data are drawn from the input-output tables of the German Federal Statistical Office, which is crucial for the analysis because it explicitly distinguishes between domestically and foreign-produced inputs (Winkler and Milberg, 2012, p. 40). The data are publicly available in the *Fachserie 18, Reihe 2* compiled by the Federal Statistical Office. Compare this source, for instance, to data from UN Comtrade, which do not explicitly distinguish between final and intermediate goods and the respective using industries.

While the LIAB consistently denotes employers according to the industries in the NACE rev.1 classification, the input-output tables of the German Federal Statistical Office from 1995 to 2007 follow the German classification of economic activities 2003, which is harmonized with NACE Rev.1.1. Since substantial changes occurred at low levels of aggregation, the differences between the two schemes are negligible at the two-digit level. The same applies to the correspondence between NACE rev. 1.1 and ISIC rev. 3.1.

For each two-digit industry j, I utilize the ratio of inputs M that industry j imports from offshore industries of the same classification j^* relative to its gross output Y in year t:

$$OS_{jt} = \frac{M_{jt}^{j^*}}{Y_{jt}}.$$

Then, OS_{jt} indicates the share of value added abroad that could, instead, be produced by the respective domestic industry. Technically, $M_{jt}^{j^*}$ comprises the diagonal in the input-output table of imports.

The focus on intra-industry imports is based on the idea of trading comparable sets of tasks (labor inputs). Thus, it is better suited for this analysis than alternatives such as affiliate employment or FDIs, where expansions also result from horizontal objectives (e.g., market access). Specifically, increasing OS_{jt} implies, on the one hand, that some domestic tasks are substituted by foreign factors and, on the other hand, that other domestic tasks are complemented by foreign factors. Note that even if new firms in foreign countries trade new components, these account for offshoring activities, as they substitute for potential economic expansions of onshore firms. The implicit assumption is that technological capabilities are not exclusive to offshore firms. Hence, the resulting effects on the labor market cannot be straightforwardly estimated since they depend on the respective tasks.

This analysis has several implications. First, it suggests that the effects of offshoring cannot be completely captured at the firm level. For instance, within industries, the substitution of a domestic supplier by a foreign supplier may adversely affect the demand for tasks at the domestic supplier, while it increases productivity and labor demand at the processing firm. Second, it highlights the difference between intra- and inter-industry trade. As *intra*-industry trade both complements and substitutes the tasks of the importing industry, *inter*-industry trade is complementary to tasks in the importing industry but substitutes tasks in industries that produce such goods. Then, it impacts multiple industries, the one that imports and the nontrading supplier. Although the counteracting effects may evolve similarly, it is almost impossible to disentangle them. Inter-industry imports are therefore not considered in the offshoring measure. Third, the substitution of particular task sets immediately suggests that offshoring exhibits heterogeneous effects not only with respect to job complexity but also with respect to the underlying tasks of imported inputs. Thus, I map similar offshoring destinations into groups and broadly distinguish between high- and low-wage countries. If high-wage countries possess a comparative advantage in the performance of particular complex tasks, such inputs will affect different sets of tasks in the importing country than inputs from low-income countries. Specifically, I map the countries into groups with respect to their affiliation with a trade bloc, their geographic proximity, and the similarity of their economic structures. Then, I focus only on the most relevant offshoring destinations for Germany during the period considered because including more regions impedes the separate identification of the respective causal effects. These regions include the countries belonging to the former EU15 and the CEECs (although Bulgaria and Romania had the lowest labor costs of the new entrants in the 2000s, their slow progress toward a market economy hampered their economic integration. Similar to Carstensen and Toubal (2004), I focus on Visegrad countries since they reflect a more homogeneous region and because of their proximity to Germany.

Since the data from the Federal Statistical Office do not provide information on the origin of imported inputs, I combine these data with the WIOT (for a detailed description of the WIOT and its usage of an proportionality assumption, see Timmer et al., 2015, p.591f.). In doing so, I adopt the assumption that imported inputs from a supply region are equally distributed across the domestic importing industries of such inputs. For instance, if Germany sources 40 percent of its imported car parts for intermediate use from Central and Eastern Europe, then each industry that imports car parts is assumed to source 40 percent of those imports from Central and Eastern Europe. As the bulk of imported inputs is typically processed by the same industry as the producing industry, the resulting distortion of this "weaker kind" of proportionality assumption is considered to be relatively small, especially if offshoring is narrowly defined as in equation (1). Recall, that the data from the German Federal Statistical Office is not distorted by an proportionality assumption. Their data compilation is a direct measurement the industries' import or use of inputs (vs. the usage of these goods as final goods). The usage of the WIOT directly—so also for the distinction between input and final use—would, on the contrary, have needed to rely on the full proporionality assumption meaning that a given imported input is used by the same proportion in each industry (Winkler and Milberg, 2012).

The offshoring measure OS_{jt} becomes region specific due to the weighting by the share of intra-industry imports from a particular region r in the total intra-industry imports of sector j in year t:

$$Ofs_{jtr} = \phi_{jtr} OS_{jt},$$

where

$$\phi_{jtr} = \frac{M_{jtr}^{j^*}}{M_{jt,World}^{j^*}}.$$

The industry-specific offshoring measure is reasonable if the labor market variation stems from differences between industries rather than from differences between occupations. However, in Germany (and the US; see Ebenstein et al., 2014), the occupation level comprises the relevant and wage-determining labor market. The underlying idea is related to the costs and possibility of finding a new job. A bookkeeper, for instance, can switch from one industry to another at a relatively low cost. Entering a new occupation, however, is likely to adversely affect a worker's income since job changes are typically associated with higher costs of prior occupational retraining and with the loss of compensated productivity, which originates from occupational tenure. Gathmann and Schönberg (2010) show that the burden of occupational switches also depends on the similarity of tasks between jobs. Turning to the data, this finding is supported by similar evolutions of wages within occupations rather than within industries. Intraclass correlations of wages within industries and occupations amount to 0.093 and 0.499, respectively. Moreover, the within (between) variation of industries is relatively high (low) compared to the within variation of occupations. However, not only are occupations the more relevant unit of analysis, their initial cross-industry variation in (industry-level) offshoring exposures also allows for increasing the degrees of freedom in the analysis. I therefore weight the region-specific offshoring exposures of 24 industries Ofs_{jtr} by the number of workers in occupation q and industry j relative to the total number of employees in occupation q in manufacturing in 1995. This weighting yields 243 annual occupation-specific exposures to region-specific offshoring, which is insensitive to subsequent alterations in the composition of jobs across industries:

$$OccOfs_{qtr} = \sum_{j=1}^{J} \frac{L_{qj,1995}}{L_{q,1995}} Ofs_{jtr}.$$

B.4 Occupational Classifications of Offshorability

In a robustness check, I apply the preferred offshorability measure from the Princeton Data Improvement Initiative (PDII) (Blinder and Krueger, 2013). This measure is based on the assessment of professional coders who determine whether a job can generally be reallocated overseas. Originally, the data are collected in the 6-digit Standard Occupational Classification of the year 2000 (SOC00) and thus need to be mapped to the German KldB88. Since, to the best of my knowledge, there exist no publicly available crosswalks from SOC00 to KldB88, I follow a similar procedure to Goos, Manning and Salomons (2014) and apply a series of crosswalks. First, if the same occupation code features more than one value of offshorability, I calculate the weighted average using the respective weights from the PDII. Second, I map SOC00 to the International Standard Classification of Occupations in 1988 (ISCO88), employing the crosswalk provided by the Institute for Structural Research (the data are publicly available at http://ibs.org.pl/en/resources/). Again, if the same occupation code (now in ISCO88) features more than one value, I assign the weighted average using the adjusted weights from the PDII. Third, I exploit the coding of the work survey in 2006. There, workers are assigned to KldB88 and ISCO88. Moreover, the survey contains weights that reflect the German workforce composition. With these three variables, it is possible to map ISCO88 to KldB88 using the respective weights of the work survey in 2006 for any many-to-one mapping. This process renders 339 occupations in KldB88.

As argued by Baumgarten, Irlacher and Koch (2020), the mapping of SOC to KldB comes at some cost. Hence, to reduce the distortions caused by measurement error, I follow their procedure and rely on the occupational ranking of offshorability. Thus, in table C10, I apply a binary variable that takes a value of one for jobs that belong to the top 25 percent of the ranked offshorability values.

Table B2: Job Activities, Knowledge, Performance Requirements, and Tools Associated with a Job's Complexity

		Wave 1998/99	
Group	Var	Task	Coding of frequency
Activities	v189	Forming, teaching	Never - 0; seldom - 1; often - 1.5
	v190	Other advising, informing	Never - 0; seldom - 1; often - 1.5
	v193	Repairing	Never - 0; seldom - 1; often - 1.5
	v194	Buying, procurement, selling	Never - 0; seldom - 1; often - 1.5
	v195	Organizing, planning the work processes of others	Never - 0; seldom - 1; often - 1.5
	v196	Advertising, communication, public relations	Never - 0; seldom - 1; often - 1.5
	v197	Collecting, analyzing information, investigating	Never - 0; seldom - 1; often - 1.5
	v198	Negotiating	Never - 0; seldom - 1; often - 1.5
	v199	Developing, researching	Never - 0; seldom - 1; often - 1.5
	v201	Serving, attending, caring for people	Never - 0; seldom - 1; often - 1.5
Knowledge	v213	Mathematics	yes - 1; no - 0
	v214	German	yes - 1; no - 0
	v215	Presentation skills	yes - 1; no - 0
	v216	Foreign language	yes - 1; no - 0
	v217	Sales, marketing and public relations	yes - 1; no - 0
	v218	Design	yes - 1; no - 0
	v219	Standard programs of computers	yes - 1; no - 0
	v220	System analysis	yes - 1; no - 0
	v221	Computer engineering	yes - 1; no - 0
	v222	Other technical acquaintance	yes - 1; no - 0
	v223	Labor legislation	yes - 1; no - 0
	v224	Other legal knowledge	yes - 1; no - 0
	v225	Management	yes - 1; no - 0
	v226	Finance	yes - 1; no - 0
	v227	Controlling	yes - 1; no - 0
	v228	Labor protection	yes - 1; no - 0
	v229	Medical knowledge	yes - 1; no - 0
	v230	Other special knowledge	yes - 1; no - 0
Performance	v264	Work under great deadline pressure	Always - 4; often - 3; sometimes - 2; seldom - 1; never - 0
	v265	Work is stipulated in the minutest details	Always - 0; often - 1; sometimes - 2; seldom - 3; never - 4
	v266	Same work cycle/process is repeating in the minutest details	Always - 0; often - 1; sometimes - 2; seldom - 3; never - 4
	v267	Confronted with new problems	Always - 4; often - 3; sometimes - 2; seldom - 1; never - 0
	v268	Tasks include process optimization or trying out new things	Always - 4; often - 3; sometimes - 2; seldom - 1; never - 0
	v272	Multitasking	Always - 4; often - 3; sometimes - 2; seldom - 1; never - 0
	v274	Mistakes/inattention leads to high financial losses	Always - 4; often - 3; sometimes - 2; seldom - 1; never - 0

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Table B2: *(Continued)*

Group	Var	Task	Coding of frequency
		Wave 1998/99	
Tools	v32	Precision mechanical, special tools	yes - 1; no - 0
or	v64	Fixed telephone	yes - 1; no - 0
activities	v65	Telephone with ISDN	yes - 1; no - 0
	v66	Answering machine	yes - 1; no - 0
	v67	Mobile phone, walkie-talkie, pager	yes - 1; no - 0
	v69	Dictating machine, microphone	yes - 1; no - 0
	v70	Overhead projector, beamer, TV	yes - 1; no - 0
	v71	Camera, video camera	yes - 1; no - 0
	v73	Bicycle, motorcycle	yes - 1; no - 0
	v74	Automobile, taxi	yes - 1; no - 0
	v75	Bus	yes - 1; no - 0
	v76	Truck, conventional truck	yes - 1; no - 0
	v77	Trucks for hazardous good special vehicles	yes - 1; no - 0
	v78	Railway	yes - 1; no - 0
	v79	Ship	yes - 1; no - 0
	v80	Airplane	yes - 1; no - 0
	v81	Simple means of transport	yes - 1; no - 0
	v83	Tractor, agricultural machine	yes - 1; no - 0
	v84	Excavating, road-building machine	yes - 1; no - 0
	v93	Therapeutic aids	yes - 1; no - 0
	v94	Musical instruments	yes - 1; no - 0
	v95	Weapons	yes - 1; no - 0
	v97	Fire extinguisher	yes - 1; no - 0
	v98	Cash register	yes - 1; no - 0
	v99	Scanner cash register, bar-code reader	yes - 1; no - 0
	v104	Graphics program	yes - 1; no - 0
	v106	Special, scientific program	yes - 1; no - 0
	v108	Program development, systems analysis	yes - 1; no - 0
	v109	Device, plant, system support	yes - 1; no - 0
	v110	User support, training	yes - 1; no - 0
	v111	Professional use of personal computer	yes - 1; no - 0
	v113	Installation of program-controlled machinery	yes - 1; no - 0
	v114	Programming of program-controlled machinery	yes - 1; no - 0
	v115	Monitoring of program-controlled machinery	yes - 1; no - 0
	v116	Maintenance, repairs	yes - 1; no - 0

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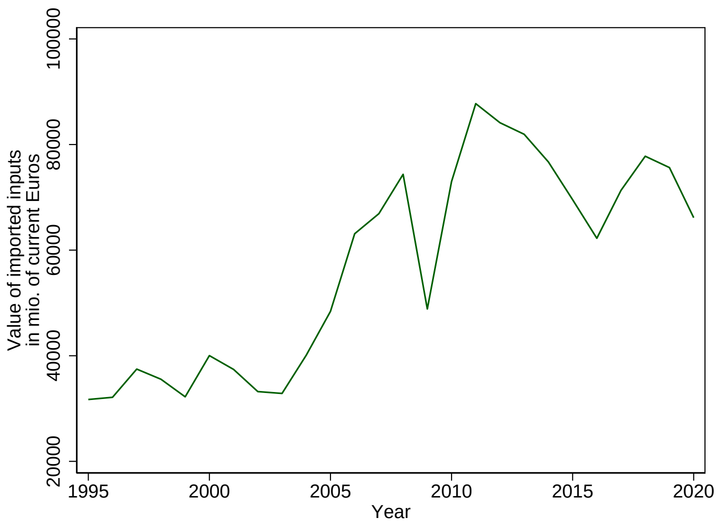
Table B2: *(Continued)*

		Wave 2006	
Group	Var	Task	Coding of frequency
Activities	f312	Training, instructing, teaching, educating	Never - 0; seldom - 1; often - 1.5
	f314	Providing advice and information	Never - 0; seldom - 1; often - 1.5
	f306	Repairing, refurbishing	Never - 0; seldom - 1; often - 1.5
	f307	Purchasing, procuring, selling	Never - 0; seldom - 1; often - 1.5
	f310	Organizing, planning, ...others' work processes	Never - 0; seldom - 1; often - 1.5
	f309	Advertising, marketing, public relations	Never - 0; seldom - 1; often - 1.5
	f313	Gathering information, investigating, documenting	Never - 0; seldom - 1; often - 1.5
	f325_3	Negotiating	Never - 0; seldom - 1; often - 1.5
	f311	Developing, researching, constructing	Never - 0; seldom - 1; often - 1.5
	f315, f316	Serving, attending, caring for people	Never - 0; seldom - 1; often - 1.5
Knowledge	f403_01	Science	no - 0; basic - 1; specialized - 2
	f403_02	Manual	no - 0; basic - 1; specialized - 2
	f403_03	Pedagogical	no - 0; basic - 1; specialized - 2
	f403_04	Legal	no - 0; basic - 1; specialized - 2
	f403_05	Project management	no - 0; basic - 1; specialized - 2
	f403_06	Medical and nursing	no - 0; basic - 1; specialized - 2
	f403_07	Design	no - 0; basic - 1; specialized - 2
	f403_08	Mathematics and statistics	no - 0; basic - 1; specialized - 2
	f403_09	German	no - 0; basic - 1; specialized - 2
	f403_10	Special IT	no - 0; basic - 1; specialized - 2
	f403_11	Technical	no - 0; basic - 1; specialized - 2
Performance	f411_01	Work under great deadline pressure	Always - 3; often - 2; seldom - 1; never - 0
	f411_02	Work stipulated in the minutest details	Always - 0; often - 1; seldom - 2; never - 3
	f411_03	Same work cycle/process repetitive in the minutest details	Always - 0; often - 1; seldom - 2; never - 3
	f411_04	Confronted with new problems	Always - 3; often - 2; seldom - 1; never - 0
	f411_05	Tasks including process optimization or trying out new things	Always - 3; often - 2; seldom - 1; never - 0
	f411_09	Multitasking	Always - 3; often - 2; seldom - 1; never - 0
	f411_11	Mistakes/inattention leading to high financial losses	Always - 3; often - 2; seldom - 1; never - 0
Tools	f308	Transporting, storing, sending	Never - 0; seldom - 1; often - 1.5
or	f317	Protecting, guarding, patrolling, directing traffic	Never - 0; seldom - 1; often - 1.5
activities	f325_01	Responding to and solving unforeseen problems	Never - 0; seldom - 1; often - 1.5
	f325_02	Imparting difficult matters comprehensibly	Never - 0; seldom - 1; often - 1.5
	f325_04	Making an important decision independently	Never - 0; seldom - 1; often - 1.5
	f325_05	Self-initiated solving of knowledge gaps	Never - 0; seldom - 1; often - 1.5
	f325_06	Talks or speeches	Never - 0; seldom - 1; often - 1.5
	f325_07	Contact with customers, clients, or patients	Never - 0; seldom - 1; often - 1.5
	f325_08	Many different problems and tasks	Never - 0; seldom - 1; often - 1.5
	f325_09	Responsibility for the wellbeing of others	Never - 0; seldom - 1; often - 1.5

Notes: Overview of activities, knowledge, performance requirements, and tools associated with a job's complexity.

Online Appendix C: Figures and Tables

Fig. C1: Imported Inputs by Germany, 1995 - 2020



Source: Federal Statistical Office of Germany: Foreign Trade, Imports by Commodity Groups.
Notes: Figure C1 illustrates the importance of the late 1990s and early 2000s for the extension of international value chains in terms of imported inputs (measured in current Euros). In contrast to the period after the financial crisis, the aggregate value of imported inputs between 1996 and 2007 is not characterized by consecutive periods of decreases.

Table C1: Offshoring Intensity by Destination Region in German Manufacturing

	Western Europe		Eastern Europe		Other high-wage countries		Other low-wage countries	
t	Offshoring	Δ(t-1996)	Offshoring	Δ(t-1996)	Offshoring	Δ(t-1996)	Offshoring	Δ(t-1996)
1996	0.037		0.003		0.008		0.003	
2002	0.045	0.008	0.011	0.007	0.008	0.000	0.005	0.002
2007	0.046	0.009	0.014	0.011	0.009	0.001	0.010	0.007
Growth								
1996-2007	24.5%		317.8%		12.7%		250.2%	

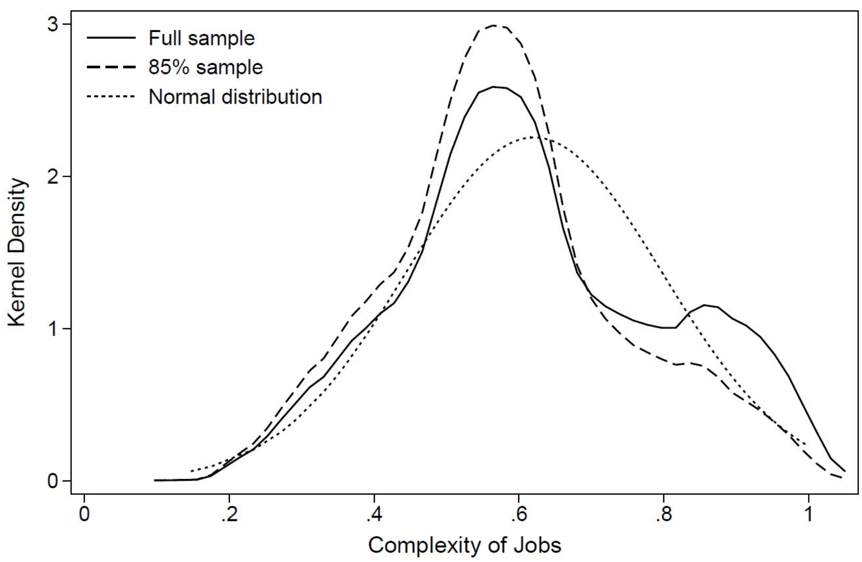
Notes: Table C1 reports offshoring intensity and its growth by region (as defined in section 2) for the years 1996, 2007, and 2007.

Table C2: Correlations of Selected Tasks Indices and Wages

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Task complexity index	(three-digit occup.)	1								
(2) Average skill	(three-digit)	0.93	1							
Becker et al. (2013):										
(3) Nonroutine tasks	(two-digit)	0.85	0.85	1						
(4) Interactive tasks	(two-digit)	0.71	0.73	0.68	1					
Spitz-Oener (2006):										
(5) NR activities	(two-digit)	0.89	0.92	0.86	0.80	1				
(6) NR interactive	(two-digit)	0.88	0.90	0.81	0.76	0.98				
Brändle and Koch (2017):										
(7) Offsh. Potential	(two-digit)	-0.88	-0.91	-0.90	-0.70	-0.94	-0.90	1		
Blinder and Krueger (2013):										
(8) Offshorability (D)	(three-digit)	0.02	0.02	0.14	-0.19	-0.09	-0.11	-0.01		
(9) Daily real wage*	(individual level)	0.65	0.66	0.60	0.49	0.64	0.65	0.61	0.01	1

Source: German Qualification and Career Survey by BIBB-IAB work survey, LIAB.
Notes: The table presents the correlation coefficients of selected task indices from the literature utilizing the full sample. NR activities and NR interactive are based on the definitions developed by Spitz-Oener (2006). The nonroutine and interactive task indices follow the strict definitions of Becker, Ekholm and Muendler (2013) and consider only information from the 1998 wave to maintain comparability with Baumgarten, Geishecker and Görg (2013). Offshoring potential is taken from Brändle and Koch (2017). * Daily real wages include top-coded entries.

Fig. C2: Relative Frequency of Workers Along the Task Dimension



Source: BIBB-IAB work survey and LIAB.
Notes: Kernel density of male workers along the complexity measure (bandwidth=0.05). The solid line represents the full sample, which has a greater probability mass at the upper end than the subsample (dashed line) that only contains workers without censored wage entries and cuts off workers above the 85th percentile of the wage distribution. For comparison, the normal distribution is referenced by the dotted line ($\mu = 0.6208; \sigma = 0.1768$).

Table C3: Descriptive Statistics

	Unit	Specified			Full sample		
		Observations	Mean	Std. Dev.	Observations	Mean	Std. Dev.
Worker-level		85 percent sample			Imputed wages		
Age	years	6,828,223	41.31	28.08	8,185,759	40.98	9.52
Tenure	years	6,828,223	10.52	7.89	8,185,759	10.52	7.94
Wage	euros	6,828,223	96.51	21.70	8,185,759	117.39	56.57
Work Experience	years	6,828,223	16.54	8.07	8,185,759	16.88	7.95
Occupation-level		Occupation-year			Worker-occupation-year		
$OccOfs_{CEECs}$	share	4,242	0.0092	0.0059	8,185,759	0.0092	0.0050
$OccOfs_{EU15}$	share	4,242	0.0426	0.0217	8,185,759	0.0427	0.0120
Task complexity	index	3,123	0.6179	0.1748	8,185,759	0.6215	0.1770
Interactivity (by Becker et al.)	index	1,014	0.4288	0.2074	8,165,710	0.4296	0.1770
Nonroutine (by Becker et al.)	index	1,014	0.3727	0.2318	8,165,710	0.4521	0.2259
IA-activities (by Spitz-Oener)	index	1,100	0.4445	0.2288	8,185,759	0.4293	0.2138
NR-activities (by Spitz-Oener)	index	1,100	0.4864	0.2152	8,185,759	0.4917	0.2116
Plant-level		Plant-year			Worker-plant-year		
Average wage	euros	16,136	2,479.92	1,131.06	2,428,759	2,657.48	1,215.07
Capital per worker	euros	13,815	7,633.21	20,171	2,022,078	8,503.72	14,529.42
Employees	number	190,726	273.65	997.162	8,185,759	2,816	6,285.761
Export share (of revenues)	share	12,778	0.2859	0.2767	1,809,119	0.3999	0.2776
Revenue (in thous.)	euros	11,924	166,000	848,000	1,681,343	961,000	3.62e+09
Wage agreement: No	dummy	190,726*	0.0605	0.2384	8,185,759	0.0859	0.28018
Firm-level bargaining	dummy	190,726*	0.0224	0.1480	8,185,759	0.0747	0.2629
Industry-level bargaining	dummy	190,726*	0.1470	0.3541	8,185,759	0.6345	0.48157
Wage bill (in thous.)	euros	16,136	1,790	1.1310	2,428,759	6,644	1.6900
Industry-level		Industry-year			Worker-industry-year		
Ofs	share	299	0.0862	0.0729	8,185,759	0.0741	0.0395
Ofs_{CEECs}	share	299	0.0097	0.0104	8,185,759	0.0094	0.0091
Ofs_{EU15}	share	299	0.0462	0.0401	8,185,759	0.0429	0.0290

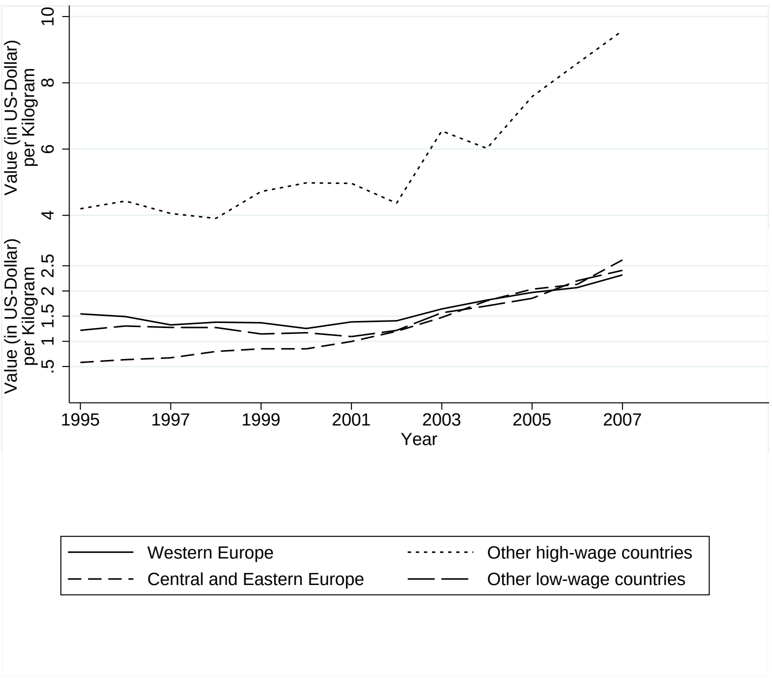
Notes: The table presents the descriptive statistics. It shows worker-year, occupation-year, plant-year, industry-year, worker-occupation-year, worker-plant-year, and worker-industry-year observations in the respective panels. A * indicates interpolated values in the LIAB following the procedure described in Table B1.

Table C4: Single Regressions of Offshoring on Plant-Level Outcomes

	Cross-section, 1995 State FE			Panel, 1996 - 2007 Plant FE		
	$Ofs_{2005,OHI}$	$Ofs_{2005,LMI}$	$Ofs_{2005,DOut}$	Ofs_{OHI}	Ofs_{LMI}	Ofs_{DOut}
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Plant outcomes						
ln Wage bill	16.630***	-6.432*	4.975***	1.610	-1.854**	0.254**
ln Avg. wage	3.023**	-4.654***	1.310***	-0.075	3.177***	-0.283***
ln Employees	13.778***	-1.704	4.036**	0.653	-4.896***	0.477***
ln Capital per worker	-0.119	-3.521	2.278**	-11.755*	8.753*	0.076
ln Revenue	15.888***	-5.355	3.405**	0.761	3.521**	0.039
Exports (share)	4.265***	1.006	0.269	-0.565	1.309**	-0.138***
Wage agreement: No	0.511***	0.283***	-0.017	-0.006	0.099***	-0.012***
Firm level	-0.057	0.014	0.016*	0.015	0.037*	0.002
Industry level	0.680***	0.441***	0.176***	-0.014	-0.135***	0.010**
Panel B: Worker task profiles						
Simple Job (D)	-6.154***	-4.567***	-0.095	0.601*	-0.924***	0.027
Medium Job (D)	-0.304	-3.073***	0.477***	-0.134	-0.582***	0.020
Complex Job (D)	6.458***	7.640***	-0.381**	-0.467	1.505***	-0.046

Source: Annual report on local units in manufacturing, mining and quarrying by the Federal Statistical Office, LIAB.
Notes: Each cell shows the estimate of a regression, where the dependent variable is listed in the same row and the explanatory variables are along the columns. Note that in the presence of plant fixed effects, the coefficient of wage agreements can be determined only by changes in status. Data on the wage bill, average wages, revenue, employees, and exports are extracted from the Federal Statistical Office: *42111-0128 Persons employed and turnover of local kind-of-activity units in manufacturing: FT/NL, years, economic activities.* Other data from the table are from the LIAB. Standard errors are clustered at industry-state levels in columns 1 - 3 and at industry-year levels in columns 4 - 6.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Fig. C3: Unit Values in Germany's Imported Manufactured Goods, by Country Groups



Source: UN Comtrade.
Notes: Figure C3 depicts the evolution of commodities (HS 1992) of the manufacturing sector (using OECD convergence tables from HS 1992 to ISIC rev. 3) that are imported by Germany from different country groups. For better readability, the y-axis changes its scale above the value 2.5.

C.1 Nonmonotone Wage Effects Along the Job Complexity Measure

This specification tests whether the effects in the baseline regression are monotonic along the complexity index. To do so, I assign each worker to one of five groups that constitute the quintiles of the complexity distribution. A worker's affiliation with a group is then recorded by a binary variable. In columns 1 and 2 of table C5, I drop wages above the 85th percentile. Now, the group sizes become unequal, with fewer individuals in the more complex groups. For comparison reasons, I also rerun the specifications for the full sample (columns 3 and 4), in which I impute missing wage information. Since the task complexity groups enter the regression equation as binary variables that are interacted with occupational exposures to offshoring, the interpretation of the respective coefficients is relative to those of the other groups. For example, the wage elasticity of group 3 is relative to that of groups one, two, four and five, whereas the wage elasticity of group 5 is relative to that of groups one to four. Moreover, it impedes the use of an IV regression because the instruments are still too weak to predict the endogenous variables in ten first-stage regressions.

C.2 The Influence of Labor Market Reforms in Germany

This specifications tests whether the baseline results are driven by the introduction of the German Hartz reforms. I do so by splitting the sample into two parts. The first sample ranges from 1996 to 2002 and captures a relatively homogeneous growth period prior to the labor market reforms. The average growth of both types of offshoring is very similar during this period (Figure 1, right panel), which makes the coefficients very comparable for the magnitude of the actual wage effects. The second sample, from 2003 to 2007, potentially contains omitted variable bias due to the Hartz reforms. Note that here, I forgo an instrumental variable approach because the instruments become too weak after dividing the sample. In this case, the OLS approach provides more robust results.

Table C5: Wage Elasticities of Offshoring for Five Occupational Groups

	Dependent variable: log daily wages			
	Method of estimation: OLS			
	No censored wages		Imputed wages	
	(1)	(2)	(3)	(4)
$OccOfs_{EU15}\times$ complexity1	0.188**	0.334	0.499***	0.637**
	(2.04)	(1.55)	(2.98)	(2.45)
$OccOfs_{EU15}\times$ complexity2	0.023	-0.047	0.018	-0.071
	(0.38)	(-0.15)	(0.14)	(-0.18)
$OccOfs_{EU15}\times$ complexity3	0.039	-0.656***	0.390**	-0.471
	(0.43)	(-2.81)	(2.02)	(-1.63)
$OccOfs_{EU15}\times$ complexity4	-0.731***	-0.641*	-0.874***	-0.682
	(-3.89)	(-1.88)	(-3.05)	(-1.48)
$OccOfs_{EU15}\times$ complexity5	-0.568***	-0.927***	-1.740***	-1.231***
	(-4.05)	(-4.76)	(-4.13)	(-3.22)
$OccOfs_{CEECs}\times$ complexity1	-1.923***	-1.577**	-4.305***	-3.479***
	(-9.81)	(-2.50)	(-11.48)	(-4.89)
$OccOfs_{CEECs}\times$ complexity2	-1.813***	-1.962**	-4.129***	-3.826***
	(-9.24)	(-2.22)	(-10.97)	(-4.19)
$OccOfs_{CEECs}\times$ complexity3	-0.516***	1.007*	-2.410***	-0.423
	(-2.84)	(1.71)	(-6.89)	(-0.62)
$OccOfs_{CEECs}\times$ complexity4	3.728***	4.593***	4.631***	5.870***
	(8.06)	(4.69)	(6.58)	(4.84)
$OccOfs_{CEECs}\times$ complexity5	4.666***	7.378***	9.063***	9.978***
	(17.85)	(12.05)	(14.19)	(10.80)
Plant controls	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Plant-year FE	Yes	No	Yes	No
Observations	6,874,354	1,011,290	8,185,759	1,259,626

Notes: Wage elasticities of offshoring for five occupational groups that include worker quintiles of the task distribution. Columns 1 - 2 omit censored entries and cut off the sample at the 85th percentile of the wage distribution. Columns 3 - 4 use the full sample with imputed wages. All specifications include a full set of worker controls and match and occupation fixed effects. Robust t statistics are in parentheses. Standard errors are clustered at occupation-year levels.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C6: Split Sample, Manufacturing Sector, Occupational Exposure

	Dependent variable: log daily wage							
	1996-2002				2003-2007			
	No censored wages		Imputed wages		No censored wages		Imputed wages	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Occupational offshoring	0.493	0.528	3.368***	4.044***	-0.246	2.018	3.125**	4.281**
exposure to EU15	(1.55)	(0.89)	(4.02)	(3.29)	(-0.49)	(1.48)	(2.30)	(2.12)
× job complexity	-1.064**	-1.601*	-6.023***	-8.101***	0.764	-4.993**	-4.862**	-8.881**
	(-2.03)	(-1.74)	(-4.36)	(-3.92)	(0.82)	(-2.08)	(-1.98)	(-2.39)
Occupational offshoring	-7.602***	-7.973***	-19.577***	-22.528***	-7.571***	-9.207**	-24.962***	-22.33***
exposure to CEE	(-8.63)	(-5.52)	(-11.88)	(-9.32)	(-4.78)	(-2.05)	(-6.05)	(-4.00)
× job complexity	13.80***	17.49***	32.786***	41.100***	13.43***	21.77***	37.597***	40.64***
	(10.38)	(7.72)	(14.16)	(12.13)	(5.27)	(3.62)	(6.43)	(5.30)
Plant Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Plant-Year FE	Yes	No	Yes	No	Yes	No	Yes	No
Observations	3,686,577	448,550	4,434,278	540,396	2,503,082	412,127	3,002,695	486,896

Notes: Table C6 presents the results after the sample is divided with respect to the adoption of influential labor market (Hartz) reforms in Germany. All specifications include a full set of worker controls and match and occupation fixed effects. Robust t statistics are in parentheses. Standard errors are clustered at occupation-year levels.
* $p < 0.10$, ** $p < 0.05$, ** $p < 0.01$.

Table C6 shows the results for the two successive periods. Although they differ in the elasticity estimates of offshoring to the EU15 and the estimates of inputs from CEE become higher in magnitude, overall, the estimates suggest that the baseline results are not driven by confounding wage effects of the Hartz reforms.

C.3 Endogeneity of the Job Complexity Index

To test the robustness towards the endogeneity of changes in the complexity index, I rerun the baseline specification from 2000 onward and omit the second wave of the BIBB-IAB work survey, such that job complexity is now measured prior to the exposure of offshoring.

The estimates from the alternative specification of the baseline regressions are reported in Table C7. The first two columns show the coefficients from the regressions using the truncated wage distribution, the latter two are derived from the full wage distribution including imputed wages. While the coefficients in column 1 are still fairly robust compared to their analogs in column 1 of Table 6, columns 2 to 5 hint to an attenuation bias of the estimates in column 5 of Table 6, as well as columns 1 and 2 in Table 7. Since all coefficients of interest are larger in absolute values in this specification, it suggests that the results from the baseline regression are a rather conservative estimate of the true effects.

C.4 Alternative Instrument

In this robustness exercise, I test the IV regressions of the baseline specification to an alternative definition of the instrument. Thereby the new definition ESI^{Alt} only considers remote high-income export destinations of the ESI. These are Australia, Canada, Japan and the USA.

I then rerun the main specifications on the industry and on the occupation level and present the results in Table C8. The bottom panel also reports the most important information from the first stages. These are, at first, the coefficients of the region specific instruments on the respective endogenous offshoring variable. For instance, it shows that the coefficient of the industry exposure of offshoring to the CEECs on ESI^{Alt}_{CEECs} is 2.103 and statistically significant at the 1 percent level. Furthermore, the bottom panel reports the statistics of the SW F-tests per first stage. So, for the given example, the respective statistic is 50.62, which—although being only valid under homoscedasticity—would rather hint to sufficiently high instrument strength. However, worries about instrument strength arise, when looked at the relevant first stage coefficients of offshoring to EU15. While the coefficient size may still be sufficient for the specification in column 1, it seems too weak for all other specifications (also in terms of the SW F-statistics). I suspect different kind of input trade between the EU15 or CEECs and other high-income countries. The large distance makes it very likely that input trade is hindered for goods of relatively low value or relatively heavy weight. As Figure C3

Table C7: Exogenous Job Complexity, Manufacturing Sector, Occupational Exposure

	Dependent variable: log daily wage			
	Job complexity measured in 1999, sample 2000-2007			
	No censored wages		Imputed wages	
	(1)	(2)	(3)	(4)
Occupational offshoring	0.663^{***}	2.152^{***}	1.815^{***}	2.469^{***}
exposure to EU15	(2.68)	(4.03)	(3.47)	(3.45)
× job complexity 1999	-1.180^{*}	-5.640^{***}	-3.514^{***}	-6.423^{***}
	(-1.91)	(-5.62)	(-3.05)	(-4.20)
Occupational offshoring	-8.036^{***}	-7.068^{***}	-11.578^{***}	-10.52^{***}
exposure to CEE	(-11.57)	(-4.48)	(-10.11)	(-5.75)
× job complexity 1999	16.33^{***}	17.27^{***}	21.429^{***}	23.95^{***}
	(14.57)	(10.04)	(12.80)	(10.20)
Plant Controls	No	Yes	No	Yes
Year FE	No	Yes	Yes	Yes
Plant-Year FE	Yes	No	Yes	No
Observations	4,072,530	655,448	4,899,399	777,077

Notes: Table C7 presents the estimation results for an exogenous job complexity index. The sample starts in the year 2000 and ends in the year 2007. All specifications include a full set of worker controls and match and occupation fixed effects. Robust t statistics are in parentheses. Standard errors are clustered at occupation-year levels.
* $p < 0.10$, ** $p < 0.05$, ** $p < 0.01$.

in the appendix shows, the unit values of imported commodities manufactured by other high-income countries are substantially higher than Germany's imports of respective goods from other country groups.

Since weak instruments may also bias the estimates in the second stage, the coefficients in the upper panel of Table C8 must be interpreted with caution. Column 2 seems to be biased (downward) at least for the interaction term of offshoring to the EU15 and job complexity. Columns 4 and 6 show not even the expected positive correlation of ESI^{Alt}_{EU15} and offshoring to the EU15 in the first stage, but a negative coefficient. The estimated magnitudes in the second stage, however, are similar to the baseline results. They mainly differ in the statistical significance of offshoring to the EU15. With respect to the first stage estimations, the more reliable estimations can be derived from the specifications of columns 1 and 3, as well as column 5. While the former two are in line with the baseline results, the latter specification casts doubts on the estimates of offshoring to the EU15 and its interaction term. Since these doubts, however, build on the weak first stage regression (coefficient estimate of 1.), I conjecture that this caveat to the robustness of the baseline results is rather weak.

C.5 Alternative Measures for Offshoring

In this robustness analysis, I borrow the narrow definition of offshoring from Feenstra and Hanson (1996, 1999):

$$OS^{FeHa}_{jt} = \frac{M^{j^*}_{jt}}{M^{jj^*}_{jt}}, \tag{22}$$

where $M^{j^*}_{jt}$ denotes all imported inputs from the same industry abroad as the using industry and $M^{jj^*}_{jt}$ are all inputs from the same industry—domestic j and foreign j^*—purchased by the domestic industry j. This measure has the particular advantage that offshoring is not normalized by output and thus is not diminishing the channel of offshoring induced productivity. To obtain regional variation and occupation specific exposures, I apply the same weighting as in equations (2)-(4) and rerun the baseline specifications.

Columns 1 and 2 of Table C9 show the estimates for industry level exposures. While the first column includes plant controls, which control for revenues and other variables that capture a plant's productivity, the second column does not comprise controls for productivity. I repeat the same exercise for occupational exposures in columns 3 to 8, whereby I control for the productivity effect either by using plant-year fixed effects (columns 3 and 6) or plant controls (columns 4 and 7). Notably, the estimates of all specifications that take in the productivity channel (columns 5 and 8) suggest that the productivity effect is particularly strong for complex jobs. This is either driven by higher wage increases from offshoring to the CEECs (column 2) or by lower adverse wage effects for those jobs from offshoring to the EU15 (columns 5 and 8). Especially, in the specification of column 5, the insignificant estimates suggest that increased profitability due to offshoring to the EU15 is also shared with complex jobs, or those that are

Table C8: Alternative Instrument, IV-Regressions, Truncated Wage Distribution

	Dependent variable: log daily wage					
	Industry Exposure			Occupational Exposure		
	(1)	(2)	(3)	(4)	(5)	(6)
Offshoring to EU15	1.044	1.281		3.501	-0.786	2.617
	(1.01)	(0.30)		(1.32)	(-0.37)	(0.69)
× job complexity	-2.477**	-5.001***	-4.856***	-4.330	-0.963	-5.407
	(-2.00)	(-2.85)	(-3.91)	(-1.24)	(-0.33)	(-1.09)
Offshoring to CEE	-3.931***	-4.592		-6.418***	-6.105***	-5.223***
	(-3.88)	(-1.55)		(-4.53)	(-4.37)	(-2.75)
× job complexity	9.011***	8.871***	7.070***	13.39***	16.16***	15.04***
	(4.47)	(4.11)	(4.48)	(9.35)	(9.95)	(7.52)
Job complexity	0.127*	0.307***	0.326***			
	(1.94)	(3.72)	(4.92)			
Plant Controls	Yes	No	No	No	Yes	Yes
Occupation FE	No	No	No	Yes	Yes	Yes
Industry-Year	No	No	Yes	No	No	No
Plant-year FE	No	No	No	Yes	No	No
Year FE	Yes	Yes	No	No	Yes	Yes
Observations	1,004,810	7,032,791	7,032,791	6,828,205	1,004,810	7,032,791
Results of first stages	Dependent variables: offshoring to EU15, … × complexity, offshoring to CEE, … × complexity					
Relevant coefficients						
1. ESI^{Alt} from EU15	0.932	0.153		-0.144	0.2138	-0.237
2. × job complexity	2.103***	1.765***	1.396***	1.487***	1.769***	1.711***
3. ESI^{Alt} from CEE	1.305***	1.804***		1.432***	1.219***	1.719***
4. × job complexity	0.898***	1.547***	2.054***	2.592***	1.818***	2.375***
SW F-tests						
1. SW F-statistic	38.51	1.98		3.79	13.23	3.05
2. SW F-statistic	53.03	16.55	15.52	4.47	22.34	3.62
3. SW F-statistic	50.62	6.60		4.90	88.58	4.89
4. SW F-statistic	51.54	56.85	70.05	14.16	124.52	19.62

Notes: Table C8 shows the estimations from IV-regressions using export supply of intra-industry goods from the respective offshoring destination to Australia, Canada, Japan and the USA. All specifications include a full set of worker controls and match fixed effects. Robust t statistics are in parentheses. Standard errors are clustered at at industry-year levels in columns 1-3 and at occupation-year levels in columns 4-6.
* $p < 0.10$, ** $p < 0.05$, ** $p < 0.01$.

expected to have a high substitutability with this kind of offshoring. Overall though, the patterns and relative magnitudes of the effects from the two types of offshoring remain relatively similar to the baseline regressions.

C.6 Alternative Measures for Task Profiles

The last specifications tests the robustness of the baseline results to three other indices of jobs' task profile. The first measure (Table C10, column 1) is based on Brändle and Koch (2017) and results from a principal component analysis of similar variables in the work surveys of 1998/99 and 2006. Therefore, it is also possible to approximate the small (time-variant) adjustments of tasks within jobs using yearly increments between the two waves. Since the authors define the index as the potential for offshoring (to low-wage countries), it is interpreted conversely such that high values indicate low job complexity.

In column 2, I apply a subset of the complexity index, namely, the nonroutine index developed by Becker, Ekholm and Muendler (2013) (see section 2.2). Column 3 then captures a different job characteristic, that is, offshorability, as defined by Blinder and Krueger (2013). The information derives from the Princeton data improvement initiative (PDII) and is designed to measure the international tradeability of American jobs in the Standard Occupational Classification 2000. It is thus necessary to map the offshorability to the German $KldB88$ as described in B.4. Similar to Baumgarten, Irlacher and Koch (2020), I mark German jobs as offshorable when they belong to the upper quartile of the offshorability distribution. The choice of fixed effects is similar to the baseline regression. Standard errors are clustered at occupation-year levels.

The first two columns estimate an overidentified two-stage least squares regression in the 85 percent sample. Again, the coefficients support the finding that the two types of offshoring feature counteracting wage effects for jobs of different complexity. While the relative wages of jobs with high offshoring potential (relatively low complexity) will decline if offshoring to CEECs expands, the opposite is true for offshoring to the EU15. Note that the coefficients decrease after the occupations are classified

Table C9: Alternative Measure of Offshoring, Manufacturing Sector, Industry and Occupational Exposure

	Dependent variable: log daily wage							
	Industry Exposure		Occupational Exposure					
	No censored wages		No censored wages			Imputed wages		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Offshoring to EU15	0.136***	0.137***	0.167**	0.282***	0.00924	0.674***	0.687***	0.566**
	(2.74)	(4.31)	(2.02)	(2.81)	(0.07)	(3.70)	(3.82)	(2.25)
× job complexity	-0.326***	-0.330***	-0.331**	-0.808***	-0.332	-1.130***	-1.527***	-1.313***
	(-4.63)	(-7.10)	(-2.45)	(-4.62)	(-1.56)	(-3.92)	(-4.97)	(-3.34)
Offshoring to CEE	-1.163***	-1.229***	-1.873***	-2.676***	-2.467***	-3.599***	-4.595***	-4.278***
	(-11.45)	(-18.11)	(-15.08)	(-12.32)	(-11.89)	(-18.10)	(-14.85)	(-14.44)
× job complexity	1.877***	2.128***	3.553***	4.232***	4.298***	6.590***	7.779***	7.645***
	(9.40)	(14.49)	(17.86)	(14.04)	(14.99)	(21.08)	(18.07)	(18.82)
Job complexity	0.0732***	0.150***						
	(3.33)	(11.43)						
Plant Controls	Yes	No	No	Yes	No	No	Yes	No
Occupation FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Plant-Year FE	No	No	Yes	No	No	Yes	No	No
Observations	1,004,810	7,032,791	6,828,205	1,004,810	7,032,791	8,185,748	1,201,832	8,392,755

Notes: Table C9 presents the estimation results for the narrow offshoring measure as in Feenstra and Hanson (1996, 1999), i.e., imported inputs as a fraction of all inputs. All specifications include a full set of worker controls and match fixed effects. Robust t statistics are in parentheses. Standard errors are clustered at industry-year levels in columns 1 and 2 and at occupation-year levels in columns 3-8.

* $p < 0.10$, ** $p < 0.05$, ** $p < 0.01$.

into broader groups (2-digit occupations) that contain more within-group heterogeneity. Moreover, offshoring to the EU15 loses statistical significance when jobs are distinguished only by routineness, although the signs still suggest that the two types of offshoring have counteracting effects.

In column 3, an overidentification test rejects the instrument's validity. Therefore, I draw on the full sample with imputed wages and compute OLS estimates. Since all offshoring terms become insignificant, the estimation suggests that the concept of offshorability is substantially different from that of complexity. One reason for this difference may be that the index was designed for jobs in the service sector, while in services, the tradability of jobs may play a major role in the international supply and wage of particular tasks. In manufacturing, virtually every worker is offshorable, and wage effects may depend on specialization. Hence, it remains an interesting research avenue to determine how offshorability is related to wages in the service sector.

In summary, the results seem to be fairly robust to measures that closely measure occupational complexity.

Table C10: IV Regressions with Alternative Measures of Job Complexity

	Dependent variable: log daily wage		
	Alternative measures of task profiles:		
	PCA, time-varying Brändle and Koch, 2017	Nonroutine Becker et al., 2013	Offshorability Blinder and Krueger, 2013
	(1)	(2)	(3)
Panel A: Second stage or OLS			
Occupational offshoring	-0.236*	0.312	0.220
exposure to EU15	(-1.83)	(1.08)	(0.91)
× task profile	0.321***	-0.581	-0.268
	(4.70)	(-0.76)	(-0.68)
Occupational offshoring	3.205***	-2.855***	0.531
exposure to CEE	(10.54)	(-11.51)	(0.92)
× task profile	-3.001***	11.19***	0.639
	(-17.11)	(24.02)	(0.98)
Occupation classification	2 digits	2 digits	3 digits
Observations	6,893,383	7,106,395	7,845,555
Panel B: First-stage statistics			
Additional instrument	TC China	TC China; × nonroutine	
KP-F	54.65	25.47	
SW-F	135.02; 738.51;	69.32; 56.82;	
	584.59; 2498.01	368.33; 158.77	
Hanson J	$\chi^2_1 = 0.174$	$\chi^2_2 = 2.327$	
Overidentification	$p = 0.676$	$p = 0.312$	

Notes: Column 1 applies the task measure developed by Brändle and Koch (2017) with constant yearly increments (1999 and 2006 waves of the work survey). Columns 2 and 3 employ the nonroutine index developed by Becker, Ekholm and Muendler (2013) and the offshorability index from the Princeton data improvement initiative (Blinder and Krueger, 2013), respectively. The latter is mapped to the German classification $KldB88$ using a series of crosswalks, as explained in B.4. If the first-stage statistics are reported in panel B, the coefficients are estimated using 2SLS. These specifications comprise overidentifying restrictions by including ad valorem trade costs with China or additionally adding their interaction. Furthermore, each specification contains a full set of worker controls and match and plant-year fixed effects. Robust t statistics are in parentheses. Standard errors are clustered at respective occupation-year levels.

* $p < 0.10$, ** $p < 0.05$, ** $p < 0.01$.