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Abstract

This paper analyzes the labor market effects of offshoring in a high-wage home country and how these effects crucially depend on (1) job complexity and (2) the characteristics of the destination country. It thereby links several sources: rich administrative data on individuals and plants in the German manufacturing sector, information on a job's task bundle, and the evolution of imported inputs from low- or high-wage destinations, which are represented by Eastern and Western Europe, respectively. Offshoring to these origins has opposing effects on German wages with respect to the relative task complexity of jobs: While offshoring to the West puts pressure on the wages of complex jobs and increases the wages of simple jobs, offshoring to the East entails the opposite effect. The overall effect adds up to a 4.2 percent increase in wages for jobs with high complexity, while low-complexity jobs see a 3.9 percent decrease in wages.

Zusammenfassung

In dieser Arbeit werden die heimischen Lohneffekte von Offshoring untersucht. Dabei wird der Produktionsfaktor Arbeit nach der Komplexität seines Aufgabenspektrums unterschieden und Offshoring je nach Lohnniveau des Ziellandes eingeteilt. Letzteres geschieht am Beispiel Westeuropas für Hochlohnländer und am Beispiel der Visegard-Länder bzw. Osteuropa für Niedriglohnländer. In den Lohnregressionen nach Mincer können so die heterogenen Effekte von Offshoring geschätzt werden. Die dafür notwendigen Daten stammen aus verschiedenen Quellen, wie Input-Output-Tabellen (zu mehreren Ländern), Arbeitsmarktdaten der Bundesagentur für Arbeit sowie Umfragedaten zu den Aufgaben im Job. Die Ergebnisse weisen darauf hin, dass Offshoring nach Westeuropa zu relativen Lohngewinnen für eher wenig komplexe Jobs in Deutschland führt, während der Lohn komplexer Jobs negativ beeinflusst wird. Offshoring nach Osteuropa hingegen hat genau die entgegengesetzten Lohneffekte. Zudem wird in diesem Kapitel gezeigt, dass Offshoring nach Westeuropa zu einer arbeitsintensiveren Produktion und Offshoring nach Osteuropa zu einer kapitalintensiveren Produktion führt.

JEL

F15 · F16 · J31

Keywords

Offshoring · Tasks · Trade · Fragmentation · Wages · Globalization

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1 Introduction

The most recent wave of globalization has broadly been driven by fostering international value chains and increasing trade in intermediate goods (Johnson/Noguera, 2017). Lower transport costs and new information technology have enabled industries to divide the manufacturing process into multiple parts, each of which fabricates a tradable output. Consequently, some production steps are offshored to benefit from international price differences. Specifically, relatively labor-intensive parts are moved to low-wage countries, whereas human capital-intensive inputs are manufactured in high-wage countries (e.g., Carluccio et al., 2019). The resulting international value chain exploits comparative advantages through greater specialization in particular sets of tasks in source and destination countries. For the domestic labor market, this development emphasizes two counteracting forces. On the one hand, importing inputs substitutes for tasks formerly performed by domestic workers and thus places pressure on their wages. On the other hand, it also reduces an industry's costs and boosts its productivity. Therefore, the industry's output expands, which, in turn, increases the demand for the remaining tasks in more specialized production and raises associated wages (Grossman/Rossi-Hansberg, 2008, 2012). In essence, any analysis of labor effects needs to consider the tasks substituted by imported inputs and the tasks that are allocated to complementary production.

Assuming that high-wage countries are skill abundant and specialize in particular human capital-intensive goods, offshoring to these countries has different effects in terms of job substitution than offshoring to low-wage countries. Motivated by a steep increase in historically small trade flows (Figure 1, or Krugman 2000), these effects have been the subject of fruitful discussion in recent decades. The literature has largely reached consensus that when not considering the characteristics of offshore production, offshoring lowers the relative demand for onshore workers without a college degree or for jobs with routine task profiles (e.g., Feenstra/Hanson, 1996; Becker/Ekholm/Muendler, 2013; Baumgarten/Geishecker/Görg, 2013; Ebenstein et al., 2014; Hummels et al., 2014; Dauth/Findeisen/Suedekum, 2021).[1] Disagreement persists about the effects of offshored labor that is human capital intensive, which is particularly surprising since the bulk of offshoring is between high-income countries and this type of trade has increased dramatically (Figure 1). While Hummels et al. (2014: p. 1618 ff.) find a negative impact of offshoring to high-income countries on the Danish wages of low-skilled workers or routine jobs, Ebenstein et al. (2014: p. 588) reveal a positive wage impact on routine jobs in the US. Additionally, Mion/Zhu (2013) provide evidence from Belgian firms showing that imports from OECD countries negatively impact these firms' share of

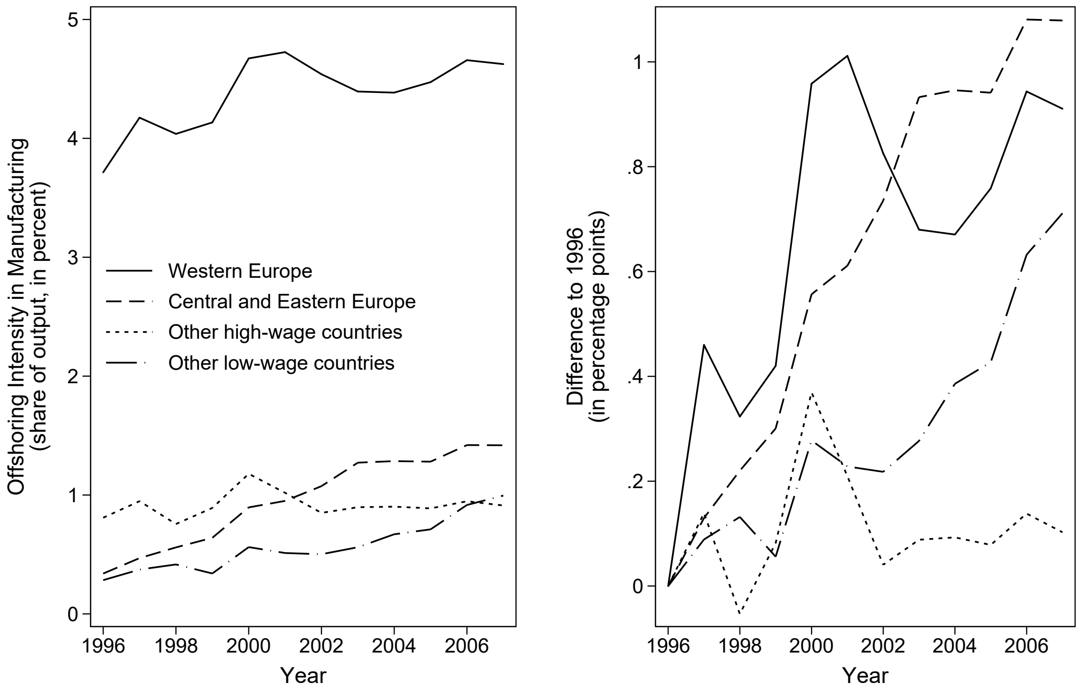
[1] Related literature that does not distinguish either the type of affected labor or the type of imported inputs includes Moser/Urban/Weder Di Mauro (2015) and Eppinger (2019), who focuses on the service sector. Beyond these examples, I refer to Hummels/Munch/Xiang (2018) for a comprehensive overview of the large body of literature on offshoring and labor markets.

highly educated workers.

These studies show that it is essential to distinguish the type of labor in onshore and offshore (the type/origin of imported inputs) production when estimating the heterogeneous impact of offshoring on wages. In earlier studies, onshore labor has been distinguished by a *worker's* education, whereas more contemporary works, such as Autor/Handel (2013), have shown that a *job's* task profile is more relevant when estimating wage compensation. Moreover, the task approach is used to distinguish labor by the costs of moving the job offshore, a characteristic that Blinder (2009) calls offshorability. In a recent contribution, Blinder/Krueger (2013) find that well-paid workers and college graduates tend to hold jobs with higher offshorability and that they perform rather nonroutine tasks (e.g., mathematicians or programmers who can directly transfer their output via the Internet). While offshorable jobs are indeed prone to substitution with offshore labor (Goos/Manning/Salomons, 2014), this vulnerability seems to be at odds with the fact that they are also the main gainers in terms of wages (e.g., Baumgarten/Geishecker/Görg, 2013). It is therefore doubtful whether the costs of moving a job offshore are the proper proxy for the manufacturing industry. In this sector, virtually every job is offshorable, as its tasks create a tangible good that can be sent to other regions (Blinder, 2006: p. 120). Consequently, the determining factor may again be the countries' comparative advantage in the production of goods that intensively require a specific set of tasks or type of labor. Regarding the wage effect of offshoring, these task inputs will then determine the substitutability of jobs.

The present paper closes the research gap in several regards. First, it adds to Baumgarten/Geishecker/Görg (2013) and distinguishes offshoring with respect to the income level of its destination to approximate the human capital intensity in imported inputs. New stylized facts show that these imports have crucially distinct effects on factor intensity in production. Complex-task intensive industries offshore to high-income countries and become less complex-task intensive over time, while the opposite is true for offshoring to low-income countries. Second, this paper combines existing complexity indices by Becker/Ekholm/Muendler (2013) and Brändle/Koch (2017), so that a single measure is able to distinguish groups of heterogeneous labor that respond differently to the substituting and complementary forces of typical inputs from high- or low-wage countries. Third, this paper sheds light on the underexplored topic on wage effects of offshoring to other high-income countries. Using an instrumental variable (IV) approach, this paper finds that offshoring to high-income countries has negative wage effects for complex jobs, while it positively affects wages for simple jobs. To accomplish this, I combine rich administrative data on workers in the West German manufacturing sector during the 1995-2007 period with plant-level information, microlevel data on tasks, and offshoring data from federal input-output tables. Connecting the latter source with the World Input-Output Tables (WIOT) distinguishes offshoring destinations with respect to their income levels and approximates the complexity-intensity of imported inputs. Thereby, the paper focuses on Germany's most prominent destinations for vertical integra-

Figure 1: Offshoring Intensity by Destination Region in German Manufacturing



Notes: Offshoring intensity in German manufacturing is defined as the ratio of imported, intra-industry inputs relative to output. The left panel depicts region-specific offshoring from 1996 to 2007. The right panel displays the same shares less their 1996 values. From 1996 to 2002, offshoring to Central and Eastern Europe and offshoring to Western Europe increased by approximately 0.8 percentage points. As sudden access to CEECs also poses a supply shock from the perspective of (other) Western European countries, the expansion of offshoring to Western Europe constitutes a remarkable increase.

Sources: I-O Tables of the Federal Statistical Office of Germany (Fachserie 18, Reihe 2, Years: 1996 - 2007) and WIOT (2013), Timmer et al. (2015), own calculations.

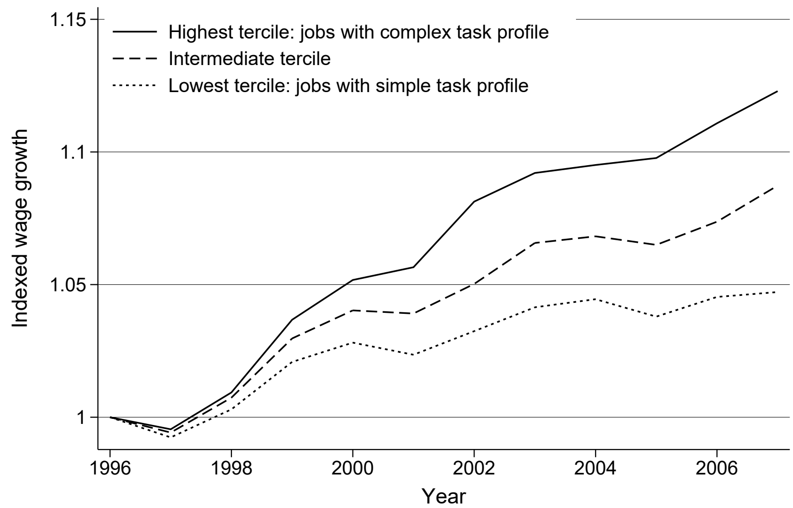
tion and groups them into economically relatively homogeneous units: the European Union in the late 1990s (EU15) and the Central and Eastern European countries (CEECs).[2] How offshoring to these destinations has evolved is depicted in Figure 1. It shows that offshoring to the EU15 exhibits substantially higher trade volumes than offshoring to any other country group. From 1996 to 2007, the share of inputs from the EU15 relative to industry output in Germany grew by 0.91 percentage points, or 25 percent of its initial value (Table C.1 in the appendix). The right panel emphasizes the increasing relevance of CEECs as offshoring destinations. While this country group exhibits low initial values of economic integration with Germany, from 1996 to 2007, offshoring to these countries increased by 1.1 percentage points, or 318 percent.[3]

[2] The CEECs include the Czech Republic, Hungary, Poland, and Slovakia.

[3] There is substantially more intra-industry trade between Germany and CEECs than with other emerging economies such as China (Figure 1, or Dauth/Findeisen/Suedekum, 2014: p. 1650 f.).

While the German goods market is characterized by large and growing trade volumes, the increase in output demand did not immediately translate into growth of the labor market. In fact, the labor market has instead been characterized by rather high rates of unemployment and wage polarization.[4] It seems that the evolution of trade comes along with a change in the demand for (or the marginal product of) certain types of labor. I quantify these types of labor by an index of job complexity, which builds on data from the micro-level German Qualification and Career Survey (BIBB-IAB work survey). This survey combines a wide variety of job information about the versatility of tasks, performance requirements (such as responsibility), and the required level of various skills and abilities (similar to Ottaviano/Peri/Wright, 2013). Across manufacturing jobs, the index is not intended to approximate the costs of moving a specific task set offshore (offshorabiliy); rather, it approximates the relative human capital intensity (e.g., skill, knowledge, and abilities) imparted in production.

Figure 2: Wage Divergence between Terciles of Job Complexity



Notes: Indexed wage growth of terciles of the task index, West Germany, manufacturing, 1996 - 2007, 85 percent sample.
Sources: BIBB-IAB Work Survey, LIAB, own calculations. ©IAB.

Figure 2 illustrates the divergence in average real wages for the terciles of the complexity distribution. It reveals that income growth is unequally distributed and varies by job complexity. While the wages of complex jobs rise by 13 percent, the compensation for intermediate jobs rises by approximately 8 percent, and wages of simple jobs increase by less than 5 percent.[5]

[4] The gap between high and low incomes remained fairly stable in the 1970s and 1980s. Starting in the 1990s, inequality rose, which is especially attributable to developments at the lower end of the wage distribution (Dustmann/Ludsteck/Schönberg, 2009; Gernandt/Pfeiffer, 2007). Dustmann et al. (2014) argues that the credible threat of relocating German jobs to CEECs led to higher rates of decentralized wage setting and the introduction of "opening clauses" in industry-wide agreements (see also Table 2). These changes led to flexibility in industrial relations and to wage moderation.

[5] Note, however, that the overall divergence tends to be understated because censored top-income earners are not included. For more detailed information on labor market developments, see Dustmann/Ludsteck/Schönberg (2009); Dustmann et al. (2014).

How offshoring impacts these changes in the price of occupational tasks is estimated using a Mincer-type wage equation, at which wages are determined at the industry or occupation level. The estimating model also includes worker-plant, occupation, and plant-year fixed effects to extract offshoring's wage impact within worker-plant matches while controlling for endogenous plant-specific shocks (e.g., the exporter wage premium and new technology) of heterogeneous firms (e.g., Melitz, 2003) and asynchronous offshoring decisions within industries.

Despite the multidimensional fixed effects, wages and offshoring remain endogenously determined. That is, because offshoring not only affects wages but wages also affect the tendency to offshore. Such reverse causality will bias the estimated coefficient of the actual impact of offshoring on wages. In the analysis, I remedy these concerns by applying an IV regression, which extracts the exogenous variation in the offshoring variables. The choice of instruments builds on Autor/Dorn/Hanson (2013) or Hummels et al. (2014) and includes time-varying and region-specific measures to suit the analysis with multiple trade partners. Accordingly, it utilizes the intermediate goods export supply of Germany's main offshoring destinations to other high-income countries. In the presence of the numerous fixed effects, these instruments depict an exogenous source of variation that is correlated with offshoring but independent of the wage-setting process in Germany.

The results confirm that offshoring has heterogeneous wage effects for manufacturing jobs that differ in complexity. Simple jobs benefit in terms of higher wage increases if domestic production expands the use of inputs from high-wage countries (EU15), while the relative wages of complex jobs suffer. Conversely, imported inputs from low-wage countries raise the wages of complex jobs but lower the wages of simple jobs. The overall effect adds up to a 4.2 percent increase in wages for a job with high complexity, while a low-complexity job sees a 3.9 percent decrease in wages.

Germany is an ideal case to explore these wage effects of region-specific offshoring after 1990. First, the country is very representative because it is Europe's largest economy. Second, it ranks among the countries with the highest trade volumes worldwide and experienced a steep rise in input trade in the late 1990s and 2000s.[6] Third, the fall of the Iron Curtain suddenly placed the country in a central position between low-wage countries in the east, the CEECs, and an established trade bloc of high-wage countries in the west, the EU15. Germany's geographic position thus became optimal to exploit international price differences

[6] Beginning in the late 1990s, Germany transformed its economy within ten years from high unemployment rates, relatively low GDP growth rates, record budget deficits, and mass protest rallies into a highly competitive ”role model” economy exhibiting better economic performance than most European countries, even in times of global economic crisis. Some authors refer to this development as the rise ”From [the] Sick Man of Europe to Economic Superstar” (e.g., Dustmann et al., 2014; Economist, 2004). German exports evolved very well, leading to substantial trade surpluses. In particular, the share of German manufacturing goods in world exports increased to more than 10% in 2012.

within a short distance. Fourth, besides the short geographic distance, other features and events were responsible for a short economic distance to the East and West. Eastward, offshoring to the formerly separated CEECs was bolstered by their similar industrial and educational structures, as well as a considerable number of German speaking workers (Winkler, 2010).[7] Several political events reduced trade costs further and enhanced the offshoring opportunities for German firms: In the early 1990s, the CEECs signed association agreements with the EU, which vastly cut tariffs. Trade flows, however, did not substantially increase until EU accession talks began in 1997. These negotiations endorsed the market system and institutions of the newly established democracies and, hence, gradually stabilized the investment climate. Moreover, it gave rise to the installation of foreign affiliates, even before these countries entered the EU in 2004. With these firms bringing in new production technology from their parent companies (Dustmann et al., 2014), the internal productivity and international competitiveness of suppliers in the CEECs rose steeply, resulting in vast expansions of imports from those regions to Germany. Westward, the EU politically reinforced the value chains among the EU15 countries. Beyond the already existing advantages of a customs union, the EU suppressed internal nontariff barriers by harmonizing regulations, laws, standards, and economic practices. European infrastructure projects and the establishment of the Schengen Area in 1995 lowered the costs of transportation, e.g., through new cross-border roads or time savings due to the abandonment of border controls. Furthermore, in 1999, the introduction of a common currency, the euro, abolished exchange rate fluctuations. Together, these measures vastly reduced the costs of offshoring.

The remainder of this paper is structured as follows. Section 2 presents the various datasets employed in the analysis. Then, Section 3 introduces the theoretical framework and explains the identification strategy for the empirical analysis. Section 4 compiles the results, which are checked for robustness in Section 5. Finally, Section 6 concludes the work.

2 Data

This section introduces the various datasets employed in the analysis and provides summary information on data construction and measurement. For details on the sampling procedure and data processing, I refer to the appendix.

[7] Poland and Hungary, for instance, practice the same focus on vocational training as Germany. Before the Iron Curtain separated the CEECs and Germany, these countries shared a long history of trade (Dustmann et al., 2014: p. 182).

2.1 Linked Employer-Employee Data

I extract matched information on workers and plants from a longitudinal version of the Linked Employer-Employee (LIAB MM 9308) dataset of the Institute for Employment Research (IAB).[8] The LIAB has important features for the analysis at hand. First, it is designed to provide a long time dimension with many entries per employer, which is well suited to the objective of capturing unobserved heterogeneity in plants or individuals through multidimensional fixed effects.

Second, the LIAB samples the most comprehensive dataset of workers in Germany, comprising the universe of employees subject to social security (approximately 80 percent of the workforce). These data are drawn from social security registers and contain worker characteristics, such as age, sex, education, work experience, job tenure, occupation, occupational status (part-time, full-time, or apprentice workers), and average daily wages during an employment spell. As stating incorrect information incurs a penalty, the recorded wage data are very reliable. Above a contribution ceiling, however, wages are top-coded and need to be imputed.

Third, the LIAB contains administrative data on plants, such as the number of employees, the location, and the industry code. It is also possible to merge a subsample of the businesses with additional information from an annually conducted survey, the IAB Establishment Panel (EP).[9] In comprehensive interviews, the plants' managers provide precise information about the composition of the plant's workforce, revenues, investments, export share, and type of union coverage.[10] Since I merge annual information on plants with worker data, which are available on a daily level, I restrict all observations to yearly intervals to arrive at a consistent time scale.

Finally, one particular advantage of the LIAB is that occupational codes are classified according to the similarity of tasks on the job (Bundesagentur für Arbeit, Statistik der, 1988). Since its scheme *KldB88* is identical to the classification in the BIBB-IAB work survey, it is possible to assess a job's typical complexity akin to the procedure developed by Autor/Levy/Murnane (2003).

[8] The Research Data Centre provides access to LIAB for noncommercial research by confidential on-site and remote data access. See Heining et al. (2012) for a comprehensive overview of access possibilities.
[9] The sample is disproportionately stratified according to establishment size. Accordingly, large plants are oversampled, whereas sampling within each cell is random.
[10] Some information is retrospectively reported in the survey. Thus, I forward impute those variables to obtain current values. Table B.1 in the appendix gives a thorough overview of the data adjustments.

2.2 Job Complexity Index

The job complexity index is intended to measure the heterogeneity of labor in the wage regression. By focusing exclusively on manufacturing, in which virtually all jobs are offshorable, this concept is associated with the comparative advantage in the production of goods and the regional specialization in particular tasks.[11]

The combined index has several advantages. In addition to featuring relatively high correlations with existing indices such as those developed by Spitz-Oener (2006), Baumgarten/Geishecker/Görg (2013), Becker/Ekholm/Muendler (2013), and Brändle/Koch (2017), it includes not only the intensity of one job characteristic (e.g., routineness) but also detailed information on a variety of tasks and requirements.[12] By using a broad set of information, it is feasible to extract the variation of 243 occupations, which produces a decisive increase in the degrees of freedom in the subsequent analysis.

The data are drawn from the BIBB-IAB work surveys, which are jointly compiled by the Federal Institute for Vocational Education and Training and the IAB.[13] Approximately every six years, randomly selected workers from the German labor force answer questions about their abilities, performance requirements, professional qualifications and tasks on the job.[14] I utilize the two cross-sectional waves of 1998/99 and 2006 since they lie within the sample period and refer to the same population as the LIAB. Each wave covers 20,000 to 34,000 individuals.

Methodologically, the task complexity index is similar to Becker/Ekholm/Muendler (2013) and Ottaviano/Peri/Wright (2013), but it combines the categories of interactive and nonroutine tasks, and extends categories such as job performance requirements and necessary abilities (as in Brändle/Koch, 2017). Table B.2 in the appendix provides an overview of the various components.

In instancing interactive tasks or tasks that require many face-to-face interactions, cultural ties, or interpersonal skills, it is difficult to evaluate the tasks individually because, for ex-

[11] The concept of offshorability renders jobs non-offshorable when their underlying tasks require geographic proximity to consumers, which is inherent to the output of, e.g., taxi drivers, barbers, or construction workers. Conjointly, they can be attributed to the real estate industry and intangible outputs in the service sector. The manufacturing sector, however, comprises tangible outputs that are typically tradable. Consequently, in the context of offshoring the production of intermediate goods, the entire sphere of tasks could be performed abroad as long as a downstream production stage remains in the home country. This finding also implies that even some managers are susceptible to substitution by foreign labor.

[12] Although Table C.2 shows the similarity between complexity and the average skill level per occupation (from the BIBB-IAB work survey), it is named complexity to distinguish it from individual worker characteristics such as the highest degree attained (which is not recorded well in the LIAB).

[13] I consider the BIBB-IAB work surveys to describe the job characteristics of German workers better than, e.g., O*NET, since they involve a sample from the same population as the LIAB and since it employs the same occupational classification as the LIAB (no crosswalk required).

[14] Cross-sectional waves are available for the years 1979, 1985/86, 1991/92, 1998/99, 2006, 2012, and 2018.

ample, collaboration with coworkers does not necessarily imply high complexity. Instead, various applications, such as dealing with consumer preferences, the legal system, various languages, and face-to-face interactions, may better approximate the human capital requirements of a job.

Furthermore, performing many nonrepetitive tasks that require customized problem-solving ability is considered relatively complex. I assess nonroutine tasks based on whether young apprentices could perform these tasks independently in their first week of work. Since the survey questions about tasks are relatively broad, the nature of tasks may still vary substantially between occupations. The nonroutine task “consult or inform”, for instance, features high affirmative response rates by telephone operators, cashiers, auditors, and managers. Thus, the different kinds of seemingly identical tasks suggest a further distinction.[15]

To approximate quality, I consider information on the requirements for job performance and on certain skills or special/sensitive knowledge. Typically, the higher such requirements are, the more they foster regional specialization within (high-wage) countries due to local knowledge spillovers, locally concentrated experience in certain tasks, and external economies of scale (Grossman/Rossi-Hansberg, 2012).

Consequently, I combine the degree of interactivity and nonroutineness of the job and the level of required abilities into a single complexity measure. To do so, I assign the responses of *each wave* to *four groups*, which differ with respect to the scaling and style of the survey questions.

In the 1998/1999 wave, the *first group* consisted of polar questions about the use of 81 workplace tools. Such tools range from machinery and diagnostic devices to computers, communication equipment, means of transport, and software. Whenever a worker reports having used a tool that is associated with a rather complex activity, this entry is marked. In the 2006 wave, the questions in the *first group* are directly intended to capture the scope of nonroutine and interactive tasks. For example, workers state how often they present something or how often they have to solve new or unforeseen problems. The questions in the other three groups are similar in the two waves.

In the *second group*, the questions are intended to explore the frequency of 13 specific activities on the job. These are described, for instance, as repairing, consulting, educating, analyzing, or producing. The more frequently a worker performs any complex activity, such as consulting and educating, the higher the respective value is.

The *third group* comprises questions on specific abilities or knowledge. This includes, for example, any job that requires profound knowledge of the German legal system or high levels

15 For example, the use of a telephone may be nonroutine for a manager but fairly codifiable in a call center.

of English, German or any other particular foreign language skill.

In the *fourth group*, workers answer questions about performance requirements on the job, e.g., the frequency of having deadlines, whether mistakes lead to vast financial losses for the firm, or whether they have to improve techniques or processes.

To establish the comparability of the BIBB-IAB work survey and the LIAB, I consider only employees with social insurance who work more than 20 hours per week. For each of the eight task groups, I mark all affirmations of complexity before I separately sum them up per individual. In a second step, I average such sums over each 3-digit occupation. A higher mean indicates an occupation that 1) is more likely to entail a larger number of different complex tasks, 2) spends a larger share of its working time on the performance of complex tasks, and/or 3) requires higher knowledge, skills, or abilities for its task set. Subsequently, I drop all occupations that encompass fewer than five individuals and normalize the remaining values by dividing the occupation averages by the maximum value of all means. The outcome is an index that ranges between zero and one for each of the eight groups.

I then separately sum up the four indexes per wave and normalize over all occupations to receive a single index for each of the two survey years. In a final step, I take the frequency-weighted average of the indices from the two waves (using the observations per occupation as weights) and obtain one static index for the analysis. A high value of the index is associated with a high relative input of human capital. While the simple combination of existing indices is an arguably arbitrary construction, it has the advantage of considering many tasks (or task dimensions) that may be related to offshoring. Note also that the resulting ranking of occupations is highly correlated with existing indices and the average educational attainment per occupation (Table C.2 in the appendix). To give insights of the resulting order, Table 1 presents a list of occupations in manufacturing with the highest or lowest values of the task complexity index.

2.3 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/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).[16] Hence, it

[16] 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.

Table 1: The Ten Most and Least Complex Occupations in Manufacturing

Occupations (top → down)	Complexity	Occupations (lowest → up)	Complexity
Physicists, physics engineers, mathematicians	1	Interior cleaning professionals	0.1468
Techn., vocational, factory instructors	0.9726	Machinery, container cleaners	0.2347
Entrepreneurs, directors, managers	0.9623	Rubber makers, processors	0.2707
Professional fire brigade	0.9525	Vehicle cleaners, servicers	0.2752
Chemists, chemical engineers	0.9312	Unskilled workers, roustabouts, helpers	0.2920
Manufacturing engineers, other	0.9292	Building laborers, building assistants	0.3289
Mechanical, motor engineers	0.9288	Pallet transporters, stockpickers, drivers	0.3368
Electrical engineers	0.9201	Tobacco preparers	0.3400
Engineers, other	0.9195	Upholsterers, mattress makers	0.3423
Economic and social scientists, statisticians	0.9089	Assistants for printing	0.3457

Notes: Table 1 presents the occupations in manufacturing with the ten highest and lowest values of the task complexity index. Thereby, the left panel presents the occupations with the highest complexity ordered from top downwards. The right panel displays the most simple jobs ordered from the bottom upwards.
Sources: BIBB-IAB work survey, LIAB, own calculations. ©IAB

contemplates firms' productivity decisions with respect to either producing those inputs or importing them.

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 (see Winkler/Milberg, 2012: p. 40, for a discussion on this topic).[17] 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:

$$OS_{jt} = \frac{M_{jt}^{j^*}}{Y_{jt}}. \tag{2.1}$$

Then, OS_{jt} indicates the share of value added abroad that could, instead, be produced by the respective domestic industry.[18]

The focus on intra-industry imports is based on the idea of trading comparable sets of tasks (labor inputs). It is better suited for this analysis than alternatives such as affiliate employment or FDI, which may affect workers in different industries than the FDI-conducting one. Specifically, increasing OS_{jt} always 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.[19] The resulting effects on the labor market depend on the respective tasks and it is essential to consider this dimension in the estimation.

[17] 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.
[18] Technically, $M_{jt}^{j^*}$ comprises the diagonal in the input-output table of imports.
[19] 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. Thus, the implicit assumption is that technological capabilities are not exclusive to offshore firms.

Other reasons favoring the intensity of intra-industry imports as a measure for offshoring are the following: First, the effects of offshoring cannot be completely captured at the firm level, since, 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. If the firms belong to different industries, the effect of offshoring is captured only partially. 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. It impacts multiple industries, the one that imports and the nontrading supplier. Although the counteracting labor market 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. I thus 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. I focus only on the most relevant offshoring destinations for Germany during the sample period because including more regions impedes the separate identification of the respective causal effects (problem of missing IVs). The considered regions include the countries belonging to the former EU15 and the CEECs.[20]

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.[21] 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:

[20] 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. I focus on Visegrad countries since they reflect a more homogeneous region and because of their proximity to Germany (see Carstensen/Toubal, 2004).

[21] For a detailed description of the WIOT, see Timmer et al. (2015). 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% 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% 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 (2.1).

$$Ofs_{jtr} = \phi_{jtr} OS_{jt}, \tag{2.2}$$

where

$$\phi_{jtr} = \frac{M^{j^*}_{jtr}}{M^{j^*}_{jt,World}}. \tag{2.3}$$

The industry-specific offshoring measure is essential for the analysis because it is able to capture its complementary and substituting wage effects. On the labor market, however, wages are determined rather at the occupation than on the industry level (Ebenstein et al., 2014). The underlying idea is related to the traded and affected task bundles and especially 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, though, 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/Schönberg (2010) show that the burden of occupational switches also depends on the similarity of tasks between jobs. It also implies higher wage elasticities for jobs that perform only few different tasks (i.e., jobs with simple task profile). Turning to the German wage data, this finding is supported by similar evolutions of wages within occupations rather than within industries.[22] 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. To obtain occupation-specific exposures, I 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:

$$OccOfs_{qtr} = \sum_{j=1}^{J} \frac{L_{qj,1995}}{L_{q,1995}} Ofs_{jtr}. \tag{2.4}$$

Due to the consideration of intra-industry imports and occupational exposures, it is feasible to reveal how imparted tasks in intermediates impact the compensation of similar or dissimilar task sets in occupations. In the appendix, Table C.3 examines the summary statistics of the described measures, and Table B.1 provides more comprehensive details on the data processing.

[22] Intraclass correlations of wages within industries and occupations amount to 0.093 and 0.499, respectively. The within (between) variation of industries is relatively high (low) compared to the within variation of occupations.

3 Framework and Empirical Strategy

The theoretical literature identifies the various channels of offshoring that can affect labor demand (e.g., Groizard/Ranjan/Rodriguez-Lopez, 2014). In essence, the embodiment of these channels depends on a job's task profile. Although I adopt the idea of task trade as the trade of specific labor inputs, I do not attempt to disentangle the diverse channels at work; instead, similarly to Hummels et al. (2014), I utilize an estimable production function framework that describes the aggregate labor market effects of offshoring on different jobs.

3.1 Framework

The framework illustrates how changes in the relative use of imported inputs affect labor demand and wages. The starting point is a Cobb-Douglas-type production function

$$Y_{jt} = A_{jt} K_{jt}^{\alpha} \prod_{q=1}^{Q} C_{qjt}^{\alpha_q}, \tag{3.1}$$

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 (3.1) with respect to the labor of occupation $\bar{q}$ yields the occupation's labor demand by plant j in year t,

$$\psi_{jt} \frac{\partial Y_{jt}}{\partial L_{\bar{q}jt}} = \psi_{jt} \alpha_{\bar{q}} A_{jt} K_{jt}^{\alpha} L_{\bar{q}jt}^{-\frac{1}{\sigma_{\bar{q}}}} C_{\bar{q}jt}^{\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1} \prod_{\substack{q=1 \\ q \neq \bar{q}}}^{Q} C_{qjt}^{\alpha_q}. \tag{3.2}$$

This equation provides the demand relationship between offshoring and the labor input of workers in occupation $\bar{q}$. As shown in equation (A.3b) in the appendix, 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 (3.2) 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 6 that the log representation of equations (3.1) and (3.2) yields

$$\ln w_{iqjt} = b_{q,M} \ln M_{qjt} + b_{q,M_{-q}} \ln M_{-qjt} + b_{q,D} \ln \psi_{jt} + b_{q,L_{-q}} \ln L_{-qjt} + \\ \ln A_{jt} + b_K K_{jt} + b_x x_{it} + \xi_{ij} + \epsilon_{iqjt}, \quad (3.3)$$

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.

3.2 Estimating Equation

Equation (3.3) becomes a feasible estimating 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 (2.2) 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}.[23,24] 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.[25] Lastly, the task complexity index $CMPLX_q$ orders occupations from low (0) to high (1) complexity. The coefficient of its interactions with the offshoring terms are the estimates of interest in this study, since they exhibit the versatile wage impact of offshoring from different regions on heterogeneous labor. After the above adjustments, the I obtain the estimating equation at the industry level:

$$\ln w_{ijqlt} = \sum_r (\beta_r + \beta_{R+r} \times CMPLX_q) Ofs_{jtr} + \delta CMPLX_q + \boldsymbol{x}_{it}\boldsymbol{\lambda} + \boldsymbol{v}_{lt}\boldsymbol{\mu} + \gamma_{il} + \eta_t + \epsilon_{ijqt}, \quad (3.4)$$

where r indexes the offshoring destination.

The analysis contemplates linkages of domestic production with international value chains. Importing inputs substitutes for only a fraction of workers in the respective producing industry, while it complements the remaining workers in this industry (C_{qjt} in (3.1)).[26] It hence results in opposing effects within industries, where some occupations benefit and others lose. Although this reasoning also indicates that industries are a well-suited unit for analyzing the ambivalent impacts of offshoring, the exposure to imported inputs can be further partitioned into occupational exposures that are even better suited to capture the wage effect of task imports (due to σ_q). By including the occupation-weighted offshoring values from equation (2.4), it is straightforward to arrive at the occupational elasticities β_r and β_{R+r}, which also capture cross-industry spillovers:

$$\ln w_{iqlt} = \sum_r \beta_r OccOfs_{qtr} + \sum_r \beta_{R+r} OccOfs_{qtr} \times CMPLX_q + \boldsymbol{x}_{it}\boldsymbol{\lambda} + \gamma_{il} + \theta_q + \kappa_{lt} + \epsilon_{iqt}, \quad (3.5)$$

where r indicates the region, $r \in \{CEECs, EU15\}$, and w_{iqlt} denotes the daily real wage of individual i in plant l, year t, and occupation q.[27] This equation is the baseline estimation for the analysis. It comprises three dimensions of fixed effects that account for unobserved heterogeneity. First, worker-plant fixed effects γ_{il} capture unobservable worker-plant-specific productivity. Second, occupation fixed effects θ_q incorporate observable and unobservable time-invariant characteristics of occupations. This term also absorbs the explanatory power of $CMPLX_q$, whereas it is still possible to identify the interaction term with offshoring due to the variation in occupational exposure. Third, plant-year fixed effects κ_{lt} capture plant-

[23] The match fixed effects account for the endogeneity of worker mobility, that is, for the workers' sorting into firms that generate a high match productivity (see e.g., Krishna/Poole/Senses, 2014).
[24] The worker-plant-specific fixed effects also incorporate variation across German regions and render redundant any region fixed effects.
[25] 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.
[26] In contrast, importing final goods with no value added at home substitutes for workers in the respective producing industry, at least under the assumption that the country does not produce at the production possibility frontier and that the country is endowed with the respective technology.
[27] I obtain real wages by deflating nominal values using the annual consumer price index that is provided by the German Federal Statistical Office. The daily real wage is then denoted in euros in year 2000-constant prices.

specific shocks that are correlated with wages and offshoring, such as plant-specific technological change.[28]

Before estimating equation (3.5), I eliminate confounding channels of wage changes that are due to variations in working hours or gender-specific wage developments and reduce the unbalanced sample to full-time male employees in West Germany (excluding West Berlin).[29] Excluding confounding overlaps of employment, I restrict the panel data and consider only the best-paid spells in full time jobs in manufacturing industries (NACE 15 - 37) on June 30 of each year from 1995 to 2007.

The LIAB reports the wage information of individuals up to the social insurance contribution ceiling, which yields 11 to 15 percent of top-coded employment spells per year.[30] Since the censored distribution biases the ordinary least squares (OLS) estimation, I either impute the missing values similarly to Card/Heining/Kline (2013) (see the description in 6) or cut off the sample at the 85th percentile of the wage distribution (85 percent sample). The latter renders attenuated estimates of the coefficients and variance (see Biørn, 2016) and therefore provides a lower bound of the absolute magnitude of the effects that need to be reaffirmed by other specifications due to the downward bias of the variance estimates.

3.3 Identification and Instruments

Identifying the causal effect of offshoring on wages requires to address endogeneity concerns. While offshoring affects wages, wages also affect the propensity to move associated tasks abroad. The latter occurs, for example, because offshoring is more probable in high-wage industries or high-wage occupations due to higher potential cost savings.[31] To still arrive at an asymptotically unbiased estimator for the wage effect of offshoring, I apply an IV strategy. This method—in order to extract the exogenous variation in the offshoring variable—requires time-varying and region-specific instruments that correlate with region-specific offshoring while being orthogonal to wage setting in Germany.[32] In the selection of suitable in-

[28] Other specifications incorporate time fixed effects η_t with and without a full set of plant controls to explore the beneficial productivity effect of offshoring.

[29] The sample is unbalanced in the sense that individuals may drop out or enter the sample. For each year, however, a full set of covariates is included. If information is missing, the individual is excluded for this period. Moreover, singleton observations are iteratively dropped from the analysis (Correia, 2015). I run the regressions in Stata 14 utilizing the (iv)reghdfe command developed by Correia (2014).

[30] The threshold is annually adjusted to the past wage trend (of the year $t - 2$).

[31] Previous studies argue that this kind of simultaneity can be neglected because it is unlikely that individual daily wages substantially influence offshoring measured in industry or occupation aggregates. For the analysis at hand, however, a Wald test on the exogeneity of occupational exposure to region-specific offshoring is rejected, suggesting that simultaneity may still persist due to correlated wages within occupations.

[32] These conditions exclude the exchange rate as a potential instrument, as it becomes fixed for many European countries with the introduction of the euro.

struments for $OccOfs_{qtr}$, I follow the work by Hummels et al. (2014) and consider the export supply of intra-industry goods ESI from the respective offshoring destination r to other high-income economies HI:[33]

$$ESI_{qtr}^{HI} = \sum_{j=1}^{J} \frac{L_{qj,1995}}{L_{q,1995}} \frac{S_{jtr}^{HI}}{Y_{jtr}}, \qquad \text{for each region } r. \tag{3.6}$$

Applying the weights from equation (2.4), $L_{qj,1995}$ denotes the number of employees in occupation q and industry j in 1995 relative to the total number of manufacturing workers in occupation q, $L_{q,1995}$, in Germany. S_{jtr}^{HI} denotes the supply of intra-industry exports that are demanded by high-wage countries other than Germany, and Y_{jtr} represents the output value of the respective foreign industry j. The trade data originate from the WIOT.[34]

To test the instrument validity, I add an overidentifying instrument akin to Baumgarten/Geishecker/Görg (2013), namely, the ad valorem trade costs of shipping containers that Europe imports from China. Although maritime trade does not capture the modes of transportation for most goods within Europe, the costs of shipping containers still seem to exhibit high explanatory power for the other European transport costs. These costs comprise an eligible instrument because they are correlated with offshoring while being orthogonal to German wages.[35] Note, however, that shocks to transportation expenses not only lower the costs of imported inputs in Germany but also decrease the costs of German goods abroad. This phenomenon positively affects foreign demand and, consequently, the outcome variables of German plants. In the baseline regression, I capture this endogeneity by including plant-year fixed effects. These additionally control for any shock within an industry that is not visible at the aggregate level. This includes the introduction of new technology, which affect, e.g., the plant's number of employees, revenue, capital per worker, and task composition. The corresponding identifying assumption is that technology shocks affect wages in plants (or industries) but not at the occupation level.

This assumption immediately raises concerns about unobservable skill-biased technological change and generally regards instrument validity, as precisely discussed in Autor/Dorn/Hanson (2013). In essence, a (technology) shock that is common to all high-income countries may

[33] The assignment to an income group follows the World Bank classification in 2000. Specifically, the other high-income economies consist of 23 countries in the WIOT: Austria, Australia, Belgium, Canada, Cyprus, Denmark, Spain, Finland, France, the United Kingdom, Greece, Ireland, Italy, Japan, South Korea, Luxembourg, Malta, the Netherlands, Portugal, Slovenia, Sweden, Taiwan, and the US.

[34] Analogously, the industry-level offshoring measure is instrumented by

$$ESI_{jtr}^{HI} = \frac{S_{jtr}^{HI}}{Y_{jtr}}. \tag{3.7}$$

[35] Ad valorem trade costs of shipping containers are extracted from the *OECD: Maritime Transport Costs database* (for methodology and data coverage, see Korinek, 2011). I map commodities denoted in 6-digit HS 1988 to ISIC rev. 3 at the 2-digit level using concordance tables provided by *World Integrated Trade Solutions*. Therefore, I weight trade costs for each commodity by its import value in 1995.

affect the demand for inputs to a similar extent. If technology is simultaneously available to all high-income countries and correlates with both occupational wages in Germany and occupational exposure to offshoring in other high-income countries (the instruments), the IV estimates could still be biased. Although it is impossible to completely disentangle those effects, various specifications substantially mitigate confounders. First, the inclusion of plant-year fixed effects alleviates a potential bias since it implicitly considers the yearly plant-specific composition of workers, tasks and technology, such as computer use rates. The identified wage effects deviate from the average annual development in the plant. For instance, the simultaneous introduction of new technology would be controlled for by capturing the annual wage bill. Second, the occupational exposures are weighted by initial worker shares per industry. This weighting creates an extra layer that mitigates the bias from technology if the other high-income countries feature a different worker-industry structure (different weighting in 1995) and if technology does not affect individual wages in Germany parallel to the sourcing of respective inputs *in* other high-income countries. Note that the latter condition describes instrument validity (no correlation of instruments with wages beyond offshoring from Germany).

4 Results

This section begins by analyzing the typical industry characteristics that are followed by high growth of offshoring to either high- or low-wage countries. It then emphasizes the adjustments within plants that accompany such increases. Then, before turning to the baseline regression results of occupational exposures to offshoring, I highlight the difference of region-specific offshoring to former estimations such as the ones by Baumgarten/Geishecker/Görg (2013).

4.1 Preliminary Analysis: Offshoring, Industry Characteristics, and Plants' Adjustments

Recalling the insights from Heckscher-Ohlin theory, low-wage countries, which are abundant in low-skilled labor, specialize and export simple task-intensive goods, whereas high-wage countries, where low-skilled labor is relatively scarce, export complex task-intensive goods. Furthermore, according to Grossman/Rossi-Hansberg (2012), the intra-industry trade between high-wage countries is explained by specialization in certain sets of tasks due to knowledge spillovers and scale economies. Table 2 shows how actual offshoring to two representatives of such regions correlates with plant-level outcomes in Germany. For comparability reasons, the table is designed to be closely related to Table 3 of Hummels et al. (2014: p. 1612). Each *cell* represents a separate simple linear regression with plant-level outcomes as dependent variables regressed on industry-level offshoring. The correlations in columns 1 and 2 provide weak suggestive evidence on the initial industry characteristics that are followed by increases in offshoring. The main interest, however, is columns 5 and 6, which present the plant adjustments that come along with increases in offshoring.

Table 2: Simple Regressions of Offshoring on Plant-Level Outcomes in Germany

	Cross-section, 1995		Panel, 1996 - 2007			
	State FE and industry-specific		Plant FE and industry-specific			
	offshoring exposure in 2005		offshoring exposure		predicted offshoring exposure	
	EU15	CEE	EU15	CEE	EU15	CEE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Plant outcomes						
ln Wage bill	9.705***	22.833***	0.484	0.560	1.921	-0.591
ln Avg. wage	0.471	-0.292	0.041	4.504***	-3.096**	8.925***
ln Employees	8.725***	24.566***	0.276	-4.170***	5.001***	-9.443***
ln Capital per worker	7.024**	5.079	-4.485**	12.017	-13.114	33.732***
ln Revenue	9.269***	16.230**	1.548*	7.752***	7.629***	10.553***
Exports (share)	2.096***	5.754***	-0.055	2.320***	-1.115	4.855***
Wage agreement: No	-0.464	-1.985***	-0.009	0.205***	-0.155*	0.350***
Plant level	-0.172	-1.725	0.021	0.034	-0.009	-0.042
Industry level	0.636	3.710***	-0.013	-0.234***	0.170**	-0.289***
Panel B: Worker tasks						
Simple job (D)	-1.369***	0.652	0.165*	-1.804***	2.798***	-2.859***
Medium-complexity job (D)	0.511*	-0.605	-0.038	-0.138	0.330	-0.150
Complex job (D)	0.857*	-0.047	-0.127	1.942***	-3.128***	3.010***
Panel C: Industry						
Domestic outsourcing	0.569***	-1.582***	-0.331*	-0.751***	1.750**	-1.097**

Notes: Each *cell* is the estimate of a separate regression, where the dependent variable is listed in the same row and the explanatory variables are along the columns. Columns 1 - 2 show cross-sectional results from 1995 values on 2005 offshoring values. These results primarily indicate the characteristics of industries that subsequently offshored parts of production. For example, the first cell of the spreadsheet displays the coefficient of the (industry-state average of the) log wage bill per plant in 1995 on offshoring to the EU15 in 2005, i.e., 9.705. Columns 3 - 6 present how changes in plant- and worker-level variables move with changes in the exposure to offshoring. Note that in the presence of plant fixed effects, the influence of wage agreements can be determined only by changes in status. Standard errors are clustered at industry-year levels. Additionally, they are adjusted as in a two-stage regression in columns 5 - 6.
$^{*}\ p < 0.10, ^{**}\ p < 0.05, ^{***}\ p < 0.01.$
Sources: Own calculations. ©IAB.

Starting with columns 1 and 2 of Panel A, I regress year-1995 industry averages of either the plant's wage bill, average wage, employment, capital per worker, revenue, export share, or the type of wage agreement on industry-level offshoring in 2005 either to the CEECs or the

EU15 (explanatory variable).[36,37] Employing future values of offshoring on a cross-section primarily yields a level effect or ex-ante characteristics of industries that are exposed to region-specific offshoring (vs. how they are affected). Included state fixed effects account for regional differences among the German federal states. The coefficients suggest that offshoring takes place mainly in industries where plants have many employees, high export shares, revenues, wage bills, and are covered by collective bargaining at the industry level. Especially, plants with high subsequent flows of offshoring to the EU15 (hereafter Ofs_{jt}^{EU15}) also feature high ratios of capital per worker. Note that all these characteristics are also typical of large and more productive firms (in line with Melitz, 2003; Antras/Helpman, 2004; Muendler/Becker, 2010).

Each cell in columns 3 - 6 shows the estimate from a panel regression from 1996 to 2007 that includes plant fixed effects in addition to the single regressor.[38] The estimates present dependencies between changes in the outcome variables and changes in offshoring. Causality, however, is not inferred from the results, since the relationship may imply that the outcome variables determine offshoring, e.g., because plants with higher revenues can afford the costs of offshoring, or offshoring determines the outcome variables, e.g., offshoring increases the revenues of plants. Alternatively, both could be true, and the variables would then be simultaneously determined due to reverse causality or due to any other shock to plants' demand or productivity, and offshoring. These links are an integral part of the identification challenge and require consideration in the subsequent analysis. I mitigate this problem in columns 5 and 6 by predicting the values for the two types of offshoring using the instruments from Section 3.3.[39]

The estimates suggest that the correlations vary substantially for predicted and non-predicted values of offshoring and between the two destination regions. Examining column 3, the intensity of Ofs_{jt}^{EU15} and plant outcomes reveal hardly any distinct relationship. One of the few exceptions is capital per worker, which decreases with rising Ofs_{jt}^{EU15}, although revenues seem to increase. In contrast, the predicted values of Ofs_{jt}^{EU15} in column 5 show a more pronounced development. This finding may imply opposing causalities that influence the coefficients, for instance, if rising average wages lead to rising intensities of Ofs_{jt}^{EU15}, while

[36] Similar to the procedure in Schank/Schnabel/Wagner (2007), capital per worker is approximated by the average of yearly investments in the three years prior to t, divided by the number of workers with social insurance in the firm. If the information is missing for at least two of the previous years, I drop the observation in year t.

[37] In columns 1 and 2, the data for the wage bill, average wage, employees, revenue, and export share in the cross-section are drawn from the *Annual Report on Local Units in Manufacturing, Mining and Quarrying*, which is publicly available from the Federal Statistical Office. The data comprise state-level information on the universe of manufacturing plants in the West German federal states, therefore avoiding reliance on a weighted regression with weights from the EP. It is, however, not available for data on capital per worker and the wage agreement, which are thus extracted from the EP in the LIAB. I apply a weighted least squares estimation using the respective expansion factor for each stratus from the EP.

[38] Table C.4 in the appendix performs an analogous assessment for offshoring destinations outside of Europe and for domestic outsourcing.

[39] I examine the first-stage regressions more comprehensively in Section 4.3.

rising intensities of Ofs_{jt}^{EU15} reduce the average wage within firms. The predicted Ofs_{jt}^{EU15} exhibits positive impacts on revenues and employment, whereas the capital per worker tends to fall and average wages decline.[40] In general, these correlations suggest that rising Ofs_{jt}^{EU15} comes along with *more labor-intensive* production (similar results are reported, e.g., for the US by Harrison/McMillan, 2011 and Ebenstein et al., 2014, for France by Hijzen/Jean/Mayer, 2011, and for Italy by Borin/Mancini, 2016).

Columns 4 and 6 reveal that rising intensities of offshoring to the CEECs (hereafter Ofs_{jt}^{CEECs}) are associated with growing revenues, increasing export shares, higher average wages, and more capital per worker, but lower numbers of employees. The plants' average wage bill does not show any significant correlation. Combining the various correlations, Ofs_{jt}^{CEECs} appears to come along with *more capital-intensive* production. With respect to higher revenues, this finding also suggests that Ofs_{jt}^{CEECs} occurs with boosts in the productivity of businesses, reductions in unit labor costs, and enhanced competitiveness (affirming the results for Germany by Dustmann et al., 2014 and Jäckle/Wamser, 2010).

Panel B explores the offshoring exposure of jobs with different degrees of complexity. It estimates a linear probability model that regresses a binary variable, which indicates workers of the respective tercile of the task distribution, on the regional offshoring measures. Again, columns 1 and 2 show the estimates from a cross-sectional regression of workers in 1995 on future values of offshoring. The coefficients suggest that Ofs_{jt}^{EU15} takes place in industries that intensively use medium-complexity and/or complex labor in production. Combined with the decreasing share of complex labor within plants when Ofs_{jt}^{EU15} increases (columns 3 and 5), the correlations suggest a substitutability of imported inputs from the EU15 and complex task bundles, as well as a complementarity with simple labor. Future values of offshoring to the CEECs, in contrast, show no pronounced relation with the frequency of jobs in the various task terciles.[41] Over time, the expansion of imported inputs correlates positively with higher relative frequencies of complex jobs, suggesting complementarity with complex labor and/or substitutability with simple labor.

[40] Rising intensities of Ofs_{jt}^{EU15} are associated with changes in collective wage bargaining to agreements at the industry level, an expected outcome considering the growth of employment per plant. Note that their identification is limited to the few changes in status if plant fixed effects are present.

[41] The indistinct exposures of jobs to Ofs_{jt}^{CEECs} are in line with earlier findings. Marin (2004), e.g., discovers that German affiliates in CEECs incorporate a relatively high share of skilled workers. Another intra-firm analysis by Becker/Ekholm/Muendler (2013: p. 100) finds insignificant impacts of offshoring to CEECs on the onshore wage bill share of workers in nonroutine and interactive jobs. In this regard, the CEECs are different from any other country group in the study.

4.2 The Wage Impact of Industry Exposure to Offshoring

In an initial assessment, this section seeks to replicate related outcomes by Baumgarten/Geishecker/Görg (2013) for comparison purposes. The starting point is equation (3.3), which employs the variation in industry exposure to imported inputs that complement or substitute for various jobs. Table 3 displays the estimated wage elasticities for the truncated 85 percent sample. Column 1 includes the aggregated measure of offshoring OS_{jt} and a full set of worker and endogenous plant controls. The latter controls for industry-specific time trends that go beyond the industry fixed effects. Moreover, the specification includes match fixed effects and year fixed effects to control for time-invariant and unobserved heterogeneity in worker-plant matches and the time trend.[42] The offshoring term without interaction shows the wage effect for a virtual job that does not contain any complex tasks, while the associated interaction term indicates the wage changes along the complexity index. The estimates confirm that performing more complex tasks shields the worker from adverse wage effects of offshoring. Their magnitudes even exceed the analogue in Baumgarten/Geishecker/Görg (2013), which is likely to be due to the higher homogeneity in their subsamples of high- and low-skilled workers or by employing match—instead of individual—fixed effects.

Column 2 omits endogenous plant controls and considers the channel of enhanced productivity. That is, offshoring raises revenues and capital per worker, which in turn increases wages. Compared to column 1, the coefficients become more pronounced and suggest an uneven distribution of the productivity gains with respect to job complexity. The output in column 3 distinguishes the origin of inputs as in equation (3.4). Notably, the coefficients of Ofs_{jt}^{CEECs} become larger in magnitude and statistical significance compared to the aggregated OS_{jt} in columns 1 and 2. It also becomes obvious that Ofs_{jt}^{EU15} features counteracting effects that are not visible in the estimates of OS_{jt}, demonstrating the heterogeneous wage effects described by theory and highlighting the importance of distinguishing not only the types of labor but also the types of inputs.

In columns 4 - 6, I run an IV regression to remedy concerns about endogeneity. The instruments are the export supply of intermediate inputs from German offshoring destinations to high-income countries other than Germany ESI_{jtr}^{HI} (equation 3.7) and ad valorem trade costs of shipping containers from China to Europe.[43] Because there is no statistic available to test the instrument strength in the presence of multiple endogenous regressors and heteroskedasticity (see Andrews/Stock/Sun, 2019 for a comprehensive explanation), I rely on a

[42] Including plant-year fixed effects would render the offshoring variable perfectly collinear.
[43] Following Wooldridge (2010), I replace the endogenous variable in the interaction terms with the instruments.

homoskedastic analogue, which are the Sanderson-Windmeijer F-statistics (Sanderson/Windmeijer, 2016).[44] These statistics indicate instrument strength in all IV specifications in Table 3, while a Hanson test confirms the instrument validity. The instruments, hence, seem to be able to extract the exogenous variation in offshoring and and to estimate its causal effect on wages. Compared to column 3, the estimated coefficients of interest become more pronounced, suggesting that reverse causality biases the coefficients opposing the effects from offshoring. While relatively high wages of complex (simple) jobs lead to higher intensities of Ofs_{jt}^{EU15}(Ofs_{jt}^{CEECs}), a higher intensity of Ofs_{jt}^{EU15}(Ofs_{jt}^{CEECs}) leads to decreasing relative wages of complex (simple) jobs. To include again the channel that offshoring has on wages by increasing productivity, Column 5 omits the plant controls. This raises wage differences along the complexity distribution for Ofs_{jt}^{EU15}, while Ofs_{jt}^{CEECs} shifts upward with fewer wage differences between jobs of different complexity levels.

The specification in column 6 includes industry-year fixed effects, which absorb any shock at the industry level that is correlated with offshoring and thus also render other industry variables, such as Ofs_{jt}^{EU15} or Ofs_{jt}^{CEECs}, perfectly collinear. The interaction term, however, can still be identified because of the within-industry-year variation in task composition. The estimates suggest even more diverse and highly significant wage effects of instrumented Ofs_{jt}^{EU15} along the task complexity index, while the influence of the interaction term with Ofs_{jt}^{CEECs} declines on a high level.

The bottom line from the above output remains that inputs from CEECs feature a much higher wage effect than inputs from the EU15. This disparity may be due to the magnitudes of the wage differences between Germany and the EU15 or CEECs and associated firm savings. Such productivity boosts would then foster the positive effect for complementary tasks and the negative effect for substitutable tasks and, hence, impact wages differently by job complexity. In this context, the findings by Gathmann/Schönberg (2010) also imply that the larger the bundle of tasks is, the more protected the worker's total labor input against substitution by imported tasks in the form of intermediate goods. Hence, performing a larger variety of tasks makes it more likely that the worker will be able to compensate for any substitution by specializing in other tasks. Regarding labor demand, this mechanism implies, on the one hand, lower (higher) onshore wage elasticities of jobs that are substituted by complex (simple) task-intensive imported inputs. On the other hand, demand shifts toward complementary tasks (to imports) may also result in shifts in the relative job frequency of complex jobs.

Recall that the industry level is important to observe the complementarity and substitutability of offshoring and domestic labor, but it is not necessarily the relevant wage-determining labor market (for the task bundles). Instead, the occupation level seems to be a more suitable unit, since the estimated standard deviation of wages between (within) occupations is 0.1337 (0.2075) and, hence, much higher (lower) than between (within) industries 0.0790 (0.2344).

[44] According to Andrews/Stock/Sun (2019), I do not report Kleibergen-Paap or robust Cragg-Donald statistics

Table 3: Industry-Level Regression Results for the Truncated Sample

	Dependent variable: Log daily wage					
	Fixed Effects OLS			Instrumental Variables 2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Offshoring exposure	-0.852***	-0.957***				
at industry level	(-5.71)	(-6.46)				
× job complexity	1.879***	2.358***				
	(8.74)	(10.66)				
Offshoring exposure			0.792***	1.544***	2.673***	
to EU15			(4.52)	(2.77)	(5.44)	
× job complexity			-1.495***	-2.468***	-4.907***	-4.075***
			(-5.85)	(-2.96)	(-5.57)	(-5.52)
Offshoring exposure			-4.580***	-4.594***	-3.956***	
to CEE			(-7.17)	(-5.85)	(-5.01)	
× job complexity			8.835***	12.48***	10.511***	8.142***
			(9.87)	(8.99)	(6.01)	(5.80)
Job complexity	-0.001	-0.002	0.121***	0.128***	0.284***	0.275***
	(-0.03)	(-0.11)	(7.93)	(3.24)	(6.12)	(7.27)
Worker controls	Yes	Yes	Yes	Yes	Yes	Yes
Plant controls	Yes	No	Yes	Yes	No	No
Match FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	No	No	No	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	No
Observations	1,004,801	7,032,785	1,004,802	1,002,574	7,004,047	7,004,047
SW-F				38.81; 23.72;	45.63; 31.90;	35.54; 142.35
				123.72 ; 93.22	86.56; 89.17	
Hansen J overid.				$\chi_1^2 = 1.651$	$\chi_1^2 = 2.980$	χ_1^2 =1.084
				p=0.438	p=0.225	p=0.298

Notes: Table 3 shows the estimates for the regressions of daily real wages on industry-level offshoring and a set of worker controls and fixed effects. Columns 1 - 3 present the OLS results. Columns 4 - 6 display results from a two-stage least squares estimation (2SLS), where offshoring is instrumented using ESI_{jtr}^{HI}, ad valorem trade costs with China, and their interactions with the task index. The Sanderson-Windmeijer (SW) first-stage F-statistics (Sanderson/Windmeijer, 2016; Andrews/Stock/Sun, 2019) provide heuristic information about instrument strength in the presence of heteroskedasticity and multiple endogenous regressors. Including plant controls reduces the sample size due to data availability in the EP (columns 3 and 4). Robust *t* statistics are in parentheses. Standard errors are clustered according to Abadie et al. (2017) at industry-year levels, i.e., the treatment level.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.
Sources: Own calculations. ©IAB.

4.3 The Wage Impact of Occupational Exposure to Offshoring

Table 4: First-Stage Results of Fixed Effects Instrumental Variable Regressions

	Occupational offshoring exposure to EU15		× job complexity		Occupational offshoring exposure to CEE		× job complexity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instruments:								
Occup. export supply	0.620***	0.806***	0.106	0.161	0.108***	0.075**	0.137***	0.124***
of inputs from EU15	(4.03)	(3.78)	(1.44)	(1.51)	(3.91)	(2.07)	(6.62)	(5.00)
× job complexity	-0.151	-0.322	0.290***	0.293**	-0.309***	-0.269***	-0.322***	-0.308***
	(-0.77)	(-1.26)	(2.75)	(2.20)	(-7.14)	(-4.90)	(-8.67)	(-7.11)
Occup. export supply	-0.391***	-0.194**	-0.168***	-0.094**	0.320***	0.326***	-0.059***	-0.048***
of inputs from CEE	(-7.90)	(-2.22)	(-6.74)	(-2.12)	(26.44)	(17.39)	(-8.03)	(-4.65)
× job complexity	0.197***	0.068	0.041	0.019	-0.024	-0.061**	0.406***	0.371***
	(2.87)	(0.73)	(1.02)	(0.40)	(-1.56)	(-2.40)	(36.21)	(22.29)
Occup. trade costs	0.007	0.016	0.011	0.018*	-0.001	0.007*	-0.005**	0.001
	(0.52)	(0.80)	(1.29)	(1.66)	(-0.33)	(1.66)	(-2.03)	(0.41)
× job complexity	0.049***	0.056**	0.023*	0.019	-0.012**	-0.021***	0.002	-0.005
	(2.77)	(2.11)	(1.95)	(1.25)	(-2.20)	(-2.80)	(0.60)	(-1.33)
Worker controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant controls	No	Yes	No	Yes	No	Yes	No	Yes
# of fixed effects:								
Spell	973,034	240,386	973,034	240,386	973,034	240,386	973,034	240,386
Occupation	240	215	240	215	240	215	240	215
Year		12		12		12		12
Plant-year	145,072		145,072		145,072		145,072	
Observations	6,828,208	1,004,804						
SW-F	22.15	23.97	23.01	26.95	55.35	322.5	59.16	321.54
R^2 (within)	0.099	0.104	0.082	0.097	0.495	0.418	0.631	0.509
R^2	0.963	0.954	0.976	0.972	0.982	0.979	0.984	0.981

Notes: Table 4 reports the first-stage regression results associated with columns 2 and 6 in Table 5. The odd-numbered columns are overidentified using ESI^{HI}_{qtr}, ad valorem trade costs with China, and their interactions with the task index. The even-numbered columns omit all terms including the trade costs with China to alleviate the bias towards OLS, which is caused by weak instruments and overidentifying restrictions. For the resulting specifications, the reported Sanderson-Windmeijer (SW) first-stage F-statistics reject weak identification (Sanderson/Windmeijer, 2016). Robust *t* statistics are in parentheses. Standard errors are clustered at occupation-year levels.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.
Sources: Own calculations. ©IAB.

The analysis now turns to the baseline regression that analyzes the wage effects of occupation-specific exposures to offshoring. Columns 1 - 4 in Table 5 are associated with equation (3.5) and estimate wage changes within occupations and worker-plant matches, and relative to the annual plant averages. They do not include other channels emerging from labor demand changes, such as the impact of workers who switch occupations, employers/plants, or unemployment.

because the 2SLS tests have the incorrect statistical size.

Table 5: Regression Results for the Truncated Wage Distribution

	Dep. variable: Log daily wage						
	OLS	2SLS	OLS	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Occup. offshoring	0.493*	2.016**	1.022***		1.164***	2.321**	5.646***
exposure to EU15	(1.81)	(2.18)	(3.10)		(2.98)	(2.11)	(3.00)
× job complexity	-0.962**	-3.579**	-1.633***		-2.602***	-3.176*	-4.161***
	(-2.13)	(-2.06)	(-3.00)		(-4.30)	(-1.73)	(-3.01)
Occup. offshoring	-8.322***	-7.885***		-8.414***	-9.395***	-5.475***	-8.843***
exposure to CEE	(-14.37)	(-10.51)		(-14.42)	(-9.34)	(-5.09)	(-2.72)
× job complexity	14.54***	14.48***		14.583***	18.87***	18.934***	15.38***
	(17.43)	(15.10)		(17.39)	(15.16)	(15.79)	(9.05)
Worker controls							
Age^2	-0.0261***	-0.0261***	-0.026***	-0.026***	-0.0310***	-0.0307***	-0.0299***
	(-40.76)	(-40.75)	(-41.19)	(-40.76)	(-36.07)	(-34.51)	(-42.38)
Tenure	0.0062***	0.0061***	0.0061***	0.006***	0.0065***	0.0067***	0.0047***
	(53.67)	(53.76)	(50.35)	(53.68)	(17.09)	(17.45)	(31.05)
Tenure^2	-0.0176***	-0.0176***	-0.0173***	-0.018***	-0.0132***	-0.0139***	-0.0101***
	(-52.52)	(-52.48)	(-48.21)	(-52.21)	(-12.77)	(-13.36)	(-25.25)
Plant controls							
Exports (share)					-0.0259**	-0.0249**	
					(-2.44)	(-2.34)	
× job complexity					0.0151	0.0127	
					(0.95)	(0.79)	
ln Capital per worker					0.0012***	0.0012***	
					(4.68)	(4.38)	
ln Employees					0.0413***	0.0403***	
					(15.78)	(15.63)	
ln Revenue					0.0187***	0.0180***	
					(10.20)	(9.99)	
Wage Agreement: No						-0.0090***	
						(-5.74)	
Firm-level					0.0009	-0.0079***	
					(0.46)	(-4.59)	
Industry-level					0.0091***		
					(5.76)		
# of fixed effects:							
Spell	973,034	973,034	973,034	973,034	240,383	240,386	1,019,733
Occupation	240	240	240	240	215	215	240
Year					12	12	12
Plant-year	145,072	145,072	145,072	145,072			
Observations	6,828,230	6,828,230	6,828,230	6,828,230	1,004,802	1,004,804	7,032,802

Notes: In columns 5 and 6, the omitted indicator dummy of the wage agreement indicates the comparable unit. An overidentification test confirms instrument validity (χ^2_2=1.351, p = 0.509) in column 2, whereas it rejects the test in column 6 (χ^2_2=16.272, p = 0.000) with endogenous plant controls. Robust *t* statistics are in parentheses. Standard errors are clustered at occupation-year level.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.
Sources: Own calculations. ©IAB.

The specifications in columns 5 - 7 replace plant-year fixed effects with controls for plant changes over time and year fixed effects that capture changes driven by the business cycle. These adjustments also indicate whether plants' exports have heterogeneous wage effects with respect to job complexity. If this were the case, the plant-year fixed effect in the baseline regression would not suffice to control for plant heterogeneity other than the effects from offshoring. While most plant-level controls yield wage impacts in accordance with economic theory, the coefficient of the export share in revenues is unexpected and reveals a negative influence. In the presence of spell fixed effects, the negative impact is supposedly associated with domestic demand shocks that affect wages and revenue at the same time. Regarding the estimation of the offshoring coefficients, the IV regression controls for such endogeneity. I cluster standard errors at the treatment level, as suggested by Abadie et al. (2017). This means that occupation-year levels account for the heterogeneity in the treatment effects.

In the OLS specifications, up to four endogenous variables remain in the equation: the two regional offshoring terms and their respective interactions with the task index. All two-stage least-squares (2SLS) regressions instrument for them, including additional instruments for overidentification: the region-specific export supply of inputs to other high-wage countries, ad valorem trade costs of shipping containers from China, and their interactions with complexity. The first-stage results (2×4) in column 2 (and 6) are shown in Table 4 in the even- (odd-) numbered columns. While the baseline specification does not reject the validity of the overidentifying instruments, the specification with endogenous plant controls rejects a Hansen test, i.e., the orthogonality of the error term to regressors in the second-stage regression. This outcome is not surprising since the test is rejected not only if the overidentifying instruments are invalid but also if the model includes endogenous controls.

Examining the first stage in more detail, the coefficients demonstrate that all instruments exhibit a plausible influence on offshoring and that their impact is significant. Some of the coefficients, however, are less trivial to interpret. For example, the correlation of the export supply of the CEECs with exposure to offshoring to the EU15 is negative, which may imply that the latter is replaced because (suppliers from) the EU15 also offshore production to the CEECs. Its positive and significant interaction term shows that the relationship is less pronounced for complex jobs. Note that the reverse effect does not occur (columns 5 and 6), but the export supply of inputs from EU15 is positively correlated with offshoring to the CEECs. This effect, as described in Baumgarten/Geishecker/Görg (2013) and Hummels et al. (2014), is the expected and could be related to trade costs that go beyond the cost of containers. The interacted container costs from China are positively correlated with offshoring to the EU15 and negatively correlated with offshoring to the CEECs. This combination may occur because Germany replaces complex task imports from the EU15 with imports from overseas if trade costs are low or because complex task imports from the EU15 react less sensitively to changes in container costs than other imports. Furthermore, I heuristically test for weak instruments following the procedure for multiple endogenous regressors (under homoscedasticity) developed by

Sanderson/Windmeijer (2016).[45] The respective F-statistics indicate that all instruments sufficiently explain the respective offshoring terms (instrument strength).

Predicting offshoring in the first stage thus incorporates exogenous variation in offshoring, which facilitates the identification of its causal effect on wages in the second stage. As columns 2 and 6 in Table 5 reveal (compared to columns 1 and 5), the elasticities of offshoring to the EU15 become more pronounced if endogeneity is removed. Either this change may be due to unobserved shocks that are positively (negatively) correlated with offshoring and have a negative (positive) effect on real wages (omitted variable bias) or reverse causality could cause bias, e.g., if high wages of complex occupations induce more offshoring activities in the EU15. In contrast, the coefficients of offshoring to the CEECs change only slightly, suggesting a smaller bias due to endogeneity.[46] It implies that offshoring to the EU15 reacts stronger to high wages, a plausible result, not only because complex-task intensive products are associated with high-wage labor, but also because firms react more sensitive to the wages. For instance, if car components are less costly in France due to high wages in Germany the firms easily change from a domestic to a foreign supplier. The CEECs, on the contrary, were economically not equally well integrated during the observation period and may rather be associated with the relocation of production, which is less sensitive to small wage differences (of complex jobs) or short-term wage changes.

Turning to the interpretation, the baseline regression in column 2 identifies the effects of offshoring to Eastern and Western Europe on wages within occupations, worker-plant matches, and plant-year observations. The opposing signs for the two types of offshoring reveal, on the one hand, that both types incorporate substitution and productivity responses on wages and, on the other hand, that these responses show contrasting signs with respect to a job's complexity. While offshoring to the CEECs suggests positive effects on the relative wages of complex jobs, offshoring to the EU15 negatively affects the relative wages of complex jobs.[47] Although the latter is lower in magnitude, it is an important factor mitigating the relatively strong effects of offshoring to CEECs. It is also able to reconcile two seemingly contradictory phenomena in the literature: the high substitutability of complex jobs with foreign labor (offshorability) and the positive wage responses of those jobs observed in response to offshoring. While input trade among the EU15 accounts for the bulk of all offshoring activities and moderately lowers wages for complex jobs, the vast expansion of offshoring to CEECs dominates those effects and results in an overall wage divergence between jobs of different complexities.

[45] It is a heuristic approach since the respective F-statistics assume homoskedasticity.
[46] Table 2 shows in column 2 that neither a specific type of job nor the average wage is significantly correlated with future values of offshoring.
[47] For example, the wage elasticity of offshoring to the CEECs amounts for a physics engineer (CMPLX = 1) to 6.595 ($= \hat{\beta}_3 + \hat{\beta}_4 * 1$ when applying the estimates of column 2 in Table 5), while the elasticity of a metal grinder (CMPLX = 0.41) is negative, at -1.948. Thus, if the occupation-specific offshoring exposure increases by 0.01 percentage points, the wages of physics engineers who remained in their jobs increase by 6.6%, whereas the wages of metal grinders who remained in their jobs decrease by 1.9% on average.

To eliminate concerns that the opposing effects of region-specific offshoring are caused by multicollinearity, I separately run regressions for each type of offshoring (columns 3 and 4). While the wage elasticity of offshoring to CEECs does not change, the elasticity of offshoring to EU15 countries becomes even more pronounced (compared to column 1). Multicollinearity is therefore unlikely to drive the coefficient signs.

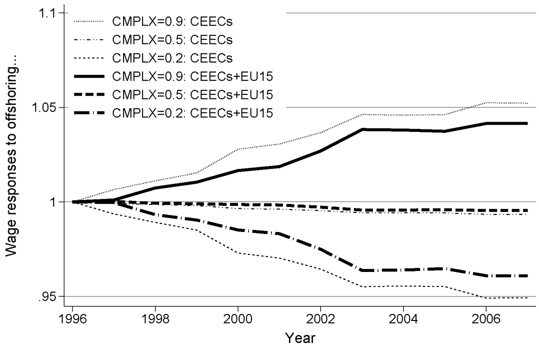
Thus far, the specifications of Table 5 eliminate any channel of induced productivity on labor demand either by including plant-year fixed effects or plant controls (e.g., capturing wage increases due to higher revenues). By omitting these, wage elasticities include the productivity effect, which augments the wage impact of imported inputs from the EU15 (column 7), while the productivity effect of imported inputs from the CEECs does not seem to play an important role (similar to column 2). A possible explanation is that a plausible threat to offshore jobs to CEECs changes the bargaining position of workers more severely, which results in a lower labor share in (national) income. Note also that in this setup, the coefficient of the EU15 offshoring term is lower than its interaction term, implying positive average wage effects for complex jobs and only negative wage effects relative to simple jobs.

Figure 3 illustrates the baseline results from columns 2 (left, exclusive of the productivity effect) and 7 (right, including the productivity effect) by using the actual evolution of offshoring and by indexing real wages of simple (task = 0.2), medium-complexity (task = 0.5), and complex (task = 0.9) jobs to their values in 1996. Starting with the left graph, it depicts that offshoring to the CEECs increases, ceteris paribus, the average wages of complex jobs by 5.2 percent, while it reduces the average wages of simple jobs by 5.1 percent. If the effect of offshoring to the EU15 is now added, the overall impact of offshoring changes to +4.2 and -3.9 percent, respectively. Adding the productivity effect, the right graph indicates that the wage effects induced by offshoring to CEECs change only slightly; they still negatively (positively) affect workers with simple (complex) task profiles. If both types of offshoring are considered instead, the wage response shifts upwards for all types of workers. Only relatively simple jobs still suffer slight wage losses, while the discrepancy with the evolution of wages of complex jobs diminishes.

Thus far, wage regressions have incorporated information up to the 85th percentile of the wage distribution. They ignore truncation, which could affect the estimates for complex jobs, for example, if only a less productive subgroup of the respective occupation is observed. Then, their wages may grow more slowly or decrease more quickly than the actual group average. To obtain information on high wage earners, it is necessary to infer the effect from observable units. I do this in several ways.

As initial evidence, Table 2 (Panel B) already indicates differences in labor market outcomes with respect to the type of offshoring and without any truncation. In summary, the correlations suggest that relative labor demand for complex jobs declines when inputs are imported

Figure 3: Wage Responses to Offshoring by Different Task Complexity



Notes: Figure 3 depicts, ceteris paribus, the evolution of average wages of simple, intermediate, and complex jobs in response to offshoring 1) to the CEECs (thin line) or 2) to the CEECs and EU15 (thick line) from 1996 to 2007. The left panel draws on the estimates in column 2 in Table 5. It shows how offshoring to the EU15 mitigates the amplification of the income gap. The right panel refers to column 7 in Table 5. The evolution of wages now includes the channel of induced productivity from offshoring, where adding offshoring to the EU15 yields more positive wage effects on all types of jobs and a reduced income gap.
Sources: Own calculations. ©IAB.

from other high-wage countries and rises when inputs are imported from low-income countries.

In a second exercise, I impute censored entries following the procedure developed by Card/Heining/Kline (2013) (see Appendix B for a description of the procedure) and rerun the main specifications from Table 5 on the full wage distribution. Table 6 presents the resulting OLS estimates, which feature the same signs but higher wage elasticities across the complexity distribution. This change is likely due to having a wider range of wages in the sample, which increases the deviations from the mean wage and the covariance with offshoring.[48] The previous tables therefore seem to present rather conservative estimates.

In another approach, I reduce the sample to workers younger than 35 years of age. Their wages are lower for reasons such as having less work experience and tenure, whereas they are not an occupational subgroup that features few productivity-enhancing individuals.[49] Selecting this subsample leaves 94 percent of the annual wage distribution non-censored. In comparison to the baseline regression, these specifications reveal more pronounced effects on relative wages, affirming the aforementioned attenuation of the elasticities from the baseline regression (Section 3.2).

[48] On the one hand, imputing wages provides conjectures on the behavior of high wage earners; on the other hand, it generates excessive noise for an instrumental variable approach.
[49] The opposite is true, as suggested by the coefficients on the polynomial of tenure in Table 3 and Table 5.

Table 6: Full Sample with Imputed Wages and the Subsample of Young Workers

	Dependent variable: log daily wage					
	Imputed wages, full sample		Workers < 35 years, until 94th percentile			
	OLS		OLS		2SLS	
	(1)	(2)	(4)	(5)	(7)	(8)
Occupational offshoring	2.043***	2.618***	1.433***	2.036***	3.362**	0.996
exposure to EU15	(3.34)	(3.70)	(3.08)	(3.86)	(1.96)	(0.58)
× job complexity	-3.540***	-5.326***	-2.585***	-4.096***	-5.374**	-2.828
	(-3.48)	(-4.50)	(-3.46)	(-4.62)	(-2.00)	(-1.02)
Occupational offshoring	-17.609***	-19.012***	-16.49***	-15.68***	-16.34***	-12.56***
exposure to CEE	(-17.92)	(-13.31)	(-12.32)	(-8.11)	(-10.16)	(-7.21)
× job complexity	28.610***	34.902***	28.31***	30.82***	29.88***	33.31***
	(21.39)	(20.30)	(14.36)	(11.42)	(14.56)	(13.69)
Plant controls	No	Yes	No	Yes	No	Yes
Year FE	No	Yes	No	Yes	No	Yes
Plant-year FE	Yes	No	Yes	No	Yes	No
Observations	8,185,768	1,201,821	2,258,657	323,409	2,258,657	323,409
Hanson J					χ^2_2= 1.584	χ^2_2=21.238
Overidentification					p = 0.453	p = 0.000

Notes: Columns 1 - 2 show the results from the full sample (along the entire wage distribution) of male employees. Top-coded wages are imputed. Columns 4 - 8 display the results of workers younger than 35 years of age and up to the 94th percentile of the wage distribution (without top-coded entires). The IV regressions in columns 7 - 8 instrument the offshoring measures and their interactions with the task index. 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.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.
Sources: Own calculations. ©IAB.

5 Further Robustness Checks

The following section explores alternative specifications and assesses the robustness of the wage effects of offshoring.

5.1 Nonmonotone Wage Effects Along the Job Complexity Measure

The previous results assume a monotone relation between the offshoring terms and the task index and identify winners and losers for each type of offshoring. If offshoring positively affects the demand for some jobs and negatively affects that for others, the estimation assumes that the transition occurs at a given point. From the neighborhood around this point, the wage elasticity further increases towards the poles of the complexity distribution. Such be-

Table 7: 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**	0.335	0.499***	0.601**
	(2.04)	(1.55)	(2.98)	(2.29)
$OccOfs_{EU15}\times$ complexity2	0.023	-0.047	0.018	-0.128
	(0.38)	(-0.15)	(0.14)	(-0.31)
$OccOfs_{EU15}\times$ complexity3	0.039	-0.659***	0.390**	-0.560*
	(0.43)	(-2.83)	(2.02)	(-1.89)
$OccOfs_{EU15}\times$ complexity4	-0.731***	-0.648*	-0.874***	-0.772*
	(-3.89)	(-1.90)	(-3.05)	(-1.67)
$OccOfs_{EU15}\times$ complexity5	-0.568***	-0.936***	-1.740***	-2.521***
	(-4.05)	(-4.80)	(-4.13)	(-4.54)
$OccOfs_{CEECs}\times$ complexity1	-1.923***	-1.552**	-4.305***	-3.625***
	(-9.81)	(-2.44)	(-11.48)	(-4.66)
$OccOfs_{CEECs}\times$ complexity2	-1.813***	-1.973**	-4.129***	-4.023***
	(-9.24)	(-2.25)	(-10.97)	(-4.18)
$OccOfs_{CEECs}\times$ complexity3	-0.516***	1.052*	-2.410***	-0.590
	(-2.84)	(1.77)	(-6.89)	(-0.79)
$OccOfs_{CEECs}\times$ complexity4	3.728***	4.628***	4.631***	5.801***
	(8.06)	(4.72)	(6.58)	(4.60)
$OccOfs_{CEECs}\times$ complexity5	4.666***	7.423***	9.063***	12.812***
	(17.85)	(12.04)	(14.19)	(13.00)
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	1,201,819

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.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.
Sources: Own calculations. ©IAB.

havior, however, could miss some information since the coefficient of the interaction term could also be driven by wage effects on either less- or more-complex jobs.

It is straightforward to put this possibility to the test by assigning 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 7, 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.

The specifications do not reject the assumption that the types of offshoring affect wages monotonically with respect to job complexity. Offshoring to the EU15 affects the wages of jobs with either few or many complex tasks. For offshoring to the CEECs, the expanded pattern of wage responses is clearer, revealing a substantial negative and significant impact on rather simple jobs and gradual increases for rather complex jobs.

5.2 The Influence of Labor Market Reforms in Germany

A major political debate in Germany persists regarding the economic impact of comprehensive labor market reforms that were introduced between 2003 and 2005, called the Hartz reforms. These reforms will bias the IV estimates if their impact is correlated with the occupational export supply of intermediate goods to other high-income countries and wage changes in Germany. Since the Hartz reforms were mainly intended to lower unemployment and the reservation wages of low-paid occupations, they may have had an adverse influence on the bargaining positions of simple jobs and thereby disturbed the causal identification of offshoring in the above approach. To control for this development, I divide the sample into two periods.

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.[50]

Table 8 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 the wage effects of the Hartz reforms.

[50] 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 8: 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	0.554	3.368***	3.898***	-0.246	2.016	3.125**	4.418**
exposure to EU15	(1.55)	(0.94)	(4.02)	(3.22)	(-0.49)	(1.48)	(2.30)	(2.25)
× job complexity	-1.064**	-1.648*	-6.023***	-7.824***	0.764	-4.990**	-4.862**	-9.149**
	(-2.03)	(-1.80)	(-4.36)	(-3.86)	(0.82)	(-2.08)	(-1.98)	(-2.53)
Occupational offshoring	-7.602***	-8.071***	-19.577***	-22.148***	-7.571***	-9.218**	-24.962***	-23.25***
exposure to CEE	(-8.63)	(-5.63)	(-11.88)	(-9.41)	(-4.78)	(-2.05)	(-6.05)	(-4.25)
× job complexity	13.80***	17.68***	32.786***	40.447***	13.43***	21.79***	37.597***	42.69***
	(10.38)	(7.91)	(14.16)	(12.39)	(5.27)	(3.62)	(6.43)	(5.62)
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	448,548	4,434,278	540,388	2,503,082	412,129	3,002,695	486,899

Notes: Table 8 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.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{**}\ p < 0.01$.
Sources: Own calculations. ©IAB.

5.3 Alternative Measures for Task Profiles

A final robustness check analyses whether the regression should rely on the tradability of tasks (offshorability) or any other particular characteristic. The selection ranges from a fairly similar index to the measure of routineness and, finally, to the measure of offshorability in Blinder/Krueger (2013). The first measure (Table 9, column 1) is based on Brändle/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/Muendler (2013) (see Section 2.2). Column 3 then captures a different job characteristic, that is, offshorability, as defined by Blinder/Krueger (2013). The information derives from the Princeton data improvement initiative (PDII) and is designed to measure

Table 9: IV Regressions with Alternative Measures of Job Complexity

	Dependent variable: log daily wage		
	Alternative measures of task profiles:		
	PCA, time-varying	Nonroutine	Offshorability
	Brändle/Koch, 2017	Becker/Ekholm/Muendler, 2013	Blinder/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/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/Muendler (2013) and the offshorability index from the Princeton data improvement initiative (Blinder/Krueger, 2013), respectively. The latter is mapped to the German classification $KldB88$ using a series of crosswalks, as explained in 6. 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.
* $p < 0.10$, ** $p < 0.05$, ** $p < 0.01$.
Sources: Own calculations. ©IAB.

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 Appendix B. Similar to Baumgarten/Irlacher/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. Strikingly, the estimated coefficients decrease after the occupations are classified 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 only to measures that closely measure occupational complexity.

6 Conclusion

The paper distinguishes types of labor by measuring the complexity of jobs. On the production side, it approximates the complexity of imports by considering offshoring to either high- or low-wage destinations. The empirical strategy identifies wage effects with respect to job complexity and with respect to the type of imported inputs. Due to continuous reductions in European trade costs, the analysis of intra-European value chains is well suited to this subject. Using the most comprehensive dataset for workers in Germany allows the application of multidimensional fixed effects and to control for much of the unobserved heterogeneity. The IV approach solves the problem of the endogenous determination of wages and offshoring by applying time-varying, region-specific instruments. With these tools at hand, the paper reveals wage changes within occupations and worker-plant matches that reach beyond plant-specific shocks.

The key insights of the paper are as follows. First, offshoring to high-income countries, such as the EU15, accounts for the bulk of Germany's imports in intermediate goods and rose substantially after 1996. In absolute terms, this increase is comparable to the increase in offshoring to the CEECs. Second, the characteristics of offshoring destinations have substantially different implications for domestic production. Precisely, the analysis suggests that increasing offshoring to the EU15 entails more labor-intensive production, while increasing offshoring to the CEECs is accompanied by more capital-intensive production. Third, the analysis identifies the causal wage effects of offshoring to high- or low-income countries with respect to job complexity. Wages of complex jobs decrease in response to offshoring to the EU15 relative to wages of jobs with few different complex tasks, whereas jobs of the latter type experience wage gains. For offshoring to the CEECs the wage impacts of offshoring reverse and they are of a much higher magnitude. Explicitly, the estimates suggest that offshoring to the CEECs increased the average wage of jobs with high complexity measures of 0.9 by 5.2 percent, while it decreased the average wage of jobs with low complexity measures of 0.2 by 5.1 percent between 1996 and 2007. If one also considers the growth of offshoring to the EU15, the corresponding wage effects are +4.2 and -3.9 percent, respectively.

The results can reconcile two seemingly contradictory phenomena in the literature: the high substitutability of complex jobs with foreign labor (offshorability) and the positive wage responses of those jobs to offshoring. While input trade among the EU15 accounts for the bulk of all offshoring activities and moderately lowers wages for complex jobs, the vast expansion of offshoring to CEECs dominates those effects and results in an overall wage divergence between jobs of different complexities. These counteracting effects of offshoring not only explain the low and often statistically nonsignificant labor market effects reported in the previous literature but also contribute to the recent debate on the effects of free trade agreements among high-income countries (e.g., between the EU and the USA).

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Appendix

A Theory

The model builds on Hummels et al. (2014):
Deriving the wage of occupation $\bar{q}$ yields

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

which is used for equation (3.2). The log transformation of equation (A.1) yields

$$\ln w_{\bar{q}jt} = \ln \left[\alpha_{\bar{q}} A_{jt} K_{jt}^{\alpha} L_{\bar{q}jt}^{-\frac{1}{\sigma_{\bar{q}}}} \right] + \left(\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1 \right) \ln C_{\bar{q}jt} + \sum_{\substack{q=1 \\ q\neq\bar{q}}}^{Q} \alpha_q \ln C_{qjt}. \tag{A.2}$$

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

$$\ln w_{\bar{q}jt} = \ln \left[\alpha_{\bar{q}} A_{jt} K_{jt}^{\alpha} L_{\bar{q}jt}^{-\frac{1}{\sigma_{\bar{q}}}} \right] + \left(\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1 \right) \left[c_{0\bar{q}} \ln L_{\bar{q}jt} + (1-c_{0\bar{q}}) \ln M_{\bar{q}jt} \right] + \sum_{\substack{q=1 \\ q\neq\bar{q}}}^{Q} \alpha_q \left[c_{0q} \ln L_{qjt} + (1-c_{0q}) \ln M_{qjt} \right], \tag{A.3a}$$

or

$$\ln w_{\bar{q}jt} = \ln \left[\alpha_{\bar{q}} A_{jt} K_{jt}^{\alpha} L_{\bar{q}jt}^{-\frac{1}{\sigma_{\bar{q}}}} \right] + \left(\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1 \right) c_{0\bar{q}} \ln L_{\bar{q}jt} + \sum_{\substack{q=1 \\ q\neq\bar{q}}}^{Q} \alpha_q c_{0q} \ln L_{qjt} + \left(\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1 \right) (1-c_{0\bar{q}}) \ln M_{\bar{q}jt} + \sum_{\substack{q=1 \\ q\neq\bar{q}}}^{Q} \alpha_q (1-c_{0q}) \ln M_{qjt}, \tag{A.3b}$$

where

$$\ln C_{qjt} \approx c_{0q} \ln L_{qjt} + (1-c_{0q}) \ln M_{qjt} + c_{1q}. \tag{A.4}$$

c_{0q} and c_{1q} are constants with codomains between 0 and 1. To obtain equation A.4, see the following proof.

PROOF:

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 $c_1 = h(y_0) - y_0 h'(y_0)$ yields equation (A.4).

$$\begin{aligned}
\ln C &= \underbrace{h'(y_0)}_{c_0} y + \underbrace{h(y_0) - y_0 h'(y_0)}_{c_1} + \ln M \\
&= c_0 \ln\left(\frac{L}{M}\right) + c_1 + \ln M \\
&= c_0 \ln L + (1 - c_0) \ln M + c_1
\end{aligned} \tag{A.5}$$

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 (A.3b) becomes

$$\left(\alpha_{\bar{q}} + \frac{1}{\sigma_{\bar{q}}} - 2\right)(1 - c_{0\bar{q}}) \ln M_{\bar{q}jt} + (1 - \alpha)(1 - c_{0\bar{q}}) \ln M_{jt}. \tag{A.6}$$

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 (3.2) and (A.3b):

$$\gamma_{\bar{q},D} = \frac{\partial \ln w_{\bar{q}}}{\partial \ln L_{\bar{q}}} = -\left[\frac{1}{\sigma_{\bar{q}}} + \left(1 - \alpha_{\bar{q}} - \frac{1}{\sigma_{\bar{q}}}\right) c_{0\bar{q}}\right] < 0 \tag{A.7}$$

To derive equation (3.3) in Section 3, assume that industry j faces

$$w_{qjt} = a L_{qjt}^{\gamma_{q,S}}, \tag{A.8}$$

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 (3.2) and (A.8), the wage elasticity of workers in occupation $\bar{q}$ is

$$b_{\bar{q},M_{\bar{q}}} = \frac{\partial \ln w_{\bar{q}jt}}{\partial \ln M_{\bar{q}jt}}\bigg|_{K,L,M_{-\bar{q}}\text{ constant}} = \frac{(\frac{1}{\sigma_{\bar{q}}} + \alpha_{\bar{q}} - 1)c_{0\bar{q}}\gamma_{\bar{q},S}}{\gamma_{\bar{q},S} - \gamma_{\bar{q},D}}, \tag{A.9}$$

Further assume that each worker i features individual yearly productivity $a_{ijt} = exp(b_1 x_{it} + \xi_{ij})$, 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

$$w_{iqjt} = w_{iqt} a_{ijt}. \tag{A.10}$$

Solving equations (3.2), (A.8), and (A.10) for $\ln w_{iqjt}$ yields equation (3.3) in Section 3.

B Data Sources and Processing

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.[51] 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.

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 record in the EP, the information on all of its workers with social insurance is included from the IEB.[52] The reference date for both entries is June 30 of each year.

[51] The direct sources for the IEB are employee histories, benefit receipt histories, participants-in-measures histories, jobseeker histories, and unemployment benefit II receipt histories.
[52] 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.

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.[53]

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

Table B.1: 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/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 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 below 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*).

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.[54]

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).

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.

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

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

by Fitzenberger/Osikominu/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 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.

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/Schönberg (2009) and Card/Heining/Kline (2013). This extends the method developed by Gartner (2005) and adds a two-step procedure.[55] 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):

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

“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).

Task Complexity Index

The task 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 B.2) 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.

Occupational Classifications of Offshorability

In a robustness check, I apply the preferred offshorability measure from the Princeton Data Improvement Initiative (PDII) (Blinder/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/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.[56] 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,

[56] The data are publicly available at http://ibs.org.pl/en/resources/.

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/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 9, 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 B.2: Job Activities, Knowledge, Performance Requirements, and Tools

		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 B.2: ***(Continued)***

	Wave 1998/99		
Group	Var	Task	Coding of frequency
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 B.2: ***(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.
Source: BIBB-IAB work surveys 1998 and 2006.

C Additional Figures and Tables

Table C.1: 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 C.1 reports offshoring intensity and its growth by region (as defined in Section 2) for the years 1996, 2007, and 2007.
Sources: Own calculations. ©IAB

Table C.2: Correlations of Selected Tasks Indices and Wages

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Task complexity index	(three-digit occup.)	1							
(2) Average skill	(three-digit)	0.93	1						
Becker/Ekholm/Muendler (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/Koch (2017):									
(7) Offsh. Potential	(two-digit)	-0.88	-0.91	-0.90	-0.70	-0.94	-0.90	1	
Blinder/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

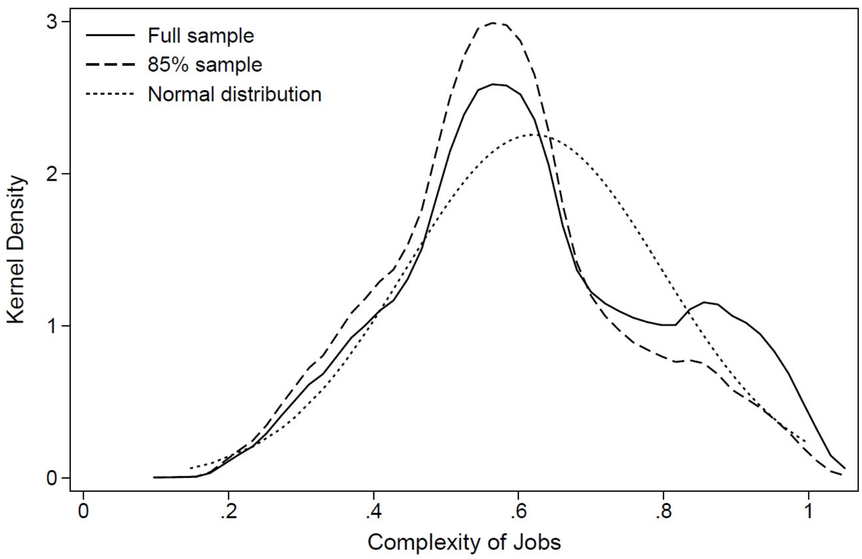
Source: German Qualification and Career Survey by BIBB-IAB work survey, LIAB.
Notes: The table presents the correlation coefficients of selected task indices from the literature utilizing the full sample. NR activities and NR interactive are based on the definitions developed by Spitz-Oener (2006). The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

Table C.3: 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. An asterisk * indicates interpolated values in the LIAB following the procedure described in Table B.1.
Sources: Own calculations. ©IAB

Figure C.1: Relative Frequency of Workers Along the Task Dimension



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 ($\mu = 0.6208; \sigma = 0.1768$).
Source: BIBB-IAB work survey and LIAB. ©IAB.

Table C.4: Single Regressions of Offshoring on Plant-Level Outcomes

	Cross-section, 1995			Panel, 1996 - 2007		
		State FE			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.

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Sources: Own calculations. ©IAB

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