Offshoring, tasks, and the skill-wage pattern

Daniel Baumgarten

(Ruhr Graduate School in Economics, RWI, Germany)

Ingo Geishecker

(Georg-August-Universität Göttingen, Germany and ASB, University of Aarhus, Denmark)

Holger Görg*

(Kiel Institute for the World Economy, University of Kiel and CEPR)

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Abstract

The paper investigates the relationship between offshoring, wages, and the ease with which occupational tasks can be offshored. We use rich individual-level panel data which allow us to measure wages, skill levels, and the nature of the tasks performed by individuals in their jobs. This is combined with data on offshoring activities of the industry. We use these data to empirically model the impact of offshoring on wages, and focus on how the wage effect of offshoring is simultaneously determined by the skill levels and tasks carried out by individuals. Our main results suggest that in an empirical setting that considers only within-industry changes in offshoring, wage effects are fairly modest but depend significantly on the extent to which the respective task requires personal interaction or can be described as non-routine. However, when

*****Corresponding author**, Christian-Albrechts-University of Kiel, Department of Economics, Wilhelm-Seelig-Platz 1, D-24118 Kiel, Phone: +49 431 880-1790, Fax: +49 431 880-1618, Email: goerg@economics.uni-kiel.de. The authors are grateful to seminar participants at Aarhus, Copenhagen, Frankfurt, Kiel, Trondheim and RWI Essen for helpful comments on earlier drafts. Daniel Baumgarten thanks the Leibniz Association for financial support. Holger Görg gratefully acknowledges financial support through the European Commission as part of the 7th Framework Programme, Grant Agreement No. 244 552.

allowing for cross-industry wage effects of offshoring the magnitude of the latter becomes substantial. Low- and medium-skilled workers experience significant wage cuts due to offshoring which, however, again strongly depend on the degree of personal interaction and non-routine content.

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JEL: F1, F2, J3

1 Introduction

Research on job tasks has become increasingly intensive in recent years. This is reflected in the labor economics literature by, for example, Autor et al. (2003), Spitz-Oener (2006) and Gathmann and Schönberg (2010). In the international trade literature, the concept of tasks has also entered into the debate on international outsourcing or offshoring. For example, Blinder (2006) argues that certain tasks that are interactive, i.e., require face-to-face contact are unlikely to be offshored (e.g., hairdressers, lawyers) while tasks without these characteristics may easily be moved abroad irrespective of their skill requirements (e.g., computer programmers). Levy and Murnane (2004) and Leamer and Storper (2001) also highlight the differences between what may be called routine and non-routine tasks, with the latter being less likely to be moved abroad. Grossmann and Rossi-Hansberg's (2008) influential paper picks up this thread, proposing a theoretical model that essentially redefines offshoring as trade in tasks rather than in the common meaning of trade in intermediate products.

What is clear from the earlier literature and also from the empirical work presented in this paper is that "tasks" are not synonymous with "skills". While there may be some overlap, non-routine or more interactive tasks are not necessarily identical with higher educational attainment. This is an important point that has strong implications for the potential labor market effects of offshoring. Traditionally, the literature has concluded that offshoring from industrialized countries has led to a shift in labor demand towards more skilled workers, implying that unskilled workers lose while skilled workers gain from this form of globalization (e.g., Feenstra and Hanson, 2001). However, when considering tasks as well as skills, the conclusions may be more subtle. This is what we show in this paper.

In the growing literature on offshoring and tasks our paper mainly relates to and expands on Becker, Ekholm and Muendler (2009) and Ebenstein, Harrison, McMillan and Phillips (2009).[1]

Becker et al. (2009) analyze the link between tasks, skills, offshoring by multinationals, and relative labor demand using German plant-level panel data. They estimate wage-bill share equations for skills and tasks, respectively, applying the trans-log cost function framework of Feenstra and Hanson (1996) and Head and Ries (2002). Their results indicate that offshore employment within multinational enterprices in manufacturing and service industries alike is related to onshore demand shifts away from routine and non-interactive job tasks suggesting that indeed offshorability is inversely related to the non-routine content and interactivity of job tasks. However, Becker et al. (2009) do no look at the interaction effect of tasks and skills. In particular, they do not examine to what extent the task-specific effects of offshoring on relative labor demand, which they document, go beyond any potential education-related heterogeneity in the offshoring effect.

employ cross sectional data from the US Current Population Surveys to assess the wage and employment effects of offshoring depending on the non-routine content of job tasks. Approximating offshoring by affiliate employment, similar to Becker et al. (2009), the authors find that individual wages are positively affected by offshoring towards high-income and negatively by offshoring towards low-income locations. However, both, positive and negative wage effects of offshoring are concentrated in occupations which are classified as most routine. What, furthermore, separates the paper of Ebenstein et al. (2009) from earlier micro-level studies (e.g., Liu and Trefler, 2008 and) is that they allow for cross-industry effects of offshoring, resulting in considerably larger wage effects of offshoring than in pure within-industry studies. Similar to Becker et al. (2009), Ebenstein et al. (2009), however, do not analyze the interaction of job tasks end educational attainment, that is they disregard within skill-group heterogeneity of offshoring effects that may be driven by the nature of occupational tasks.

Summarizing the literature on offshoring and tasks it is yet an open question whether there are indeed occupational task specific offshoring effects that go beyond any already established education-related heterogeneity. The main contribution of the paper is to shed some light on this issue. We are, to the best of our knowledge, the first to explicitly investigate the interaction between tasks and skills in order to gauge

[1] Other studies analyzing task specific offshoring effects include Crinò (2010) who looks at the impact of services offshoring on labor demand while differentiating between "tradable" and "non-tradable" occupations and Baumgarten (2009) who investigates the relationship between offshoring, tasks, and employment stability.

the effect of offshoring of activities on wages.

By using very rich individual-level panel data, we are able to assess in detail wages, skill levels, and the nature of the tasks performed by individuals in their jobs while controlling for a host of observable and unobservable characteristics at the individual and industry level.[2] This is combined with data on offshoring activities of the industry. We use these data to model empirically the impact of offshoring on wages, and focus on how the wage effect of offshoring is simultaneously determined by the skill levels and tasks carried out by individuals. Thus, we study the interaction between skill levels and tasks and investigate whether within skill groups, the nature of tasks carried out by an individual determines the effects of offshoring on wages. As Grossman and Rossi-Hansberg (2008) have suggested, the effects of offshoring depend on the cost of trading tasks, which may differ across different types of tasks. Hence, our working hypothesis is that, in the absence of a one-to-one relationship between tasks and skills, the interaction of the two variables matters. Our empirical results support this hypothesis.

We use two strategies for identifying a link between offshoring and wages. The first is to use within-industry changes in offshoring intensity and wages. Here, we rule out any wage effects that occur indirectly through offshoring in other industries. This makes our analysis essentially a short-run, partial equilibrium analysis.[3]

The second identification strategy is based on the idea that, in general equilibrium, individual i's wage is determined not only by offshoring activity in the industry in which i is employed, but also by offshoring and associated demand effects in other industries. Specifically, the wages of i holding occupation k will depend on offshoring activities affecting occupation k in any industry. Take, for example, electrical engineers working in the automobile and machinery industries. Offshoring an engineer's tasks in automobiles affects not only engineers in this industry, but also in the machinery industry, as engineers may move from automobiles into machinery and vice versa. Note, of course, that actual movement of workers is not required to generate these cross-industry effects: the potential for movement is sufficient.

Our empirical results show that wage effects of offshoring are heterogeneous within

[2]While the analysis of Ebenstein et al. (2009) is also at the individual level, the nature of their data does not allow them to control for many observed individual characteristics or unobserved individual effects.

[3]This is a common assumption in the literature. It is, for example, implicit in the studies examining the relationship between relative labor demand and offshoring using aggregate industry-level data (Feenstra and Hanson, 2001). Studies using individual-level data, such as Geishecker and Görg (2008) or Liu and Trefler (2008) are based on the same assumption.

skill groups, depending on the degree of interactivity or non-routine content of the respective tasks of workers. Thus, the more traditional dichotomy between high-skilled and low-skilled workers may need to be revised, taking the nature of tasks into account.

Another important finding is that the standard partial equilibrium effect, that is, the impact of offshoring in the individual's own industry, is quite low. However, when allowing for wage effects across industries we find the latter to be substantial and economically highly significant. In the next section, we provide a brief review of the theoretical background that motivates our empirical analysis. We then give a detailed account of our data and the classification of tasks according to their degree of interactivity and non-routine content. Section 4 explains the empirical model and addresses potential caveats. Our partial equilibrium, within-industry results are presented in Section 5, while Section 6 shows our estimates when allowing for cross-industry wage effects of offshoring. Section 7 concludes the analysis.

2 Theoretical Background

The theoretical model of Grossman and Rossi-Hansberg (2008) can serve as a guide to motivate our empirical analysis. In their model, a firm produces output using a continuum of tasks that are performed by either low-skilled (L-tasks) or high-skilled (H-tasks) workers. These tasks can be carried out either at home or abroad. Offshoring tasks is costly, and these costs differ across tasks. Carrying out tasks abroad may be advantageous due to factor cost differences, but these potential savings have to be weighed against the costs of offshoring.

In this setup, there are three types of effects on wages if offshoring costs for one set of tasks decline, that is, if offshoring of one set of tasks increases. First, increased offshoring of a specific set of tasks raises the productivity of the factor that usually performs these tasks, and thereby generates a real wage increase for this factor. Second, there is a labor supply effect. The excess workers who have been freed up through offshoring have to be re-absorbed in the economy, which leads to a fall in the real wage for the factor that performs the offshored tasks. Third, there is a relative price effect, whereby the price of the final good that uses offshoring declines. This will, via the familiar Stolper-Samuelson effect, also negatively affect the wages of the workers that carry out the offshored task. In sum, the model predicts an ambiguous effect of increased offshoring depending on the relative strength of the positive productivity and negative factor supply and relative price effects.

Note that, for our empirical strategy, it is important to point out that the productivity and labor supply effects are elaborated in the Grossmann and Rossi-Hansberg model in a setting where they focus on a single sector with a fixed supply of low- and high-skilled workers. This scenario corresponds to a short-run view of the economy, where labor is immobile between industries, and thus to our first identification strategy, where we examine the impact of changes in within-industry offshoring on within-industry wages, abstracting from the mobility of labor across industries. These two effects also hold in general equilibrium, where the additional relative price effect also comes into play.

Rather than solely testing the model predictions for low-skilled and high-skilled workers, we expand on the idea that different sets of tasks have different offshoring costs, which may be only loosely related to skills. Thus, we go beyond simply associating what Grossman and Rossi-Hansberg call "L-tasks" and "H-tasks" with low-skilled and high-skilled workers. If it is indeed the case that, for example, non-routine tasks are less easily offshored (i.e., have higher costs of being offshored), as suggested in recent papers, then we would expect that, within the group of, say, low-skilled workers, the wage effects of offshoring should differ for those individuals carrying out non-routine tasks as compared to those who perform simple routine tasks. The same goes for high-skilled workers. Our empirical results are in line with this contention.

3 Data and Methodology

The empirical strategy in this paper rests on combining individual-level data on wages and worker characteristics with more aggregate data on offshoring activity and other observable industry characteristics. For the former, we use data from the German Socio-Economic Panel (SOEP), a representative longitudinal survey of private households in Germany, for the years 1991-2006.[4] We restrict our unbalanced sample to prime-age (18–65 years) employees in the manufacturing sector (NACE/ISIC 15–36). To abstract from gender-specific labor market outcomes (see, e.g., Prasad, 2004; Beaudry and Green, 2003) we focus exclusively on males. In our empirical model, we

[4]Specifically, we use sample A–F of SOEP. Wagner, Frick and Schupp (2007) provide a detailed description of the SOEP. Our data was extracted using the add-on package PanelWhiz for Stata. Panelwhiz (http://www.PanelWhiz.eu) was written by Dr. John P. Haisken DeNew (john@PanelWhiz.eu). See Haisken-DeNew and Hahn (2006) for details. The do-file generated by PanelWhiz to retrieve the data in the present paper is available from the authors upon request. Any data or computational errors in the paper are our own.

utilize retrospectively collected yearly labor earnings and yearly work hours from the Cross-National Equivalent files (CNEF), including payments from bonuses, overtime, and profit-sharing. Excluding observations with missing or imputed wage information, this yields 13,189 observations for 2,063 individuals.[5,6]

In order to obtain task-based measures of *offshorability* we employ occupational information following the classification of the German Federal Statistical Office (*Klassifizierung der Berufe – KldB92*) that has only recently become available in the SOEP. On the basis of this disaggregated occupational coding, we can map associated task contents, which are calculated using yet another micro-level data set, the German Qualification and Career Survey 1998/99. The main part of our analysis is based on the mapping procedure used by Becker et al. (2009).[7]

To make the German Qualification and Career Survey sample comparable to the one used in our wage regression, we restrict the sample to males aged 18 to 65, which leaves us with some 19,000 individuals (out of about 34,000). Our occupational grouping is based on the two-digit level of the KldB92, which is available in both data sets. Only in cases where occupational cells become too small do we switch to the next-highest level of aggregation.[8]

The distinct advantage of this survey is that respondents not only state their occupation but also give a detailed account of the tasks they perform on the job and the associated work tools they use to do so. Using this detailed information, Becker et al. (2009) propose a mapping of tasks into occupations.

In a first step, each of the 81 surveyed tools and thereby each task is classified as (i) routine or non-routine and (ii) interactive or non-interactive, where the former grouping refers to non-repetitive tasks and the latter to tasks requiring interpersonal contact. For illustration, the use of an overhead projector or beamer is coded as

[5]According to Frick and Grabka (2003), the imputation procedure disregards industry-level information such as offshoring. As a result, the imputation of missing wage information compresses the wage distribution with respect to the industry-level variables that are of most interest for our analysis and is therefore not suitable for this application.

[6]In principle, it would also be possible to conduct the analysis relying on the IAB Employment Sample (IABS), a considerably larger micro data set based on administrative social security records. For the question at hand, we prefer the SOEP for several reasons. First, wages are not top-coded as in the IABS. Second, in contrast to the IABS the SOEP contains information on the hours of work. Third, the IABS follows the NACE industry classification – which enables us to merge offshoring information from input-output tables – only from 1999 onwards whereas it is available in the SOEP as early as 1991.

[7]The German Qualification and Career Survey was previously used, for example, by DiNardo and Pischke (1997). Like Becker et al. (2009) we rely on the most recent wave as it follows a comparable occupational classification (KldB92).

[8]The classification contains five levels of aggregation. The two-digit level is the third-highest and distinguishes 88 occupational groups. The next-highest consists of 33 occupational sections while the highest level differentiates between six broad occupational areas (Statistisches Bundesamt, 1992).

both non-routine and interactive, whereas the opposite holds for computer-controlled machinery. Simple means of transport are an example of tools denoting an interactive but routine task, whereas precision-mechanical tools are coded as non-routine and non-interactive (see Table A1 in Appendix 1 for a list of surveyed tools and their respective classifications).[9] To check the robustness of our results, we also use an alternative task classification which is based on a separate list of 13 job descriptions that is available in the same data set (see Table A2 in Appendix A). It is the same set of questions that was first used by Spitz-Oener (2006). For ease of exposition, we will in the following refer to this alternative task classification as Spitz-Oener-based mapping even though it is not strictly identical.

In a next step, the number of non-routine and of interactive tasks are averaged over occupations. Accordingly, a higher number implies a more intensive use of the associated task category.

Finally, for every occupation, a continuous task intensity measure in the range of 0 to 1 − where 1 denotes maximum intensity − is derived by normalizing the figures by the maximum sum of non-routine and interactive tasks in any occupation. Thus, in compact form, the formula reads as follows:

$$Task\,Intensity_{kz} = \frac{\text{Average number of } z\text{-tasks in occupation } k}{\text{Maximum average number of } z\text{-tasks}}, \tag{1}$$

where k denotes the occupation and $z \in \{\text{non-routine, interactive}\}$ the task category.

On the basis of these mappings, occupations are classified according to their non-routine or interactive task contents, irrespective of the associated educational attainment of workers. Accordingly, it is in principle possible to observe, for example, some highly non-routine (interactive) tasks to be performed by low-skilled workers, and vice versa.

To what extent non-routine and interactive tasks and skills, measured in terms of educational attainment, are related is summarized in Table 1.[10] As becomes apparent in the mean comparison tests, high-skilled workers on average have occupations with a significantly higher content of interactive as well as non-routine tasks. However, from Figures 1 and 2 it also becomes clear that although high-skilled workers indeed tend to have occupations with higher interactive and non-routine content than low-

[9] We use the authors' preferred strict classification, where only a few tasks are coded as interactive (non-routine). However, the results stay virtually the same when relying on the authors' lenient classification instead.

[10] The exact definition of skills is provided in the next section.

skilled workers, there is significant heterogeneity within skill groups. Thus, while higher skills and non-routine and more interactive tasks seem to be correlated, we can nevertheless identify low-skilled manufacturing workers that occupy positions that are highly interactive or non-routine and vice versa.

Among the low-skilled, a typical occupation characterized by low non-routine content is “storekeeper, warehouse keeper” while “assemblers” is an example of an occupation with low interactivity. “Metalworkers,” the largest occupational group among low-skilled workers, score low in our interactivity index but are in the medium range of our non-routine indicator. On the other hand, “truck drivers” display a low intensity of non-routine tasks but have frequent interactions with co-workers or third parties.

“Technicians” are the largest occupational group among the medium-skilled. They carry out a rather high proportion of both non-routine and interactive tasks. By contrast, a typical occupation that displays considerably lower task intensities is that of “office clerk”.

“Engineers” are the most frequently encountered occupational group among the high-skilled, followed by “managers”. Both occupations are characterized by high degrees of non-routine and interactive tasks, which also explains the rather low standard deviation of the task indices for the group of the high-skilled. However, there is still heterogeneity. For example, “computer scientists” are characterized by a high non-routine content but are less intensive in interactive tasks.

The question for the econometric analysis is now whether workers with highly interactive or non-routine occupations are indeed differently affected by increased offshoring than their counterparts with occupations that have low interactivity and are fairly routine. To answer this question, we first proceed by assuming that that workers' wages are affected by offshoring activity in the industry in which the worker is employed, similar to, e.g., Feenstra and Hanson (1996), Geishecker and Görg (2008) and Crinò (2010).[11]

In order to implement this strategy, we merge our individual-level data with industry-level offshoring measures. Offshoring is constructed by utilizing input-output tables provided by the German Federal Statistical Office that separately report industry by industry imported intermediate inputs.[12] We follow a narrow concept of materials offshoring by focusing on imported intermediate inputs that correspond to

[11]In Section 6 we relax this assumption and consider cross-industry effects of offshoring.

[12]The earliest input-output table that follows a comparable industry classification scheme is available for the year 1991. The latest is from 2009 for the year 2006. See e.g., Statistisches Bundesamt (2009), Table 1.2.

a make-or-buy decision, that is, inputs that in principle could be produced by the importing industry itself (see Feenstra and Hanson, 1999). Accordingly, we focus on the main diagonal of our input-output table for imports. We consider this offshoring measure to be more accurate than relying solely on affiliate employment (as in, e.g., Ebenstein et al., 2009) since i) affiliate employment also reflects horizontal MNE activities and ii) not all offshoring takes place through foreign direct investment.

Formally we can denote offshoring as:

$$OS_{jt} = \frac{IMP_{j^*t}}{Y_{jt}} \tag{2}$$

with IMP_{j^*t} denoting imported intermediate inputs from industry j^* as reported in input-output tables and Y_{jt} the production value of industry j at time t.

Figure 3 depicts the weighted average offshoring intensity in manufacturing for the years 1991 to 2006. The average offshoring intensity grew substantially during our sample period: between 1991 and 2006 it increased from 6.6 to 10.3 percent.

4 Empirical Model

To assess the wage impact of offshoring conditional on observed and unobserved heterogeneity, we estimate variants of the following Mincer wage equation:[13]

$$
\begin{aligned}
\ln WAGE_{ijt} &= \alpha + \beta\ DEMOG_{it} + \gamma\ WORK_{it} \qquad (3)\\
&+ \sum_{e-1} \delta_e\ EDUC_{eit} + \sum_{e} \eta_e EDUC_{eit} \times TASK_{it}\\
&+ \theta\ IND_{jt} + \sum_{e} \lambda_e OS_{jt} \times EDUC_{eit}\\
&+ \sum_{e} \nu_e OS_{jt} \times EDUC_{eit} \times TASK_{it}\\
&+ \rho R\&D/Y_{jt} + \tau_j + \mu_t + \iota_i + \epsilon_{ijt}
\end{aligned}
$$

where $WAGE_{ijt}$ denotes individual i's hourly wage in industry j at time t and $e = 1, ..., 3$ represents high-, medium-, and low-skilled workers.

Our controls include the standard variables in such wage regressions, see, for example, Mincer (1974), Brown and Medoff (1989), Schmidt and Zimmermann (1991). Descriptive statistics on all control variables are provided in Appendix D. $DEMOG$ denotes the demographic control variables for marital status, children, and geographic region.[14] The second set of control variables ($WORK$) refers to workplace-related characteristics such as firm size and firm ownership as well as tenure.

We also control for time-changing observable industry characteristics (IND) by including the size of the industry (measured in terms of output Y) and equipment and plant capital intensity ($Cap_{Equ,Plant}/Y$). To capture industry-level technological change we include research and development intensity ($R\&D/Y_j$) as an input-based industry-level technology measure. However, the three panel dimensions also allow us to include a full set of industry-specific time trends that capture industry-level technological change over and above common macroeconomic trends accounted for by μ_t. We employ these trends as an alternative to industry-level research and development intensity in a robustness regression.

To control for as much unobserved heterogeneity as possible, we make full use of the three dimensions, i, j, and t, in our panel data and decompose the error term

[13] Our empirical model builds on Geishecker and Görg (2008) but goes further by incorporating heterogeneous tasks into the model.

[14] We do not control for age as age together with individual fixed effects and time dummies would result in perfect collinearity.

into industry fixed effects τ_j, time fixed effects μ_t, individual fixed effects ι_i and a remaining error term ϵ_{ijt}.[15]

Since we combine micro-level and aggregate data we calculate cluster-robust standard errors applying the sandwich formula proposed in White (1980) and Arellano (1987). However, this approach has its limitations if the number of clusters is small relative to the number of observations per cluster. In our application, we look at 21 industries, that is, 21 clusters, each containing a fairly large number of individuals. In order to check how sensitive our results are to this type of cluster adjustment, we also apply a pairs-cluster bootstrap-t procedure with 500 repetitions that, as demonstrated in Monte-Carlo simulations by Cameron et al. (2008), yields considerably more precise t-tests.

Particular attention is paid in the empirical model to educational controls based on the International Standard Classification of Education (ISECD). $EDUC$ contains educational dummies for high education ($e = 1 : High{-}Skilled$) and medium ($e = 2 : Medium{-}Skilled$) education; low education ($e = 3 : Low{-}Skilled$) is the omitted category.[16]

In addition, we control for the nature of job tasks of individuals by including our constructed interactivity and non-routine indices, respectively. We do this by interacting the respective task index with the educational attainment dummies, thereby allowing for heterogeneous task effects across skill groups ($EDUC \times TASK$). To account for the potentially heterogeneous impact of offshoring across skill groups and tasks, we interact offshoring with the educational dummies ($OS \times EDUC$) and also include triple interaction terms for offshoring ($OS \times EDUC \times TASK$).[17]

Accordingly, the marginal effect of offshoring for the different skill groups $e = 1, ..., 3$ can be denoted as:

$$\left(\frac{\partial \ln WAGE_{ijt}}{\partial OS_{jt}}\right)_e = \lambda_e + \nu_e \times TASK_{it} \ . \tag{4}$$

[15] Industry fixed effects are not perfectly collinear with individual fixed effects, since individuals can change industry. For these cases, industry fixed effects control for level differences in our time-changing industry variables such as output or offshoring.

[16] Low-skilled workers are workers with second-stage basic education, lower secondary education, or less. Medium-skilled workers have upper secondary education, post-secondary non-tertiary education, or first-stage tertiary education. High-skilled workers have at least second-stage tertiary education.

[17] Note that we include a complete set of interactions, i.e., interactions of three education dummies with the respective variables. Hence, there is no omitted category and no need for the inclusion of the interaction term $OS \times TASK$. Education itself is controlled for by two dummies for high- and medium-skilled workers. The constant controls for the default category low-skilled workers.

We therefore allow for heterogeneous effects of offshoring within skill groups depending on the corresponding non-routine or interactivity index. Thereby, we also make sure that any task-related heterogeneity in the offshoring effect is not already accounted for by education-related heterogeneity, which was the focus of previous empirical work (e.g., Geishecker and Görg, 2008).

One particular concern with our empirical analysis is that offshoring may be endogenous to wages. This would be the case if, for example, offshoring took place in high wage industries in order to exploit cost savings potentials abroad. We have two replies to this concern. Firstly, since individual wages must have a substantially higher variance than industry averages, potential endogeneity bias is considerably reduced, that is, individual wages are unlikely to affect industry-level aggregates such as offshoring. We expand and illustrate this argument in Appendix B. Secondly, we test for exogeneity of our offshoring measures and are unable to reject the H_0 of exogeneity within reasonable confidence bounds. To do so, we utilize offshoring of UK industries as excluded instruments, applying a narrow and broad definition of offshoring as in Feenstra and Hanson (1996,1999). To the extent that the within industry variation of offshoring in German manufacturing is driven by European or worldwide trade liberalisation or changes in production and transportation technologies one would expect a similar variation of industry-level offshoring in UK manufacturing while orthogonality of UK offshoring and German wages can be maintained (see Haskel, Pereira and Slaughter, 2007, for an application in similar spirit). As indicated by the test statistics in Table B1 in Appendix B, industry-level offshoring in Germany the UK are indeed sufficiently correlated while orthogonality cannot be rejected.[18]

5 Within-Industry Results

We estimate various specifications of Equation 3 for different task groupings. The main estimation results are presented in Table 2 for the interactivity task index and

[18] A second possible concern about endogeneity is the potential endogeneity of individuals' tasks (as stressed by Autor and Handel (2009)) since workers may readily switch between different sets of tasks depending on associated wages. However, in contrast to Autor and Handel (2009), we do not look at within-occupation task variations. In our approach, every task intensity is linked precisely to one occupation. Arguably, we thereby miss a potentially important source of within-occupation wage differentials. However, individuals rarely change occupation and when they do they are more likely to choose occupations with a similar task content (see Gathmann and Schönberg, 2010) in order to minimize task-specific human capital losses. In our sample, only 445 occupation changes (of 13,188 observations) take place between 1991 and 2006. We therefore consider simultaneity between wages and tasks to be of lesser concern when looking at task-specific offshoring effects. The importance of unobserved characteristics for determining initial occupational choices is taken into account in our model through the inclusion of individual fixed effects.

Table 3 for the non-routine task index following the methodology proposed by Becker et al. (2009).

The results presented in Column (a) refer to a baseline specification, where our offshoring indicator enters in a non-interacted way. The specification in Column (b) allows the effect of offshoring to vary with the skill level, and Column (c), finally, presents the results of our fully interacted model, including triple interaction terms between offshoring, skills, and our task intensity measures.

Furthermore, the last column in Tables 2 and 3 reports the significance levels corresponding to the pairs-cluster bootstrapped t-statistics, which we perform for the third specification only. Note that these bootstrapped t-statistics generally confirm the conventional cluster-robust t-tests or even point to statistical significance when conventional t-statistics do not. Thus, in our application, the number of clusters (industries) seems large enough to avoid the serious over-rejection problems discussed by Cameron et al. (2008).

In the present analysis, we are of course mainly interested in the effects of offshoring and merely control for any observable and unobservable heterogeneity that may otherwise bias our results. Regarding the standard demographic and workplace-related control variables, coefficients are identified through time variation and generally have the expected sign and magnitude but, conditional on our comprehensive unobserved heterogeneity controls, often cannot be estimated with sufficient precision.

Focusing on statistically significant coefficients according to our pairs-cluster bootstrapped t-statistics in Tables 2 and 3 (last column), we find, ceteris paribus, that workers who change into firms with 20 to 199 employees experience wage cuts of four percent, compared to firms with more than 2,000 employees, our default category.[19]

Furthermore, overall work experience in full-time employment plays an important role. The coefficients on full-time work experience in levels and squared are jointly statistically significant[20] and have opposite signs, suggesting a concave relationship between hourly wages and work experience. While initially every additional year of full-time work experience raises hourly wages by about two percent, the effect becomes smaller as work experience increases, and from 32 years of work experience onwards, actually turns negative. For part-time work experience (linear and quadratic) as well as tenure, however, we find no statistically significant effects.

[19]The effect is also identified through individuals who stay in firms that grow and switch between categories.

[20]F-test for interactivity based regression: F=6.68, p=0.01. F-test for non-routine content based regression: F=6.99, p=0.01.

In addition, we find recent unemployment spells to play a significant penalizing role for wages over and above work experience and unobserved time-constant individual characteristics. Individuals who experienced an unemployment spell during the year preceding the interview month experienced hourly wage cuts of 15 percent ($(e^{-0.16} - 1) * 100$) when re-entering employment. Whether this wage penalty of unemployment experience works through, for instance, actual human capital deterioration or is the result of labor market signaling is beyond the scope of the present analysis.

Regarding educational attainment, we only identify weakly significant direct wage premia for medium skilled workers in the interactivity-based regression and for high-skilled workers in the non-routine-based regression. However, in a specification with individual fixed effects, this is what one would expect, as few individuals switch between skill groups. Furthermore, if one were actually interested in the overall skill wage premium one has to take into account all education interaction terms.

Likewise, we only find a statistically significant direct wage effect with respect to the interactivity-based task index when interacted with medium skills, and a weakly statistically significant direct wage effect with respect to the non-routine content of tasks when interacted with high skills. Again, this is likely due to the fact that individuals rarely change between different types of tasks.[21]

Regarding time-changing industry-level control variables other than offshoring, we find a statistically significant positive wage effect of research and development intensity ($R\&D/Y$), which is particularly true for low- and medium-skilled workers. For them, a percentage point increase in R&D intensity is associated with a rise in wages by about one percent. In contrast, the coefficients on the capital-output ratio (for equipment and plant capital) are not statistically significant.[22]

Conditional on our large set of controls for observed and unobserved heterogeneity, we can look at the offshoring coefficients and their respective interaction terms. As becomes apparent from Columns (a) and (b) in Tables 2 and 3 we find no statistically significant wage effect of overall offshoring and offshoring by skill-group. However, in line with the reasoning of Leamer and Storper (2001), Levy and Murnane (2004), and Blinder (2006) one would expect that the effects of offshoring are fairly heterogeneous within skill groups depending on the ease with which different tasks can be offshored.

[21] Nevertheless, as educational attainment and task intensity are part of our interaction terms, it is essential to also include them in a non-interacted way.

[22] Regarding the wage impact of output changes, which is not our concern in the present analysis, it is important to note that one needs to take into account the coefficients on all variables were output is in the denominator when calculating the marginal effect.

To see this, however, one cannot rely solely on the reported coefficients and t-test in Column (c) of Tables 2 and 3.

Equation 4 denotes the marginal effects of offshoring for the different skill groups. Accordingly, the specific wage impact of offshoring is not constant and can only be evaluated at some value of the interactivity or non-routine task index. What matters for the statistical significance of offshoring for the different skill groups $e = 1, ..., 3$ is the joint significance of the coefficients λ_e and ν_e, i.e., the coefficients of skill-interacted offshoring $(OS_{jt} \times EDUC_{eit})$ and the triple interaction terms of skill, task index, and offshoring $(OS_{jt} \times EDUCeit \times TASK_{it})$. Accordingly, at the bottom of Tables 2 and 3 we report corresponding F-test of joint significance. In addition we illustrate the changing marginal effect of offshoring and its corresponding confidence band in Figures 4 and 5. When applying our interactivity-based task classification we find jointly significant offshoring coefficients and corresponding interaction terms for low- and medium-skilled workers, respectively. As can be seen in Figure 4, a one percentage-point increase in offshoring reduces hourly wages for medium- and low-skilled workers in the very bottom category of interactivity by about two and one percent, respectively, an effect that with a rising degree of interactivity becomes less severe and eventually positive.

When applying our task classification based on non-routine content we find a jointly significant effect of offshoring for low-skilled workers but not for medium-, and high-skilled workers. As visible in Figure 5 a one percentage point increase in offshoring reduces hourly wages of low-skilled workers in the bottom category of non-routine content by about one percent.

Clearly, these wage effects of offshoring appear to be rather small. However, rather than focusing on statistical significance and the size of the marginal effect, what we are really interested in is economic significance that takes into account the actual change in offshoring intensity, i.e., how much wages have changed due to increased offshoring. Obviously, this information is not contained in standard regression output.

We engage in a thought experiment and ask how much hourly wages would have increased or decreased had offshoring remained constant at its 1991 value.[23] We do this separately for low-, medium-, and high-skilled workers, and further distinguish between the types of tasks within skill groups by looking at the 10th, 50th, and 90th percentiles of the respective interactivity and non-routine content of tasks. Table 4

[23]Note that to do so we assume that changes in offshoring intensity are essentially marginal.

presents the outcome of this exercise for our interactivity and non-routine content task classification, respectively. Bold figures represent simulations where coefficients on the skill-interacted offshoring measures and the triple interaction terms are jointly statistically significant.

Focusing first on low-skilled workers, variables and interaction terms that relate to offshoring are, according to the reported F-tests, found to be jointly statistically significant for the interactivity as well as the non-routine content task classification. Applying the interactivity-based task classification, we find that had offshoring remained constant at its 1991 value instead of increasing by 3.75 percentage points, low-skilled workers in the lowest decile of interactivity, ceteris paribus, would have earned 46 euro cents (i.e., 3.07 percent of 1991 average low-skilled wages) more per hour in 2006 than they actually did. Low-skilled workers in the 50th percentile, however, only incur wage cuts of 13 euro cents, or 0.86 percent, while low-skilled workers in the 90th percentile experience small wage increases of 16 euro cents, or 1.06 percent.

When instead classifying offshorability along the lines of non-routine contents of tasks, we find very similar effects. Taken together, the cumulative effect of increased offshoring is a 41 euro cent (2.78 percent) reduction in hourly wages for low-skilled workers in the bottom decile of non-routine tasks content. Low-skilled workers in the 50th percentile of non-routine content only experience wage cuts of 18 euro cents (1.20 percent), while workers in the 90th percentile gain 30 euro cents (2.04 percent).

Clearly, these partial equilibrium effects have some economic relevance. To signify the size of the effects, assuming 1,500 work hours per year, offshoring accounts for a 690 (interactivity-based task classification) to 615 (non-routine content based task classification) euro reduction in yearly gross wages (in constant 2000 prices) for low-skilled workers whose tasks are most easily offshored. However, low-skilled workers whose tasks are most difficult to offshore, that is, workers whose tasks are most interactive or have the highest non-routine content, are only positively affected by industry offshoring. Due to offshoring, their gross yearly income (in constant 2000 prices) increases by between 240 and 450 euros.[24]

For medium-skilled workers, coefficients are only estimated with sufficient precision when applying the interactivity-based task classification. Again, the within-industry effects of offshoring follow a similar pattern as for low-skilled workers. Medium-skilled

[24] Accordingly, our results also imply that task-specific offshoring effects are one potential source of the recent increase in wage inequality within skill groups that has been documented in, for example, Dustmann et al. (2009) and Antonczyk et al. (2009).

workers with the lowest degree of interactivity experience cumulative wage cuts of 68 euro cents (4.03 percent), while medium-skilled workers at the 50th and 90th percentile experience cumulative wage gains of 11 and 47 euro cents, respectively. For high-skilled workers, however, statistical significance has to be generally rejected.

To test for the robustness of our findings with respect to an alternative classification of tasks, we proceed by employing the methodology based on Spitz-Oener (2006), which is illustrated in Appendix A and re-estimate Equation 3. For the sake of brevity we only report the estimates of economic significance, they are shown at the bottom of Table 4. While the effects of offshoring are identified with considerably less precision there are some striking similarities across the different task classification schemes, at least for low skilled workers. We find that low-skilled workers who carry out tasks in the bottom decile of interactivity and non-routine content experience cumulative wage cuts of 26 and 29 euro cents, respectively. Low-skilled workers in the 50th percentile of interactivity and non-routine content, however, only experience wage cuts of 20 and 17 euro cents, respectively. At the same time, we find low-skilled workers in the 90th percentile of interactivity and non-routine content to gain 6 and 9 euro cents respectively. These effects are, however, only weakly statistically significant.[25]

6 Cross-Industry Results

We proceed by explicitly dropping the assumption that workers are immobile between industries, that is, we want to look at the effects of offshoring that may be considered more long run. As already discussed in Section 1, in general equilibrium, individual i's wages are not only determined by offshoring activity in the industry j in which i is employed, but also by offshoring activities in other industries $l \in J$, insofar as these activities affect the overall demand for labor that individual i faces. What is important is that no actual movement of workers is required to generate these cross-industry effects; the potential for movement suffices.

One way of approximating these wage effects of offshoring is to use occupation-

[25] In order to further test for the robustness of our findings we re-estimate the model employing industry-specific time trends instead of industry research and development intensity as an alternative control for technological progress. As reported in Table C1 in Appendix C offshoring effects have a similar magnitude and follow the same pattern with respect to the degree of interactivity and non-routine content. We also estimate the model restricting the sample to individuals who do not switch between industries in order to rule out the possibility that the offshoring effect is driven by the endogenous reallocation of workers across industries. As indicated by the coefficients reported in Table C1 in Appendix C the magnitude and the pattern of our previous findings is hardly altered although for the non-routine content task classification the effects are not identified with sufficient precision.

specific measures of offshoring. Thus, we allow for cross-industry effects of offshoring by making the identifying assumption that workers are reluctant or unable to change occupation but readily switch between industries. In order to implement this, we build on Ebenstein et al. (2009) and construct occupation-specific offshoring by re-weighting industry-level offshoring measures (cf. Equation 2) with respect to industry employment within a given occupation k as a share in total employment L within occupation k in 1991.

$$OS_{kt} = \sum_{j=1}^{J} \frac{L_{kj}}{L_k} OS_{jt} \tag{5}$$

Accordingly, we re-estimate Equation 3 substituting OS_{jt} for OS_{kt}.

$$\begin{aligned} \ln WAGE_{ikt} &= \alpha + \beta\ DEMOG_{it} + \gamma\ WORK_{it} \\ &+ \sum_{e-1} \delta_e\ EDUC_{eit} \\ &+ \theta\ OCC_{kt} + \sum_{e} \lambda_e OS_{kt} \times EDUC_{eit} \\ &+ \sum_{e} \nu_e OS_{kt} \times EDUC_{eit} \times TASK_{it} \\ &+ \rho R\&D/Y_{kt} + \tau_k + \mu_t + \iota_i + \epsilon_{ikt} \end{aligned} \tag{6}$$

where $WAGE_{ikt}$ denotes individual i's hourly wage in occupation k at time t and $e = 1, ..., 3$ represents high-, medium-, and low-skilled workers.[26]

We now control for occupation-specific observable characteristics by including occupation-specific output, capital, and R&D intensity that are constructed applying the same methodology as in Equation 5. Occupation-specific unobservable characteristics are captured by a full set of occupation dummies τ_k. Since each occupation corresponds to exactly one time-constant task intensity in our data, we have perfect collinearity between the two variable sets. Accordingly, our occupation dummies also capture the respective interactivity and non-routine content of associated tasks.

Tables 5 and 6 report the parameter estimates applying the task classification scheme of Becker et al. (2009). Regarding our standard control variables, coefficients are very similar to the ones in Tables 2 and 3. However, when applying the occupation-

[26]We now have 61 clusters (occupations) instead of 21 (industries) in the previous analysis. Thus, we consider standard cluster-robust standard errors and corresponding t-tests to suffice and do not construct pairs-cluster bootstrapped t-statistics.

specific measure from Equation 5 we find a much more pronounced effect of offshoring. Irrespective of whether we apply the interactivity or non-routine content based task classification we find occupation-specific offshoring and its task interaction term to be jointly significant for low- and medium-skilled workers while (as with industry-specific offshoring) effects for high-skilled workers cannot be identified with sufficient precision(see Tables 5 and 6). As becomes apparent in Figures 6 and 7 the marginal effects of occupation-specific offshoring are sizable: a one percentage point increase in offshoring reduces hourly wages for medium and low-skilled workers in the lowest category of interactivity or non-routine content by four to five percent.

We now look at the economic significance of occupation-specific offshoring for each skill group at selected reference points for the degree of interactivity and non-routine content. Clearly, as is reported in Table 7, we find occupation-specific offshoring effects for low- and medium-skilled workers to be strong and to significantly differ across different degrees of interactivity and non-routine content of tasks.

Low-skilled workers in the 10th percentile of interactivity experience cumulated wage cuts of 1.80 euros (12.13 percent) per hour. For low-skilled workers in the 50th percentile of interactivity, this cumulated wage cut is 1.12 euros while low-skilled workers with the highest degree of interactivity only experience wage cuts of 0.53 euros. These wage effects are substantial and considerably larger than in the within-industry case. Assuming 1,500 yearly work hours, low-skilled workers earn between 795 and 2,700 euros less due to offshoring depending on the degree of interactivity of the tasks they perform.

A similar pattern can be observed for medium-skilled workers although at a generally more pronounced level. The cumulative wage cut due to offshoring is highest for workers in the lowest interactivity decile (2.36 euros) and becomes less severe the higher the degree of interactivity becomes (1.08 euros for the top decile). Again assuming 1,500 yearly work hours, we can calculate a cumulative wage reduction of 3,540 euros for medium-skilled workers in the lowest interactivity decile, 2,205 euros for the median interactivity degree, and 1,620 euro for the top interactivity decile.

These figures are robust to the application of different task classification schemes. When applying the task classification scheme by Becker et al. (2009) but looking at the non-routine content of tasks instead of their degree of interactivity, we find very similar wage effects. Also, we find very similar economic effects when considering the classification scheme based on Spitz-Oener (2006), as shown in the bottom panel of the table.[27]

7 Conclusion

The paper analyes the effects of offshoring on individual-level wages, taking into account the ease with which individuals' tasks can be offshored. Our analysis relates to contributions such as Blinder (2006), Levy and Murnane (2004), and Leamer and Storper (2001), who postulate that there is only a loose relationship between the suitability of a task for offshoring and the associated skill level. Instead, these authors stress that the degree of offshorability depends on the relative importance of routine versus non-routine tasks and on the extent to which personal interaction is needed on the job.

For the empirical analysis we combine individual-level data and industry-level offshoring measures and classify tasks according to their degree of interactivity and non-routine content, applying two alternative classification schemes that build on Becker et al. (2009) and Spitz-Oener (2006). By studying the effects of industry-level offshoring at the individual level we can control for a host of observable and unobservable individual characteristics, thereby avoiding aggregation and reducing potential endogeneity bias. By using micro-level data we can investigate the interaction between tasks and skills; thus, we can identify task-specific wage effects of offshoring within as well as between the groups of high-, medium-, and low-skilled workers.

In line with earlier research, we find the within-industry impact of offshoring on individual wages to be rather modest. However, our empirical results also indicate that the within-industry wage effects offshoring are heterogeneous within skill groups depending on the degree of interactivity or non-routine content of the respective tasks of workers.

When looking at the cross-industry effects of offshoring, we find substantial negative wage effects of offshoring for low- and medium-skilled workers. Hence, in the context of the model proposed by Grossman and Rossi-Hansberg (2008), the wage-reducing labor supply and terms-of-trade effects in most cases appear to dominate the positive productivity effect of offshoring for low- and medium-skilled workers in our

[27] As in our discussion on the within-industry effects of offshoring we further test for the robustness of our results by applying an alternative set of technology controls as well as focusing on pure within-occupation changes, thus excluding individuals who have changed occupation during our sample period. As reported in Table C2 in Appendix C the size and pattern of our coefficients generally do not change significantly.

data.

Furthermore, the magnitude of these effects strongly depends on the type of tasks workers perform. For instance, for low-skilled workers carrying out tasks with the lowest degree of interactivity (which, arguably, are also the tasks that can most easily be offshored), increased offshoring between 1991 and 2006 accounts for a cumulative yearly wage reduction of 1,965 euros. For low-skilled workers with the highest degree of interactivity, offshoring can only explain a yearly wage reduction of 435 euros. Thus, in line with the argument put forward in, for example, Blinder (2006), a higher degree of interactivity or non-routine content can indeed shield against the negative wage impact of offshoring.

Figures and Tables

Table 1: Description of Task Indices

	All	High-Skilled	Medium-Skilled	Low-Skilled
Interactivity Index based on Becker et al. (2009)				
Mean	0.362	0.491	0.401	0.323
Standard Deviation	0.146	0.092	0.136	0.138
Mean Comparison Test			$H_0 : \mu_{High} = \mu_{Medium}$	$H_0 : \mu_{Medium} = \mu_{Low}$
			p=0.000	p=0.000
Non-Routine Index based on Becker et al. (2009)				
Mean	0.500	0.797	0.572	0.413
Standard Deviation	0.237	0.173	0.221	0.187
Mean Comparison Test			$H_0 : \mu_{High} = \mu_{Medium}$	$H_0 : \mu_{Medium} = \mu_{Low}$
			p=0.000	p=0.000
Interactivity Index based on Spitz-Oener (2006)				
Mean	0.350	0.608	0.420	0.273
Standard Deviation	0.231	0.179	0.225	0.191
Mean Comparison Test			$H_0 : \mu_{High} = \mu_{Medium}$	$H_0 : \mu_{Medium} = \mu_{Low}$
			p=0.000	p=0.000
Non-Routine Index based on Spitz-Oener (2006)				
Mean	0.435	0.715	0.512	0.352
Standard Deviation	0.239	0.168	0.216	0.199
Mean Comparison Test			$H_0 : \mu_{High} = \mu_{Medium}$	$H_0 : \mu_{Medium} = \mu_{Low}$
			p=0.000	p=0.000
Observations	13188	2080	2155	8953

Figure 1: Distribution of Interactivity-Index by Skill (based on Becker et al., 2009)

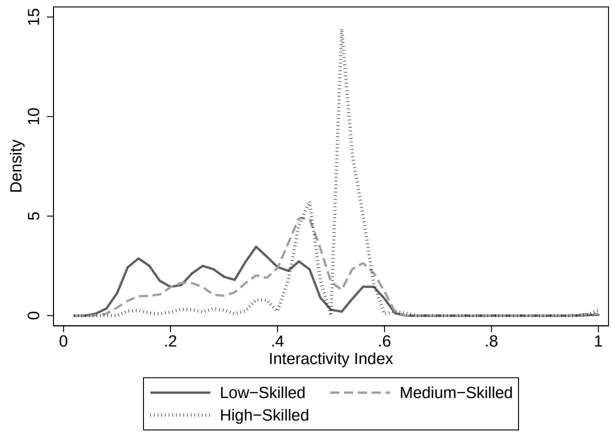


Figure 2: Distribution of Non-Routine-Index by Skill (based on Becker et al., 2009)

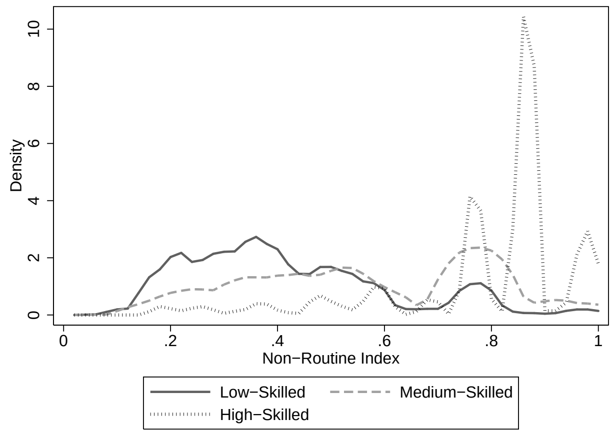
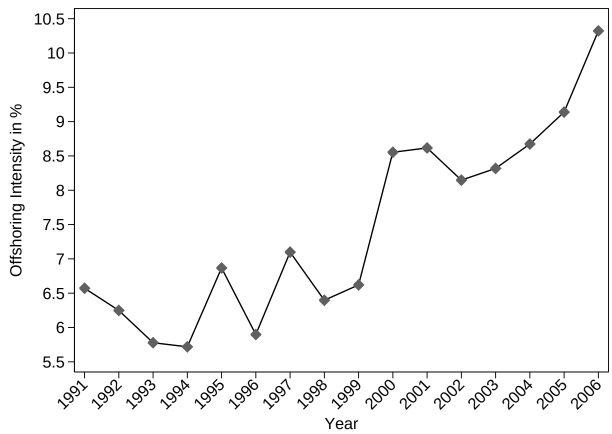


Figure 3: Offshoring in Manufacturing



Note: $\Delta OS_{1991-2006} = 3.75\ \% - pts$

Table 2: Industry-Level Offshoring: Interactive Tasks, Becker et al. (2009)-Classification

	(a)	(b)	(c)	Pairs-Cluster Boot-t
Dependent variable: Log hourly wage				
D: Married	0.0227	0.0244	0.0241	
	[0.0163]	[0.0159]	[0.0156]	
D: Has Children	0.0089	0.0083	0.0086	
	[0.0089]	[0.0088]	[0.0089]	
D: $FirmSize < 20$	0.0029	0.006	0.0061	
	[0.0371]	[0.0366]	[0.0373]	
D: $FirmSize$ 20-199	-0.0425	-0.0434	-0.044	
	[0.0234]*	[0.0234]*	[0.0230]*	**
D: $FirmSize$ 200-1999	-0.0125	-0.0126	-0.0126	
	[0.0163]	[0.0156]	[0.0153]	
D: Public Firm	-0.0026	-0.0028	-0.0018	
	[0.0410]	[0.0415]	[0.0422]	
D: Firm Owner not reported	0.0000	-0.0015	-0.0033	
	[0.0509]	[0.0517]	[0.0521]	
$Tenure$	0.0036	0.0035	0.0032	
	[0.0025]	[0.0025]	[0.0024]	
$WorkExperienceFull - time$	0.0205	0.0193	0.019	
	[0.0196]	[0.0191]	[0.0189]	
$WorkExperienceFull - time^2$	-0.0003	-0.0003	-0.0003	
	[0.0001]***	[0.0001]***	[0.0001]***	**
$WorkExperiencePart - time$	0.0274	0.0297	0.0288	
	[0.0420]	[0.0420]	[0.0409]	
$WorkExperiencePart - time^2$	-0.0075	-0.0077	-0.0075	
	[0.0092]	[0.0093]	[0.0091]	
D: Recent Unemployment	-0.1591	-0.1614	-0.1618	
	[0.0289]***	[0.0290]***	[0.0288]***	***
D: High-Skilled	0.0339	0.1611	-0.0648	
	[0.0315]	[0.1478]	[0.2002]	
D: Medium-Skilled	0.0589	0.107	0.1353	
	[0.0309]*	[0.0608]*	[0.0774]*	
Task Index	0.0408			
	[0.1014]			
Task Index × High-Skilled		-0.141	0.1941	
		[0.2711]	[0.3579]	
Task Index × Medium-Skilled		-0.0458	-0.2636	
		[0.0922]	[0.1065]**	**
Task Index × Low-Skilled		0.123	-0.0409	
		[0.1069]	[0.1160]	
...				

Table 2: ...Continued

	(a)	(b)	(c)	Pairs-Cluster Boot-t
Production Value Y	0.0002	0.0002	0.0002	
	[0.0003]	[0.0003]	[0.0003]	
$R\&D/Y$	0.0084			
	[0.0039]**			
$R\&D/Y \times High-Skilled$		0.0000	0.001	
		[0.0039]	[0.0034]	
$R\&D/Y \times Medium-Skilled$		0.0119	0.0153	
		[0.0081]	[0.0078]*	**
$R\&D/Y \times Low-Skilled$		0.0104	0.0114	
		[0.0041]**	[0.0036]***	***
Cap_{Equ}/Y	0.0023	0.0022	0.0018	
	[0.0017]	[0.0017]	[0.0018]	
Cap_{Plant}/Y	-0.0047	-0.0045	-0.0039	
	[0.0030]	[0.0028]	[0.0030]	
OS_{Narrow}	-0.0003			
	[0.0018]			
$OS \times High-Skilled$		0.0014	0.0205	
		[0.0039]	[0.0138]	
$OS \times Medium-Skilled$		0.0007	-0.0193	
		[0.0036]	[0.0090]**	*
$OS \times Low-Skilled$		-0.0016	-0.0124	
		[0.0026]	[0.0049]**	*
$OS \times Task\ Index \times High-Skilled$			-0.0384	
			[0.0272]	*
$OS \times Task\ Index \times Medium-Skilled$			0.0477	
			[0.0170]**	**
$OS \times Task\ Index \times Low-Skilled$			0.029	
			[0.0103]**	***
Constant	2.46	2.4424	2.464	
	[0.3342]***	[0.3095]***	[0.3174]***	***
Observations	13188	13188	13188	
R^2	0.82	0.82	0.82	
Joint Significance Test				
OS×High-Skilled, OS×Task Index×High-Skilled			F=1.10, p=0.3521	
OS×Medium-Skilled, OS×Task Index×Medium-Skilled			F=5.40, p=0.0133	
OS×Low-Skilled, OS×Task Index×Low-Skilled			F=4.00, p=0.0345	

Note: *, **, *** significant at 10%, 5%, 1% error probability.
Default categories: D: Age 18-24, D: $FirmSize >= 2000$, D: ISCED Low-Skilled.
All specifications contain individual fixed effects and full dummy sets for federal state, time and industry.
Inverse sample probability weighted regression with cluster-robust standard errors.

Table 3: Industry-Level Offshoring: Non-Routine Tasks, Becker et al. (2009)-Classification

	(a)	(b)	(c)	Pairs-Cluster Boot-t
Dependent variable: Log hourly wage				
D: Married	0.0229	0.0241	0.0252	
	[0.0165]	[0.0158]	[0.0156]	
D: Has Children	0.0089	0.0087	0.0079	
	[0.0089]	[0.0088]	[0.0089]	*
D: $FirmSize < 20$	0.0032	0.008	0.0053	
	[0.0375]	[0.0359]	[0.0368]	
D: $FirmSize$ 20-199	-0.0414	-0.0405	-0.043	
	[0.0229]*	[0.0224]*	[0.0221]*	***
D: $FirmSize$ 200-1999	-0.0121	-0.0118	-0.013	
	[0.0162]	[0.0154]	[0.0154]	
D: Public Firm	-0.0023	-0.0013	-0.0011	
	[0.0409]	[0.0421]	[0.0422]	
D: Firm Owner not reported	-0.0001	-0.0022	-0.0003	
	[0.0512]	[0.0520]	[0.0528]	
$Tenure$	0.0036	0.0036	0.0034	
	[0.0025]	[0.0025]	[0.0025]	
$WorkExperienceFull-time$	0.0214	0.0212	0.02	
	[0.0189]	[0.0188]	[0.0184]	
$WorkExperienceFull-time^2$	-0.0003	-0.0003	-0.0003	
	[0.0001]***	[0.0001]***	[0.0001]***	**
$WorkExperiencePart-time$	0.0273	0.0306	0.03	
	[0.0414]	[0.0417]	[0.0410]	
$WorkExperiencePart-time^2$	-0.0075	-0.0078	-0.0078	
	[0.0092]	[0.0092]	[0.0090]	
D: Recent Unemployment	-0.1598	-0.1599	-0.1594	
	[0.0283]***	[0.0284]***	[0.0278]***	***
D: High-Skilled	0.0336	0.1193	0.2438	
	[0.0311]	[0.1297]	[0.1496]	*
D: Medium-Skilled	0.0589	0.1115	0.0746	
	[0.0306]*	[0.0667]	[0.0901]	
Task Index	0.0266			
	[0.0753]			
Task Index×High-Skilled		-0.0534	-0.2833	
		[0.1439]	[0.1991]	*
Task Index×Medium-Skilled		-0.0665	-0.1041	
		[0.1268]	[0.1456]	
Task Index×Low-Skilled		0.0646	-0.0678	
		[0.0838]	[0.0924]	
...				

Table 3: ...Continued

	(a)	(b)	(c)	Pairs-Cluster Boot-t
Production Value Y	0.0002	0.0002	0.0002	
	[0.0003]	[0.0002]	[0.0003]	
$R\&D/Y$	0.0085			
	[0.0038]**			
$R\&D/Y\times$ High-Skilled		0.0002	0.0006	
		[0.0037]	[0.0038]	
$R\&D/Y\times$ Medium-Skilled		0.0122	0.0132	
		[0.0081]	[0.0080]	
$R\&D/Y\times$ Low-Skilled		0.0111	0.0122	
		[0.0040]**	[0.0040]***	***
Cap_{Equ}/Y	0.0023	0.0023	0.0021	
	[0.0017]	[0.0017]	[0.0017]	
Cap_{Plant}/Y	-0.0047	-0.0046	-0.0041	
	[0.0030]	[0.0029]	[0.0031]	
OS	-0.0004			
	[0.0018]			
$OS\times$High-Skilled		0.0014	-0.0196	
		[0.0038]	[0.0122]	**
$OS\times$Medium-Skilled		0.0008	-0.0027	
		[0.0034]	[0.0073]	
$OS\times$Low-Skilled		-0.0017	-0.0115	
		[0.0025]	[0.0034]***	**
$OS\times$Task Index$\times$High-Skilled			0.0272	
			[0.0173]	**
$OS\times$ Task Index$\times$Medium-Skilled			0.0063	
			[0.0084]	
$OS\times$ Task Index$\times$Low-Skilled			0.022	
			[0.0063]***	***
Constant	2.4559	2.4404	2.4319	
	[0.3215]***	[0.3031]***	[0.3163]***	***
Observations	13188	13188	13188	
R^2	0.82	0.82	0.82	
Joint Significance Test				
OS×High-Skilled, OS×Task Index×High-Skilled			F=1.29, p=0.2976	
OS×Medium-Skilled, OS×Task Index×Medium-Skilled			F= 0.51, p=0.6088	
OS×Low-Skilled, OS×Task Index×Low-Skilled			F=7.33, p=0.0041	

Note: *, **, *** significant at 10%, 5%, 1% error probability.
Default categories: D: Age 18-24, D: $FirmSize >= 2000$, D: ISCED Low-Skilled.
All specifications contain individual fixed effects and full dummy sets for federal state, time and industry.
Inverse sample probability weighted regression with cluster-robust standard errors.

Figure 4: Marginal Effect of Industry-Specific Offshoring with Confidence Band: Interactive Tasks

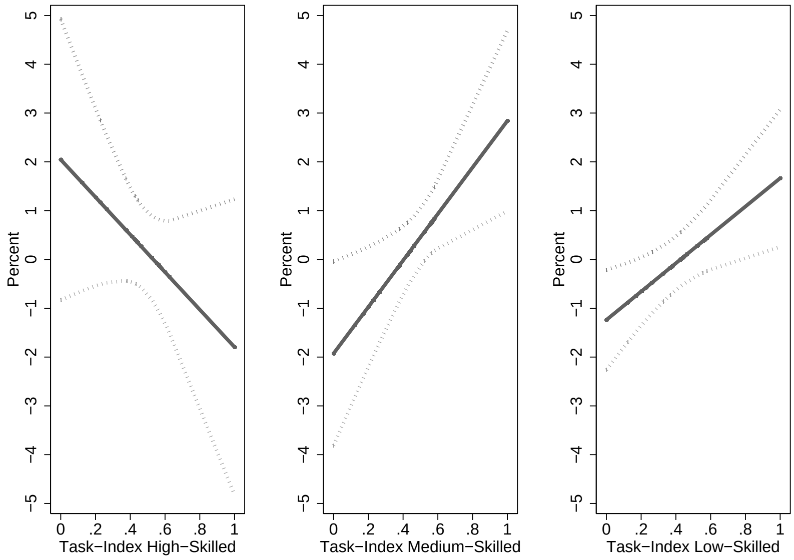


Figure 5: Marginal Effect of Industry-Specific Offshoring with Confidence Band: Non-Routine Tasks

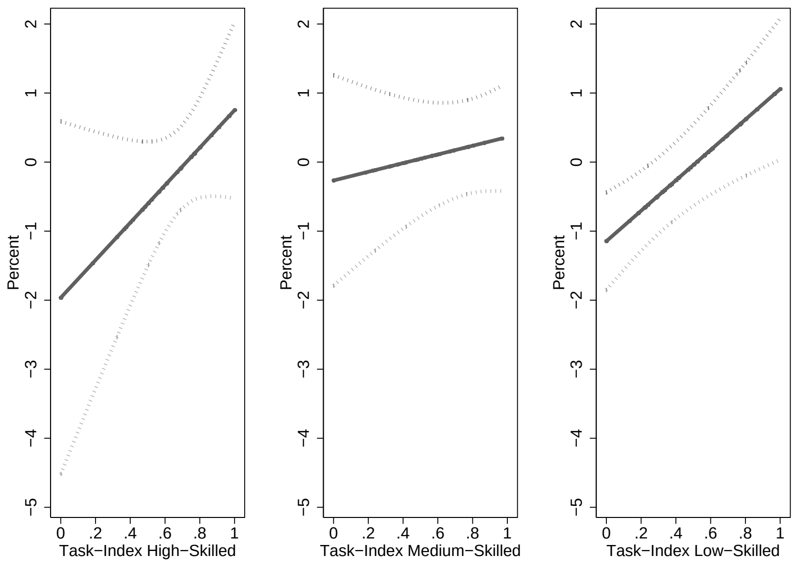


Table 4: Industry-Level Offshoring: Economic Significance Calculations

Average Hourly Wage 1991	Low-Skilled		Medium-Skilled		High-Skilled	
in Euro	14.85		16.81		26.40	
Task Classification following Becker et al. (2009)						
Interactive Tasks						
Joint Significance of OS	**F=4.00**		**F=5.40**		F=1.10	
	p=0.0345		**p=0.0133**		p=0.3521	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Interactive 10th percentile	**-0.46**	**-3.07**	**-0.68**	**-4.03**	0.41	1.55
Interactive 50th percentile	**-0.13**	**-0.86**	**0.11**	**0.68**	0.03	0.12
Interactive 90th percentile	**0.16**	**1.06**	**0.47**	**2.78**	-0.08	-0.30
Non-Routine Tasks						
Joint Significance of OS	**F=7.33**		F=0.51		F=1.29	
	p=0.0041		p=0.6088		p=0.2976	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Non-Routine 10th percentile	**-0.41**	**-2.78**	-0.06	-0.37	-0.37	-1.40
Non-Routine 50th percentile	**-0.18**	**-1.20**	0.06	0.33	0.38	1.46
Non-Routine 90th percentile	**0.30**	**2.04**	0.22	1.28	0.66	2.49
Task Classification based on Spitz-Oener (2006)						
Interactive Tasks						
Joint Significance of OS	**F=2.70**		F=0.86		F=0.09	
	p=0.0916		p=0.4373		p= 0.9124	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Interactive 10th percentile	**-0.26**	**-1.76**	-0.21	-1.23	0.15	0.56
Interactive 50th percentile	**-0.20**	**-1.36**	0.09	0.55	0.13	0.51
Interactive 90th percentile	**0.06**	**0.40**	0.48	2.83	0.11	0.42
Non-Routine Tasks						
Joint Significance of OS	**F= 2.93**		F=0.99		F=0.08	
	p= 0.0763		p=0.3898		p=0.9208	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Non-Routine 10th percentile	**-0.29**	**-1.96**	-0.25	-1.51	0.11	0.40
Non-Routine 50th percentile	**-0.17**	**-1.14**	0.11	0.64	0.15	0.56
Non-Routine 90th percentile	**0.09**	**0.64**	0.43	2.57	0.22	0.84

Note: Bold figures correspond to jointly significant offshoring/interaction terms.

Table 5: Occupation-Specific Offshoring: Interactive Tasks, Becker et al. (2009)-Classification

	(a)	(b)	(c)
Dependent variable: Log hourly wage			
D: Married	0.0171	0.015	0.0148
	[0.0158]	[0.0156]	[0.0156]
D: Has Children	0.0096	0.0094	0.008
	[0.0117]	[0.0117]	[0.0121]
D: $FirmSize < 20$	0.006	0.0069	0.0035
	[0.0472]	[0.0468]	[0.0467]
D: $FirmSize$ 20-199	-0.0484	-0.0481	-0.0492
	[0.0338]	[0.0336]	[0.0334]
D: $FirmSize$ 200-1999	-0.0127	-0.0141	-0.0132
	[0.0138]	[0.0138]	[0.0137]
D: Public Firm	0.0011	0.003	0.0059
	[0.0422]	[0.0427]	[0.0441]
D: Firm Owner not reported	0.0017	0.0024	0.0043
	[0.0611]	[0.0597]	[0.0588]
$Tenure$	0.0022	0.0022	0.0022
	[0.0021]	[0.0021]	[0.0021]
$WorkExperienceFull-time$	0.031	0.0305	0.0303
	[0.0184]*	[0.0186]	[0.0182]
$WorkExperienceFull-time^2$	-0.0003	-0.0003	-0.0003
	[0.0001]***	[0.0001]***	[0.0001]***
$WorkExperiencePart-time$	0.0123	0.0182	0.0177
	[0.0586]	[0.0591]	[0.0595]
$WorkExperiencePart-time^2$	-0.0066	-0.0073	-0.0067
	[0.0086]	[0.0087]	[0.0087]
D: Recent Unemployment	-0.1702	-0.1696	-0.1717
	[0.0269]***	[0.0268]***	[0.0267]***
D: High-Skilled	0.0458	-0.0055	-0.0451
	[0.0449]	[0.1149]	[0.0945]
D: Medium-Skilled	0.0612	0.04	0.0533
	[0.0235]**	[0.0646]	[0.0643]
...			

Table 5: ...Continued

	(a)	(b)	(c)
Production Value Y	-0.0001	0.0001	-0.0003
	[0.0012]	[0.0011]	[0.0013]
$R\&D/Y$	0.0015		
	[0.0234]		
$R\&D/Y \times High{-}Skilled$		-0.0204	0.0021
		[0.0307]	[0.0312]
$R\&D/Y \times Medium{-}Skilled$		0.0229	0.0295
		[0.0272]	[0.0264]
$R\&D/Y \times Low{-}Skilled$		-0.0023	0.0022
		[0.0204]	[0.0174]
Cap_{Equ}/Y	0.0013	0.0014	0.0001
	[0.0034]	[0.0033]	[0.0034]
Cap_{Plant}/Y	-0.0057	-0.0047	-0.0036
	[0.0045]	[0.0043]	[0.0043]
OS	-0.0161		
	[0.0056]***		
$OS\times$ High-Skilled		-0.0036	0.0246
		[0.0070]	[0.0174]
$OS\times$ Medium-Skilled		-0.0231	-0.047
		[0.0082]***	[0.0123]***
$OS\times$ Low-Skilled		-0.0173	-0.0411
		[0.0054]***	[0.0100]***
$OS\times$ Task Index$\times$High-Skilled			-0.0498
			[0.0330]
$OS\times$ Task Index$\times$Medium-Skilled			0.0534
			[0.0253]**
$OS\times$ Task Index$\times$Low-Skilled			0.0604
			[0.0229]**
Constant	2.3416	2.3084	2.3424
	[0.3792]***	[0.3700]***	[0.3991]***
Observations	13188	13188	13188
R^2	0.82	0.82	0.82
Joint Significance Test			
OS$\times$High-Skilled, OS$\times$Task Index$\times$High-Skilled			F=1.14, p=0.3276
OS$\times$Medium-Skilled, OS$\times$Task Index$\times$Medium-Skilled			F= 8.66, p=0.0005
OS$\times$Low-Skilled, OS$\times$Task Index$\times$Low-Skilled			F=10.01, p=0.0002

Note: *, **, *** significant at 10%, 5%, 1% error probability.
Default categories: D: Age 18-24, D: $FirmSize >= 2000$, D: ISCED Low-Skilled.
All specifications contain individual fixed effects and full dummy sets for occupation, federal state and time.
Inverse sample probability weighted regression with cluster-robust standard errors.

Table 6: Occupation-Specific Offshoring: Non-Routine Tasks, Becker et al. (2009)-Classification

	(a)	(b)	(c)
Dependent variable: Log hourly wage			
D: Married	0.0171	0.015	0.016
	[0.0158]	[0.0156]	[0.0156]
D: Has Children	0.0096	0.0094	0.0091
	[0.0117]	[0.0117]	[0.0118]
D: $FirmSize < 20$	0.006	0.0069	0.0018
	[0.0472]	[0.0468]	[0.0455]
D: $FirmSize$ 20-199	-0.0484	-0.0481	-0.0489
	[0.0338]	[0.0336]	[0.0332]
D: $FirmSize$ 200-1999	-0.0127	-0.0141	-0.013
	[0.0138]	[0.0138]	[0.0137]
D: Public Firm	0.0011	0.003	0.0061
	[0.0422]	[0.0427]	[0.0427]
D: Firm Owner not reported	0.0017	0.0024	0.007
	[0.0611]	[0.0597]	[0.0587]
$Tenure$	0.0022	0.0022	0.0023
	[0.0021]	[0.0021]	[0.0020]
$WorkExperienceFull-time$	0.031	0.0305	0.0308
	[0.0184]*	[0.0186]	[0.0184]*
$WorkExperienceFull-time^2$	-0.0003	-0.0003	-0.0003
	[0.0001]***	[0.0001]***	[0.0001]***
$WorkExperiencePart-time$	0.0123	0.0182	0.0191
	[0.0586]	[0.0591]	[0.0591]
$WorkExperiencePart-time^2$	-0.0066	-0.0073	-0.0068
	[0.0086]	[0.0087]	[0.0087]
D: Recent Unemployment	-0.1702	-0.1696	-0.1694
	[0.0269]***	[0.0268]***	[0.0271]***
D: High-Skilled	0.0458	-0.0055	-0.013
	[0.0449]	[0.1149]	[0.1103]
D: Medium-Skilled	0.0612	0.04	0.0391
	[0.0235]**	[0.0646]	[0.0647]
...			

Table 6: ...Continued

	(a)	(b)	(c)
Production Value Y	-0.0001	0.0001	0.0002
	[0.0012]	[0.0011]	[0.0011]
$R\&D/Y$	0.0015		
	[0.0234]		
$R\&D/Y \times High{-}Skilled$		-0.0204	0.009
		[0.0307]	[0.0335]
$R\&D/Y \times Medium{-}Skilled$		0.0229	0.0327
		[0.0272]	[0.0258]
$R\&D/Y \times Low{-}Skilled$		-0.0023	0.0014
		[0.0204]	[0.0182]
Cap_{Equ}/Y	0.0013	0.0014	0.0018
	[0.0034]	[0.0033]	[0.0033]
Cap_{Plant}/Y	-0.0057	-0.0047	-0.0041
	[0.0045]	[0.0043]	[0.0043]
OS	-0.0161		
	[0.0056]***		
$OS \times High{-}Skilled$		-0.0036	-0.0156
		[0.0070]	[0.0229]
$OS \times Medium{-}Skilled$		-0.0231	-0.041
		[0.0082]***	[0.0124]***
$OS \times Low{-}Skilled$		-0.0173	-0.0432
		[0.0054]***	[0.0094]***
$OS \times Task\ Index \times High{-}Skilled$			0.0194
			[0.0254]
$OS \times Task\ Index \times Medium{-}Skilled$			0.0324
			[0.0151]**
$OS \times Task\ Index \times Low{-}Skilled$			0.051
			[0.0176]***
Constant	2.3416	2.3084	2.341
	[0.3792]***	[0.3700]***	[0.3640]***
Observations	13188	13188	13188
R^2	0.82	0.82	0.82
Joint Significance Test			
OS×High-Skilled, OS×Task Index×High-Skilled			F=0.30, p=0.7395
OS×Medium-Skilled, OS×Task Index×Medium-Skilled			F=5.49, p=0.0065
OS×Low-Skilled, OS×Task Index×Low-Skilled			F=11.69, p=0.0001

Note: *, **, *** significant at 10%, 5%, 1% error probability.
Default categories: D: Age 18-24, D: $FirmSize >= 2000$, D: ISCED Low-Skilled.
All specifications contain individual fixed effects and full dummy sets for federal state, occupation and time.
Inverse sample probability weighted regression with cluster-robust standard errors.

Figure 6: Marginal Effect of Occupation-Specific Offshoring with Confidence Band: Interactive Tasks

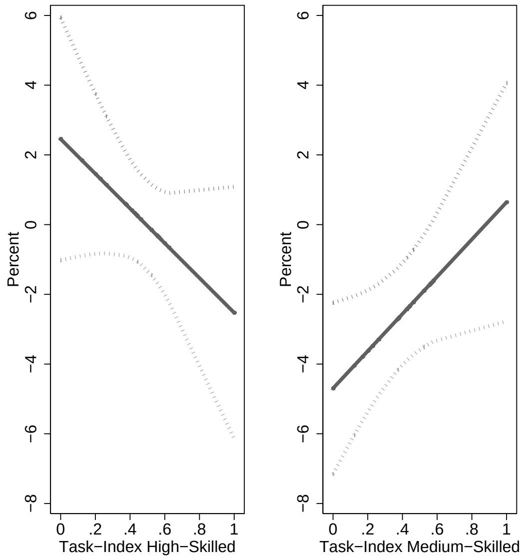


Figure 7: Marginal Effect of Occupation-Specific Offshoring with Confidence Band: Non-Routine Tasks

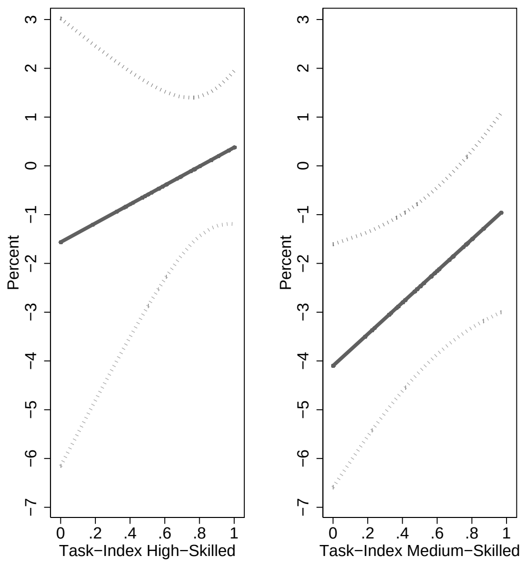


Table 7: Occupation-Specific Offshoring: Economic Significance Calculations

Average Hourly Wage 1991	Low-Skilled		Medium Skilled		High-Skilled	
in Euro	14.85		16.81		26.40	
Task Classification following Becker et al. (2009)						
Interactive Tasks						
Joint Significance of OS	**F=10.01**		**F=8.66**		F=1.14	
	p= 0.0002		**p=0.0005**		p=0.3276	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Interactive 10th percentile	**-1.80**	**-12.13**	**-2.36**	**-14.03**	0.34	1.28
Interactive 50th percentile	**-1.12**	**-7.54**	**-1.47**	**-8.76**	-0.15	-0.58
Interactive 90th percentile	**-0.53**	**-3.54**	**-1.08**	**-6.41**	-0.30	-1.14
Non-Routine Tasks						
Joint Significance of OS	**F=11.69**		**F= 5.49**		F=0.30	
	p=0.0001		**p= 0.0065**		p=0.7395	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Non-Routine 10th percentile	**-1.89**	**-12.70**	**-2.04**	**-12.11**	-0.42	-1.60
Non-Routine 50th percentile	**-1.34**	**-9.04**	**-1.43**	**-8.50**	0.12	0.44
Non-Routine 90th percentile	**-0.23**	**-1.56**	**-0.61**	**-3.61**	0.31	1.18
Task Classification based on Spitz-Oener (2006)						
Interactive Tasks						
Joint Significance of OS	**F=14.86**		**F=10.78**		F=0.19	
	p=0.0000		**p=0.0001**		p=0.8305	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Interactive 10th percentile	**-1.56**	**-10.53**	**-2.35**	**-13.96**	0.23	0.88
Interactive 50th percentile	**-1.30**	**-8.74**	**-1.18**	**-7.00**	0.36	1.36
Interactive 90th percentile	**-0.15**	**-0.98**	**0.32**	**1.89**	0.58	2.20
Non-Routine Tasks						
Joint Significance of OS	**F=16.11**		**F=10.29**		F=0.23	
	p=0.0000		**p=0.0001**		p= 0.7957	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Non-Routine 10th percentile	**-1.75**	**-11.77**	**-2.50**	**-14.86**	0.42	1.58
Non-Routine 50th percentile	**-1.25**	**-8.40**	**-1.21**	**-7.19**	0.42	1.59
Non-Routine 90th percentile	**-0.16**	**-1.05**	**-0.05**	**-0.28**	0.42	1.60

Note: Bold figures correspond to jointly significant offshoring/interaction terms.

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Appendix A: Task Classification

Table A1: Classification of tasks following Becker et al. (2009)

	Non-routine tasks	Interactive tasks
Tools or devices		
Simple tools		
Precision-mechanical, special tools	x	
Power tools		
Other devices		
Soldering, welding devices		
Stove, oven, furnace		
Microwave oven		
Machinery or plants		
Hand-controlled machinery		
Automatic machinery		
Computer-controlled machinery		
Process plants		
Automatic filling plants		
Production plants		
Plants for power generation		
Automatic warehouse systems		
Other machinery, plants		
Instruments and diagnostic devices		
Simple measuring instruments		
Electronic measuring instruments		
Computer-controlled diagnosis		
Other measuring instruments, diagnosis		
Computers		
Personal or office computers		
Connection to internal network		
Internet, e-mail		
Portable computers (laptops)		
Scanner, plotter		
CNC machinery		
Other computers, EDP devices		
Office and communication equipment		
Simple writing material		
Typewriter		
Desktop calculator, pocket calculator		
Fixed telephone	x	
Telephone with ISDN connection	x	
Answering machine	x	
Mobile telephone, walkie-talkie, pager	x	
Fax device, telecopier		
Speech dictation device, microphone		x
Overhead projector, beamer, TV	x	x
Camera, video camera	x	x
Means of transport		
Bicycle, motorcycle		x
Automobile, taxi		x
Bus		x
Truck, conventional truck		x
Trucks for hazardous good, special vehicles		x
Railway		x
Ship		x
Aeroplane		x
Simple means of transport		x
Tractor, agricultural machine		
Excavating, road-building machine		x
Lifting-aids on vehicles		x
Forklift, lifting truck		
Lifting platform, goods lift		
Excavator		
Crane in workshops		
Erection crane		
Crane vehicle		
Handling system		
Other vehicles, lifting means		
Other tools and aids		
Therapeutic aids	x	x
Musical instruments	x	x
Weapons	x	x
Surveillance camera, radar device		
Fire extinguisher	x	x
Cash register		x
Scanner cash register, bar-code reader		x
Other devices, implements		
Software use by workers with computers		
Word processing program		
Spreadsheet program		
Graphics program	x	
Database program		
Special, scientific program	x	
Use of other software		
Computer handling by workers with computers		
Program development, systems analysis	x	
Device, plant, system support	x	
User support, training	x	x
Computer use by any worker		
Professional use: personal computer	x	
Machinery handling by workers with machinery		
Operation of program-controlled machinery		
Installation of program-controlled machinery	x	
Programming of program-controlled machinery	x	
Monitoring of program-controlled machinery	x	
Maintenance, repairs	x	x

Source: Becker et al. (2009). Items refer to the list of questioned tools in the German Qualification and Career Survey 1998/99. The authors' strict classification is used.

Table A2: Classification of tasks based on Spitz-Oener (2006)

	Non-routine tasks	Interactive tasks
Training and teaching others	x	x
Consulting, informing others	x	x
Measuring, testing, quality controlling		
Surveillance, operating machinery, plants, or processes		
Repairing, renovating	x	
Purchasing, procuring, selling	x	x
Organizing, planning	x	x
Advertising, public relations, marketing, promoting business	x	x
Information acquisition and analysis, investigations	x	
Conducting negotiations	x	x
Development, research	x	
Manufacture or production of merchandize		
Providing for, waiting on, caring for people	x	x

Items refer to the list of questioned job descriptions in the German Qualification and Career Survey 1998/99.

Note: Whereas Spitz-Oener (2006) follows Autor et al. (2003) and creates five task categories, we focus on measures of non-routineness and interactivity in order to ensure comparability with the Becker et al. (2009) mapping. The construction of the task measures is analogous to the one described above. This represents a departure from Spitz-Oener (2006), since in her formula, the numerator consists of the number of tasks assigned to a given category. However, the rankings of occupations with respect to task-intensity measures are not affected by the different normalizations.

Appendix B: Exogeneity

For simplicity assume a reduced version of Equation 3

$$\ln WAGE_{ijt} = \alpha + \lambda OS_{jt} + \epsilon_{ijt} \tag{7}$$

Simultaneity bias occurs if offshoring is not only determining wages but also is a function of wages, i.e.,

$$OS = \omega + \varphi \ln WAGE + \varsigma \tag{8}$$

with $\varphi \neq 0$ must hold.

One can denote the potential simultaneity bias as:

$$\begin{aligned} bias &= \frac{Cov(OS, \epsilon)}{Var(OS)} \\ &= \frac{\varphi}{(1-\varphi\lambda)} \frac{Var(\epsilon)}{Var(OS)} \end{aligned} \tag{9}$$

with $\varphi\lambda \neq 1$. We further can derive that, ceteris paribus, the size of the bias increases in φ as $\frac{\partial bias}{\partial \varphi} > 0$.

If in our example one were to use industry-level data, as most related studies do (see e.g., Feenstra and Hanson, 2001 for a survey), it holds that:

$$\varphi_{agg} = \frac{Cov(OS_{jt}, \ln WAGE_{jt})}{Var(\ln WAGE_{jt})}.$$

With disaggregated wage data we on the other hand have:

$$\varphi_{disagg} = \frac{Cov(OS_{jt}, \ln WAGE_{ijt})}{Var(\ln WAGE_{ijt})}.$$

Since $Cov(OS_{jt}, \ln WAGE_{jt}) = Cov(OS_{jt}, \ln WAGE_{ijt})$ and $Var(\ln WAGE_{ijt}) > Var(\ln WAGE_{jt})$ it follows that $\varphi_{disagg} < \varphi_{agg}$. Thus, through the combination of industry-level offshoring measures with micro-level wage data we can utilize the larger wage variance to reduce potential endogeneity bias. To illustrate, in our individual-level data we have

$Var(\ln WAGE_{ijt}) = 0.1495$. If one aggregates the individual-level data to construct average wages at the industry level one has $Var(\ln WAGE_{jt}) = 0.0335$. Accordingly, in our application φ_{disagg} is almost 5 times lower than φ_{agg}. The same intuition, of course, applies to the multivariate case.

Table B1: Exogeneity Tests of Offshoring

	industry-Specific Interactive Column a, Table 2	Occupation-Specific Non-Routine Column a, Table 3	Interactive/Non-routine Column a, Tables 5, 6
First Stage F-test			
OS	$F = 18.74$	$F = 18.69$	$F = 40.35$
	$p = 0.0000$	$p = 0.0000$	$p = 0.0000$
Kleibergen-Paap rank LM statistic of underidentification			
	$Chi^2 = 37.54$	$Chi^2 = 37.452$	$Chi^2 = 66.827$
	$p = 0.0000$	$p = 0.0000$	$p = 0.0000$
Hansen J statistic for excluded instruments			
	$Chi^2 = 0.029$	$Chi^2 = 0.033$	$Chi^2 = 0.025$
	$p = 0.8639$	$p = 0.8565$	$p = 0.8755$
C-test of Endogeneity			
	$Chi^2 = 0.004$	$Chi^2 = 0.004$	$Chi^2 = 0.017$
	$p = 0.9473$	$p = 0.9520$	$p = 0.8951$

Excluded Instruments: $OS_{jt}^{UK-narrow}$, $OS_{jt}^{UK-broad}$

Note: The construction of offshoring measures for the UK is similar to the one for Germany described in Section 3. The main difference is that yearly input-use tables as provided by UK National Statistics do not differentiate between domestic and imported intermediate inputs. To circumvent this problem we follow Feenstra and Hanson (1996, 1999) and calculate industry-level input-use coefficients that are then multiplied with industry-level aggregate imports to obtain industry-level imported intermediate inputs. For 1991 no comparable input-use table is available, we thus utilize the input-use coefficient from 1992. Applying the narrow concept of offshoring, only imported intermediate inputs from the same industry are captured, while the broad concept corresponds to the overall sum of an industry's imported intermediate inputs from all manufacturing industries.

Appendix C: Robustness Tests

Table C1: Industry-Specific Offshoring: Robustness Regression

	Interactivity		Non-Routine Content	
	Industry Trend	Industry Stayers	Industry Trend	Industry Stayers
$OS \times High-Skilled$	0.0195	0.0216	-0.0216	-0.0148
	[0.0159]	[0.0126]	[0.0153]	[0.0132]
$OS \times Medium-Skilled$	-0.0148	-0.0257	-0.0003	-0.0046
	[0.0101]	[0.0121]**	[0.0084]	[0.0102]
$OS \times Low-Skilled$	-0.012	-0.0146	-0.011	-0.0114
	[0.0048]**	[0.0058]**	[0.0028]***	[0.0062]*
$OS \times Task\ Index \times High-Skilled$	-0.0397	-0.0348	0.0278	0.0256
	[0.0312]	[0.0261]	[0.0212]	[0.0212]
$OS \times Task\ Index \times Medium-Skilled$	0.0386	0.0618	0.0035	0.0089
	[0.0201]*	[0.0250]**	[0.0102]	[0.0155]
$OS \times Task\ Index \times Low-Skilled$	0.0285	0.0256	0.022	0.0146
	[0.0113]**	[0.0145]*	[0.0055]***	[0.0132]
Observations	13188	11284	13188	11284
R^2	0.82	0.83	0.82	0.83
Joint Significance Test				
OS×High-Skilled, OS×Task-Index×High-Skilled	F=0.81, p=0.4580	F=1.58, p=0.2313	F=1.07, p=0.3619	F=0.76, p=0.4821
OS×Medium-Skilled, OS×Task-Index×Medium-Skilled	F=2.83, p=0.0825	F=3.65, p=0.0447	F=0.40, p=0.6730	F=0.18, p=0.8326
OS×Low-Skilled, OS×Task-Index×Low-Skilled	F=3.40, p=0.0535	F=3.53, p=0.0486	F=9.78, p=0.0011	F=2.28, p=0.1279

Note: *, **, *** significant at 10%, 5%, 1% error probability.
The model contains the same set of control variables as reported in Tables 2 and 3. For brevity coefficients are not reported. All specifications contain individual fixed effects and full dummy sets for federal state, occupation and time. Inverse sample probability weighted regression with cluster-robust standard errors.

Table C2: Occupation-Specific Offshoring: Robustness Regression

	Interactivity		Non-Routine Content	
	Occu. Trend	Occu. Stayers	Occu. Trend	Occu. Stayers
$OS \times High-Skilled$	0.0163	0.0512	-0.0004	-0.0167
	[0.0215]	[0.0160]***	[0.0186]	[0.0248]
$OS \times Medium-Skilled$	-0.0564	-0.049	-0.0344	-0.0354
	[0.0175]***	[0.0162]***	[0.0168]**	[0.0124]***
$OS \times Low-Skilled$	-0.0441	-0.0435	-0.0297	-0.0409
	[0.0137]***	[0.0134]***	[0.0097]***	[0.0110]***
$OS \times Task\ Index \times High-Skilled$	-0.0443	-0.1133	-0.0075	0.0097
	[0.0423]	[0.0276]***	[0.0221]	[0.0290]
$OS \times Task\ Index \times Medium-Skilled$	0.0647	0.0413	0.0107	0.0111
	[0.0384]*	[0.0369]	[0.0241]	[0.0185]
$OS \times Task\ Index \times Low-Skilled$	0.0663	0.06	0.0225	0.043
	[0.0328]**	[0.0291]**	[0.0181]	[0.0196]**
Constant	120.1104	3.135	119.5842	2.6674
	[37.8718]***	[0.3863]***	[37.7875]***	[0.3146]***
Observations	13188	10768	13188	10768
R^2	0.83	0.83	0.83	0.83
Joint Significance Test				
OS×High-Skilled, OS×Task-Index×High-Skilled	F=0.96, p=0.3897	F=8.71, p=0.0005	F=0.47, p=0.6293	F=0.58, p=0.5634
OS×Medium-Skilled, OS×Task-Index×Medium-Skilled	F=9.70, p=0.0002	F=10.64, p=0.0001	F=5.58, p=0.0060	F=6.84, p=0.0022
OS×Low-Skilled, OS×Task-Index×Low-Skilled	F=7.42, p=0.0013	F=6.12, p=0.0040	F=7.34, p=0.0014	F=7.38, p=0.0014

Note: *, **, *** significant at 10%, 5%, 1% error probability.
The model contains the same set of control variables as reported in Tables 2 and 3. For brevity coefficients are not reported. All specifications contain individual fixed effects and full dummy sets for federal state, occupation and time. Inverse sample probability weighted regression with cluster-robust standard errors.

Appendix D: Descriptive Statistics

Table 1: Descriptive Statistics of Remaining Variables

	Mean	Standard Deviation
Hourly Wage in Euro	17.4478	8.1588
D: Married	0.7537	0.4309
D: Has Children	0.5644	0.4959
D: $FirmSize < 20$	0.0116	0.1071
D: $FirmSize$ 20-199	0.0941	0.2920
D: $FirmSize$ 200-1999	0.2745	0.4463
D: Public Firm	0.0084	0.0914
D: Firm Owner not reported	0.0105	0.1021
Tenure in years	11.8784	9.2638
Work Experience Full-time in years	18.1637	10.2259
Work Experience Part-time in years	0.2098	1.0242
D: Recent Unemployment	0.0178	0.1323
D: High-Skilled	0.1577	0.3645
D: Medium-Skilled	0.1635	0.3698
Production Value Y in Bill. Euro	99.5723	55.4327
$R\&D/Y$ in percent	2.3359	2.4613
Cap_{Equ}/Y in percent	54.5770	15.1807
Cap_{Plant}/Y in percent	30.7821	12.5249
Observations	13188	