Kiel
Working Papers

Kiel Institute for the World Economy

Offshoring, tasks, and the skill-wage pattern

by Daniel Baumgarten, Ingo Geishecker and Holger Görg

No. 1603 | March 2010

Web: www.ifw-kiel.de

Kiel Institute for the World Economy, Düsternbrooker Weg 120, 24105 Kiel, Germany

Kiel Working Paper No. 1603 | March 2010

Offshoring, tasks, and the skill-wage pattern

Daniel Baumgarten, Ingo Geishecker, and Holger Görg

Abstract:
The paper investigates the relationship between offshoring, wages, and the ease with which individuals' tasks can be offshored. Our analysis relates to recent theoretical contributions arguing that there is only a loose relationship between the suitability of a task for offshoring and the associated skill level. Accordingly, wage effects of offshoring can be very heterogeneous within skill groups. We test this hypothesis by combining micro-level information on wages and demographic and workplace characteristics as well as occupational infor- mation relating to the degree of offshorability with industry-level data on offshoring. Our main results suggest that in partial equilibrium, wage effects of offshoring are fairly modest but far from homogeneous and depend significantly on the extent to which the respective task requires personal interaction or can be described as non-routine. When allowing for cross-industry movement of workers, i.e., looking at a situation closer to general equilibrium, the magnitude of the wage effects of offshoring 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.

Keywords: Tasks, offshoring, outsourcing, skills, wages

JEL classification: F1, F2, J3

Daniel Baumgarten
RWI Essen
Hohenzollernstraße 1-3, 45128 Essen
Daniel.baumgarten@rwi-essen.de

Ingo Geishecker
University of Göttingen
37073 Göttingen
Ingo.Geishecker@wiwi.uni-goettingen.de

Holger Görg
Kiel Institute for the World Economy
24100 Kiel, Germany
Telephone +49 431 8814 258
E-Mail: holger.goerg@ifw-kiel.de

* Daniel Baumgarten thanks the Leibniz Association for financial support. Holger Görg gratefully acknowledges financial support through the European Commission FP 7 Programme (Grant No. SSH-CT-2009-244552).

1 Introduction

Research on job tasks has become increasingly popular 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 (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 change. This is what we show in this paper.

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. This is combined with data on offshoring activities of the industry. We use this 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. 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 look only at changes in the wages of individuals staying in an industry, and not those that occur due to an individual moving from one industry to another as a consequence of offshoring. This makes our analysis essentially a short-run, partial equilibrium analysis.[1]

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 what is going on in other industries. Specifically, the wages of i holding occupation k will, in general equilibrium, 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.

In the growing literature on offshoring and tasks, we are, to the best of our knowledge, the first to explicitly investigate the interaction between tasks and skills in order to gauge the effect of offshoring of activities on wages.[2] We look at the labor market effect of offshoring by examining individual-level wages rather than relative demand for labor at the firm or industry level.[3] This

[1]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.

[2]The paper most closely related to ours is by Ebenstein et al. (2009), who use micro data to define occupations as routine or non-routine. They do not consider possible interactions between tasks and skills, as suggested by other empirical work, however. Moreover, we expand on this paper by using not only the routine vs. non-routine distinction, but as an alternative approach, also classify occupations according to whether they are based on interactive vs. non-interactive tasks. In addition, Crinò (2010) looks at the impact of services offshoring on labour demand while differentiating between "tradable" and "non-tradable" occupations. Finally, Baumgarten (2009) uses micro data to investigate the relationship between offshoring, tasks, and employment stability.

[3]Feenstra and Hanson (1996) is one of the standard references for such studies at the industry

allows us to take account of individual-level heterogeneity, controlling for a host of observable and unobservable effects at the individual and industry level, thereby avoiding aggregation bias.[4]

Our empirical results show that wage effects of offshoring are heterogeneous between as well as within 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 does indeed need to be revised, taking the nature of tasks into account.

Another important finding is that the partial equilibrium effect, that is, the impact of offshoring in the individual's own industry, is quite low. However, when looking at the effects of offshoring in a situation that more closely corresponds to a general equilibrium setting—when allowing for worker mobility between industries—we find substantial wage effects that are economically highly significant.[5]

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 results are presented in Section 5, while Section 6 shows our estimates when allowing for cross-industry worker mobility. 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

level. Becker et al. (2009) analyze the link between tasks, skills, offshoring by multinationals, and relative labor demand at the firm level using German data. They estimate the relative demand for skills and tasks, respectively, applying the framework by Feenstra and Hanson (1996). They do not, however, allow for a possible interaction between skills and tasks.

[4]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.

[5]This may explain why papers (such as Liu and Trefler, 2008) that only look at the partial equilibrium (or own industry) effect often fail to find strong results and conclude that offshoring appears not to pose a significant threat to workers.

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 reabsorbed 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), an annual individual-level survey, for the years 1991-2006.[6] We restrict our unbalanced sample to prime-age (18–65 years) employees in the manufacturing industry (NACE/ISIC 15–36). To account for gender-specific labor market outcomes (see, e.g., Prasad, 2004; Beaudry and Green, 2003) we focus exclusively on males. In our empirical model, we 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.[7]

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, by applying two different procedures that are based on Becker, Ekholm and Muendler (2009) and Spitz-Oener (2006).[8]

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

[6]Specifically, we use sample A–F of SOEP. The 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.

[7]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.

[8]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).

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.[9]

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 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).

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:

$$Task\,Intensity_{ij} = \frac{\text{Average number of } j\text{-tasks in occupation } i}{\text{Maximum average number of } j\text{-tasks}}, \tag{1}$$

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

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 1). It is the same set of questions that was first used by Spitz-Oener (2006) in her work on tasks, computerization, and technical change and subsequently employed by, for example, Borghans et

[9]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).

al. (2008) and Gathmann and Schönberg (2010). 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.[10] For ease of exposition, we will refer to this alternative task classification in the following as Spitz-Oener-based mapping even though it is not strictly identical. Although both task classifications have their pros and cons, we have some preference for the Becker et al. (2009) mapping since it is based on a more detailed set of questions and hence, arguably, more suitable to reflect task content variations across occupations.

Hence, 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.[11] 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-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

[10]Note that this constitutes another 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.

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

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. Whereas "production foremen" even surpass them in both dimensions, a typical occupation that displays considerably lower values is that of "office clerk".

"Engineers" make up by far the largest share 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 follow two identification strategies. The first is based on the assumption 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).

In order to implement this strategy, we merge our individual-level data with industry-level offshoring measures. Offshoring is constructed by combining input-output tables for imports provided by the German Federal Statistical Office with commodity trade data from the Eurostat Comext database. We follow a narrow concept of materials offshoring by focusing on imported intermediate inputs that correspond to a make-or-buy decision, that is, inputs that in principle could be produced by the importing industry itself (see Feenstra and Hanson, 1999). 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:

$$OS_{jt} = \frac{IMP_{j^*t} \times \Omega_{jj^*t}}{Y_{jt}} \quad (2)$$

with IMP_{j^*t} denoting imported intermediate inputs from industry j^* and Y_{jt} the production value of industry j at time t. Ω_{jj^*t} denotes the share of imports from a foreign industry j^* that is consumed by the respective domestic industry j in t with $\sum_{j=1}^{J} \Omega_{jj^*t} \times IMP_{j^*t}$ =total imports from industry j^* which are not only used in manufacturing but also in agriculture, services, private and public consumption, and investments and exports in t.[12]

Figure 3 depicts the weighted average offshoring intensity in manufacturing for the years 1991 to 2006. Offshoring intensity showed tremendous growth during our sample period: between 1991 and 2006 it increased from 6 to 8 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]

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

where $WAGE_{ijt}$ denotes individual i's hourly wage in industry j at time t.

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 Table 2.

[12] Note that the numerator in Equation 2 could also be derived directly from the main diagonal of the input-output table. We chose, however, to only construct Ω_{jj} on the basis of input-output tables and combine it with trade data to give less weight to potential measurement error of individual input-output tables.

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

$DEMOG$ 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 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 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 into industry fixed effects τ_j, time fixed effects μ_t, individual fixed effects ι_i and a remaining error term ϵ_{ijt}. In addition, the three panel dimensions allow us to include a full set of industry-specific time trends ($TREND$) that capture industry-level technological change over and above common macroeconomic trends accounted for by μ_t. In addition, we include research and development intensity ($R\&D/Y_j$) as an input-based industry-level technology measure.

Particular attention is paid to educational controls based on the International Standard Classification of Education (ISECD). $EDUC$ contains educational dummies for high education ($e = High - Skilled$) and medium ($e = Medium - Skilled$) education; low education ($e = Low - Skilled$) is the omitted category.[15]

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 ($OS \times EDUC \times TASK$).

Accordingly, the marginal effect of offshoring for the different skill groups e can be denoted as:

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

[15] 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.

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

We therefore allow for heterogeneous effects of offshoring within skill groups depending on the corresponding non-routine or interactivity index.

The combination of micro-level data and more aggregate offshoring information can overcome a number of problems that haunt pure industry-level studies. First, due to the detailed information on educational attainment in our micro-data, we can differentiate between skill groups in a much more precise way than the commonly used manual/non-manual worker dichotomy (e.g., Feenstra and Hanson 2001; Geishecker, 2006).

Second, 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 (see Appendix 2). Nevertheless, we can also test for exogeneity of our offshoring measures using lagged values as instruments, and are unable to reject the H_0 of exogeneity within reasonable confidence bounds (see Table A2 in Appendix 2).[16]

Third, combining micro-level wage information and industry-level offshoring data results in a three-dimensional data set that allows us to control for industry technological progress by including industry-specific time trends. Arguably in our context, this is more general than to only include research and development or technology measures, sometimes of poor quality, as most studies do (e.g., Berman, Bound and Machin, 1998, Feenstra and Hanson, 1996, 1999).

Combining micro-level and aggregate data can, however, give rise to contemporaneous correlation of the error terms ϵ_{ijt} as demonstrated convincingly in, e.g., Moulton (1986). As has become standard in the literature, we therefore 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

[16] It may, of course, be problematic to use lagged values as instruments, since orthogonality must frequently be rejected. However, in our application, one- and two-year lags are likely to be orthogonal, as indicated by the low Hansen J statistic in Table A2.

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 reported by Cameron et al. (2008), yields considerably more precise t-tests.

Furthermore, Autor and Handel (2009) stress the potential endogeneity of individuals' tasks 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 13,189 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.[17]

5 Partial Equilibrium Results

We estimate various specifications of Equation 6 for different task groupings. The main estimation results are presented in Table 3 for the interactivity task index and Table 4 for the non-routine task index following the methodology proposed by Becker et al. (2009).

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.

Note that pairs-cluster bootstrapped t-statistics performed for the specifications reported in Column (c) of Tables 3 and 4 always confirm the conventional cluster-robust t-tests or even point to statistical significance when conventional

[17]The importance of unobserved characteristics for determining initial occupational choices is taken into account in our model through the inclusion of individual fixed effects.

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 various authors and summarized in Cameron et al. (2008).

Focusing on statistically significant coefficients according to our pairs-cluster bootstrapped t-statistics in Tables 3 and 4 (Column IV), we find, ceteris paribus, that workers who change into firms with 20 to 199 and 200 to 2,000 employees experience wage cuts of four and two percent, respectively, compared to firms with more than 2,000 employees, our default category.[18]

Regarding tenure, we have to reject non-linearity and find a weakly statistically significant but rather small positive effect. Ceteris paribus, each additional year of tenure generates an average wage premium of 0.3 percent. However, overall work experience in full-time employment plays a much more important role. The coefficients on full-time work experience in levels and squared are jointly statistically significant[19] 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 26 years of work experience onwards, actually turns negative. For part-time work experience, however, we find no statistically significant effects.

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 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 cannot identify any wage effects with sufficient precision. However, in a specification with individual fixed effects, this is what one would expect, as few individuals switch between skill groups.

Similarly, we find only a weakly significant direct wage effect with respect to the interactivity-based task index when interacted with medium skills, and

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

[19] F-test for interactivity based regression: F=7.14, p=0.00. F-test for non-routine content based regression: F=7.53, p=0.00.

no statistically significant direct wage effects with respect to the non-routine content of tasks. Again, this is likely due to the fact that individuals rarely change between different types of tasks.[20]

Regarding time-changing industry-level control variables other than offshoring, coefficients generally cannot be identified with sufficient precision after we control for individual and industry fixed effects and industry-specific time trends.[21] The exception is the coefficient on industry research and development intensity ($R\&D/Y$). While we find increases in research and development intensity to reduce hourly wages for all skill groups, the effect is only weakly statistically significant for high-skilled workers. A one percentage point increase in $R\&D/Y$ lowers wages for high-skilled workers by about two percent. However, over the sample period $R\&D/Y$ averaged over all industries has remained nearly constant so that the effect of technological progress is economically negligible. Note, however, that $R\&D/Y$ is only one component of our controls for technological change and is complemented by a full set of year dummies as well as industry-specific time trends.

Conditional on our large set of controls for observed and unobserved heterogeneity, we can now look at the offshoring coefficients and their respective interaction terms. As expected, the effects of offshoring are fairly heterogeneous depending on individual skills but are also shaped by the ease with which different tasks can be offshored. To see this, however, one cannot rely solely on Tables 3 and 4.

Equation 4 denotes the marginal effects of offshoring for the different skill groups. Accordingly, the specific wage impact of offshoring can only be evaluated at some value of the interactivity or non-routine task index. Furthermore, what matters for the statistical significance of offshoring for the different skill groups e 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 ($OS_{jt} \times EDUCeit \times TASK_{it}$). However, rather than focusing on statistical significance, what we are really interested in is economic significance, i.e., how much wages changed due to increased off-

[20]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.

[21]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.

shoring. Obviously, this information is not contained in standard regression output.

To ease interpretation of the coefficients and to illustrate economic significance of offshoring for various skill and task interactions, 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.[22] 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 6 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 found to be jointly statistically significant for the interactivity as well as the non-routine content task classification. However, in line with the reasoning of Leamer and Storper (2001), Levy and Murnane (2004), and Blinder (2006), the effect of offshoring is heterogeneous within the group of low-skilled workers and indeed depends on the ease with which tasks can be offshored.

Applying the interactivity-based task classification, we find that had offshoring remained constant at its 1991 value, low-skilled workers in the lowest tenth percentile of interactivity, ceteris paribus, would have earned 32 euro cents (i.e., 2.17 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 10 euro cents, or 0.66 percent, while low-skilled workers in the 90th percentile experience small wage increases of 10 euro cents, or 0.65 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 26 euro cent (1.73 percent) reduction in hourly wages for low-skilled workers with the lowest content of non-routine tasks. Low-skilled workers in the 50th percentile of non-routine content only experience wage cuts

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

of 12 euro cents (0.82 percent), while workers in the 90th percentile gain 15 euro cents (1.04 percent).

Clearly, these partial equilibrium effects seem fairly small at first glance. To signify the size of the effects, assuming 1,500 work hours per year, offshoring accounts for a 390 to 480 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 150 and 225 euros.[23]

For medium-skilled workers, coefficients are only estimated with sufficient precision when applying the interactivity-based task classification. Again, the partial equilibrium effects of offshoring follow a similar pattern as for low-skilled workers. Medium-skilled workers with the lowest degree of interactivity experience cumulative wage cuts of 38 euro cents (2.23 percent), while medium-skilled workers at the 50th and 90th percentile experience cumulative wage gains of 7 and 27 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 discussed in more detail in Section 3. For completeness, coefficient estimates of our main specification containing all interaction terms are reported in Table 5 for interactive and non-routine task indices, respectively. When looking at the F-tests for joint economic significance of our interaction terms and the respective economic significance calculations reported at the bottom of Table 6, it becomes clear that the effects of offshoring are identified with considerably less precision when applying this alternative task classification scheme. However, at least for low-skilled workers, there are some striking similarities across the different task classification schemes. Following the methodology based on Spitz-Oener (2006), we find that low-skilled workers who carry out tasks with the lowest degree of interactivity and the lowest

[23] 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).

non-routine content experience cumulative wage cuts of 17 and 19 euro cents, respectively. Low-skilled workers in the 50th percentile of interactivity and non-routine content, however, only experience wage cuts of 13 and 11 euro cents, respectively. At the same time, we find low-skilled workers in the 90th percentile of interactivity and non-routine content to gain 3 and 5 euro cents respectively. These effects are, however, only at the border of conventional statistical significance when looking at the interactivity of tasks and only weakly statistically significant when focusing on the non-routine content of tasks.

6 Results with worker mobility across industries

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 are more closely related to the general equilibrium. 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-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.

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

Accordingly, we re-estimate Equation 6 substituting OS_{jt} for OS_{kt}.

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

where $WAGE_{ikt}$ denotes individual i's hourly wage in occupation k at time t.

Note that we now have 61 clusters (occupations) instead of 21 (industries) in the partial equilibrium analysis. Thus, we consider standard cluster robust standard errors and corresponding t-tests to suffice and do not construct pairs cluster bootstrapped t-statistics as before. Furthermore, we now control for occupation-specific observable characteristics by including occupation-specific output, capital, and R&D measures that are constructed applying the same methodology as in Equation 5. In addition, to further control for occupation-specific technological change, the model also contains occupation-specific time trends $TREND_{kt}$. 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 7 and 8 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 3, 4 and 5. However, when applying the occupation-specific measure from Equation 5 we find a much more pronounced effect of offshoring. Similar to the partial equilibrium case, we ease interpretation of our offshoring-related coefficients by looking at the joint significance of the respective interaction terms and by calculating the economic significance of occupation-specific offshoring for each skill group at selected reference points for the degree of interactivity and non-routine content.

As is reported in Table 10, we find strong occupation-specific offshoring effects for low- and medium-skilled workers that vary significantly across different degrees of interactivity or non-routine content of tasks.

Low-skilled workers in the 10th percentile of interactivity experience cumulated wage cuts of 1.31 euros (8.85 percent) per hour. For low-skilled workers in the 50th percentile of interactivity, this cumulated wage cut is 0.77 euros while low-skilled workers with the highest degree of interactivity only experience wage cuts of 0.29 euros. These wage effects are substantial and considerably larger than in the partial equilibrium case. Assuming 1,500 yearly work hours, low-skilled workers earn between 435 and 1,965 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. The cumulative wage cut due to offshoring is highest for workers in the lowest interactivity decile (1.64 euros) and becomes less severe the higher the degree of interactivity becomes (0.73 euros for the top decile). Again assuming 1,500 yearly work hours, we can calculate a cumulative wage reduction of 2,460 euros for medium-skilled workers in the lowest interactivity decile, 1,515 euros for the median interactivity degree, and 1,095 euro for the top interactivity decile.

Interestingly, these figures are robust irrespective of which task classification scheme is applied. When applying the task classification scheme by Becker et al. (2009) but looking at the non-routine content of tasks instead of interactivity, we find very similar wage effects. Low-skilled workers in the bottom decile of non-routine content experience a cumulative hourly wage reduction of 1.06 euros, which is much more severe than the wage cut for low-skilled workers with tasks having a median non-routine content (0.83 euros) or a non-routine content in the top decile (0.35 euros). Again, for medium-skilled workers, the pattern looks similar. Here the cumulative hourly wage reduction ranges from 1.23 euros for the bottom non-routine decile to 0.72 euros in the top decile.

Furthermore, when applying a task classification scheme that builds on Spitz-Oener (2006) (see Table 9 for coefficient estimates), cumulative wage effects of offshoring are again very similar. For low-skilled workers, these wage cuts due to offshoring range between 1.06 euros per hour for the bottom decile of interactivity and 0.09 euros for the top decile. Applying this task classification scheme to medium-skilled workers, we find a cumulative hourly wage reduction of 1.56 euros for workers in the bottom decile of interactivity and 0.79 euros for workers with median interactivity. Medium-skilled workers at the top decile of interactivity, however, actually gain from offshoring: their hourly wages cumulatively increased by 0.20 euros. When focusing on the non-routine content of tasks, we find medium-skilled workers to experience wage cuts ranging between 1.63 euros and 0.08 euros depending on the degree of non-routine content.

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. However 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 data. What is striking is the magnitude of the effects. While in partial equilibrium offshoring only modestly affects wages, albeit in an interesting task-specific way, the wage impact of offshoring is substantial once we allow for worker mobility and, thus, cross-industry spillovers.

7 Conclusion

The paper analyses 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 Spitz-Oener (2006) and Becker et al. (2009). 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. The main contribution of the paper is, however, that 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 partial equilibrium impact of offshoring on individual wages to be rather modest and to vary according to individual skills. However, our empirical results also indicate that the partial equilibrium 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 effects of offshoring in a situation that more closely corresponds to the general equilibrium, that is, when allowing for worker mobility between industries, we find substantial negative wage effects of offshoring for low- and medium-skilled workers. 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. Accordingly, when studying the labor market effects of offshoring, we argue that the traditionally proposed skill-wage pattern needs to be altered by taking the varying degree of offshorability of tasks within skill groups into account.

Figures and Tables

Table 1: Description of Task Indices

	All	High-Skilled	Medium-Skilled	Low-Skilled
Interactivity Index				
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				
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
Observations	13189	2080	2156	8953

Figure 1: Distribution of Interactivity-Index by Skill

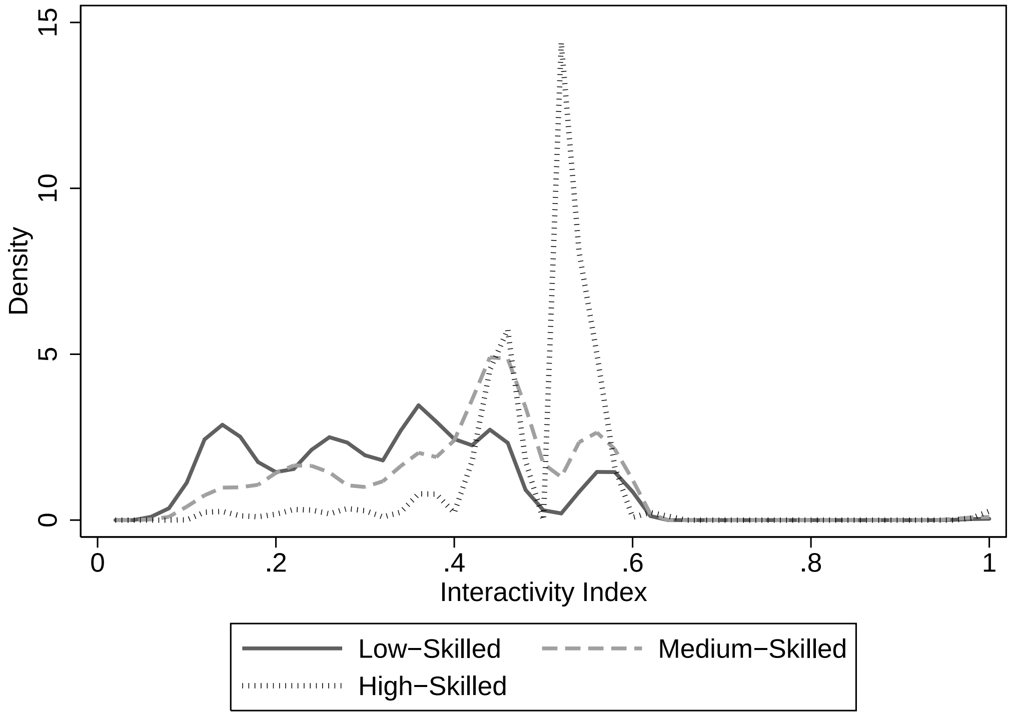


Figure 2: Distribution of Non-Routine-Index by Skill

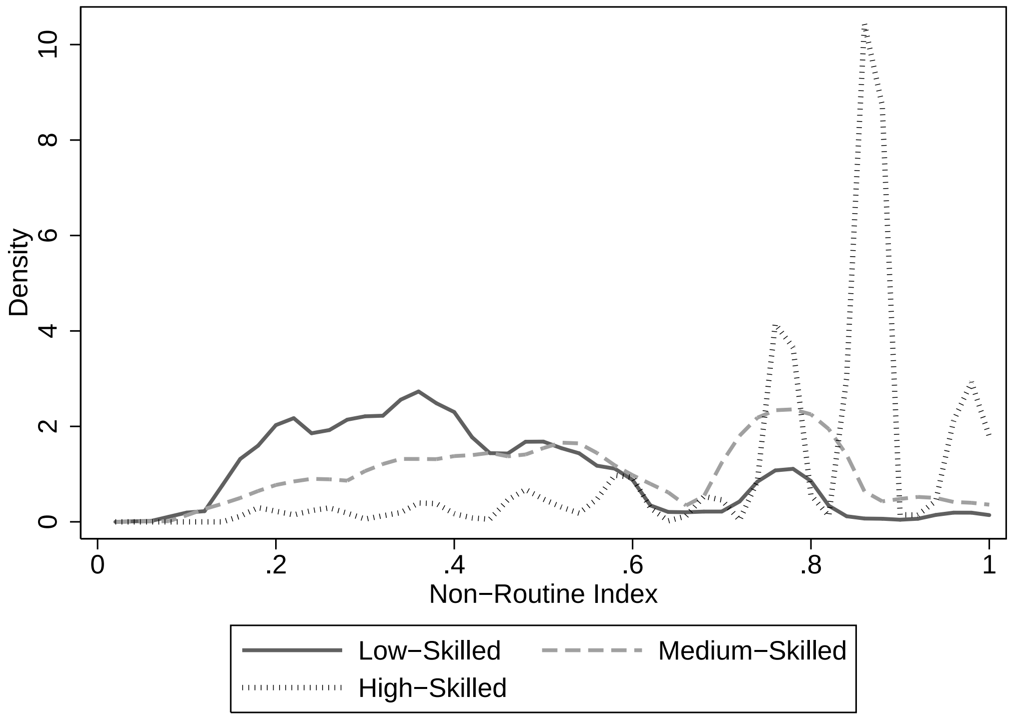
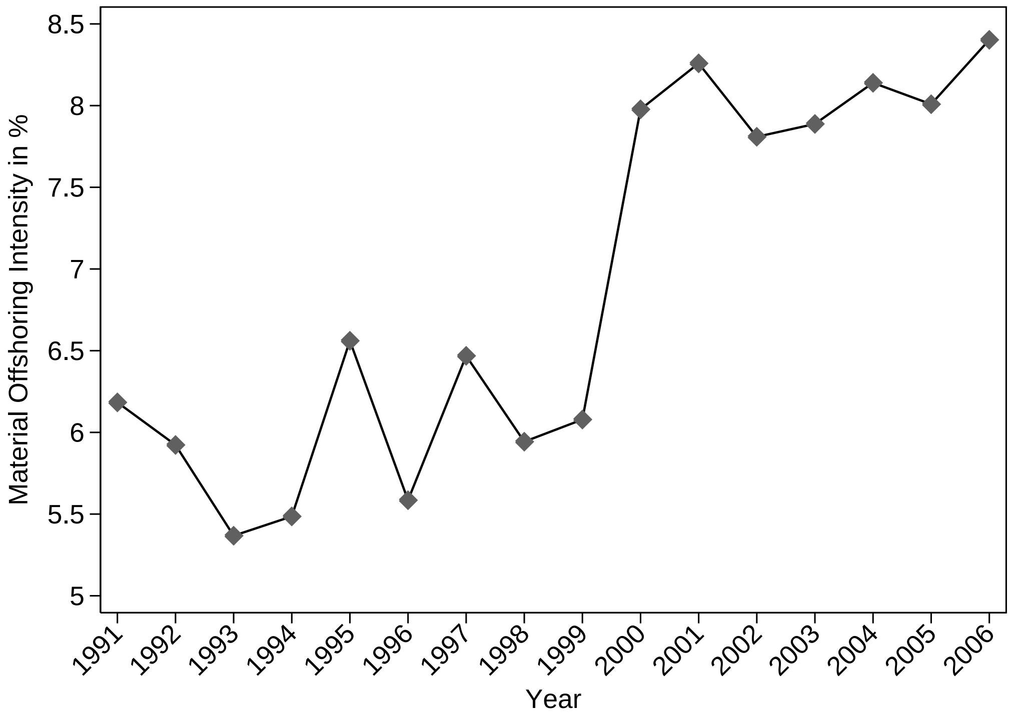


Figure 3: Offshoring in Manufacturing



Note: $\Delta OS_{1991-2006} = 2.21\ \% - pts$

Table 2: 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: ISCED High-Skilled	0.1577	0.3645
D: ISCED 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		13189

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

	(a)	(b)	(c)	Pairs-Cluster Bootstrapped-t
Dependent variable: Log hourly wage				
D:Married	0.0186	0.0205	0.0207	
	[0.0155]	[0.0152]	[0.0148]	
D: Has Children	0.0083	0.0077	0.0081	
	[0.0095]	[0.0094]	[0.0095]	
D: $FirmSize < 20$	0.0011	0.0039	0.0043	
	[0.0365]	[0.0359]	[0.0363]	
D: $FirmSize 20-199$	-0.0416	-0.0423	-0.0422	
	[0.0232]*	[0.0233]*	[0.0228]*	**
D: $FirmSize 200-1999$	-0.0155	-0.0155	-0.0154	
	[0.0153]	[0.0147]	[0.0145]	**
D: Public Firm	0.002	0.0011	0.0005	
	[0.0418]	[0.0419]	[0.0419]	
D: Firm Owner not reported	0.0013	-0.0002	-0.0021	
	[0.0516]	[0.0522]	[0.0525]	
$Tenure$	0.0038	0.0036	0.0033	
	[0.0023]	[0.0023]	[0.0023]	*
$WorkExperienceFulltime$	0.0171	0.016	0.0156	
	[0.0187]	[0.0182]	[0.0181]	
$WorkExperienceFull-time^2$	-0.0003	-0.0003	-0.0003	
	[0.0001]***	[0.0001]***	[0.0001]***	***
$WorkExperiencePart-time$	0.0261	0.0282	0.0281	
	[0.0413]	[0.0410]	[0.0399]	
$WorkExperiencePart-time^2$	-0.0067	-0.0068	-0.0068	
	[0.0091]	[0.0092]	[0.0089]	
D: Recent Unemployment	-0.1568	-0.1592	-0.1595	
	[0.0299]***	[0.0299]***	[0.0297]***	***
D: ISCED High-Skilled	0.0438	0.1795	-0.0466	
	[0.0304]	[0.1553]	[0.2246]	
D: ISCED Medium-Skilled	0.0582	0.1111	0.1199	
	[0.0304]*	[0.0570]*	[0.0713]	*
Task: Interactivity Index	0.009			
	[0.0984]			
Task: $InteractivityIndex \times High-Skilled$		-0.1766	0.1529	
		[0.2949]	[0.4097]	
Task: $InteractivityIndex \times Medium-Skilled$		-0.0863	-0.2704	
		[0.0869]	[0.1067]**	***
Task: $InteractivityIndex \times Low-Skilled$		0.0999	-0.0762	
		[0.0957]	[0.1061]	
...				

Table 3: ...Continued

	(a)	(b)	(c)	Pairs-Cluster Bootstrapped-t
Production Value Y	-0.0005	-0.0005	-0.0006	
	[0.0006]	[0.0006]	[0.0007]	
$R\&D/Y$	-0.0107			
	[0.0066]			
$R\&D/Y \times High-Skilled$		-0.0176	-0.0169	
		[0.0089]*	[0.0088]*	*
$R\&D/Y \times Medium-Skilled$		-0.0078	-0.0047	
		[0.0082]	[0.0090]	
$R\&D/Y \times Low-Skilled$		-0.0098	-0.0089	
		[0.0079]	[0.0078]	
Cap_{Equ}/Y	0.0007	0.0007	0.0002	
	[0.0021]	[0.0022]	[0.0024]	
Cap_{Plant}/Y	0.0018	0.0017	0.0024	
	[0.0033]	[0.0034]	[0.0037]	
OS_{Narrow}	-0.0011			
	[0.0018]			
$OS \times High-Skilled$		-0.0003	0.02	
		[0.0035]	[0.0185]	
$OS \times Medium-Skilled$		0.0006	-0.0181	
		[0.0041]	[0.0112]	
$OS \times Low-Skilled$		-0.0022	-0.0146	
		[0.0025]	[0.0056]**	***
$OS \times Task\ Index \times High-Skilled$			-0.041	
			[0.0360]	
$OS \times Task\ Index \times Medium-Skilled$			0.0451	
			[0.0213]**	**
$OS \times Task\ Index \times Low-Skilled$			0.0334	
			[0.0121]**	***
Constant	32.1064	29.2401	33.1992	
	[45.2464]	[44.9509]	[45.4426]	
Observations	13189	13189	13189	
R^2	0.82	0.82	0.82	

Note: *, **, significant at 10%, 5% 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 as well as industry specific linear time trends.
Inverse sample probability weighted regression with cluster-robust standard errors.

Table 4: Industry-Level Offshoring: Non-Routine Tasks, Becker et al. (2009)-Classification

	(a)	(b)	(c)	Pairs-Cluster Bootstrapped-t
Dependent variable: Log hourly wage				
D:Married	0.0184	0.0199	0.0211	
	[0.0157]	[0.0150]	[0.0148]	
D: Has Children	0.0083	0.008	0.0073	
	[0.0094]	[0.0093]	[0.0094]	
D: $FirmSize < 20$	0.0009	0.0055	0.0035	
	[0.0370]	[0.0353]	[0.0360]	
D: $FirmSize 20-199$	-0.0413	-0.04	-0.042	
	[0.0226]*	[0.0221]*	[0.0220]*	***
D: $FirmSize 200-1999$	-0.0152	-0.0147	-0.0156	
	[0.0153]	[0.0146]	[0.0146]	*
D: Public Firm	0.0021	0.0026	0.0023	
	[0.0417]	[0.0427]	[0.0429]	
D: Firm Owner not reported	0.0015	-0.0008	-0.0001	
	[0.0520]	[0.0526]	[0.0533]	
$Tenure$	0.0038	0.0037	0.0035	
	[0.0023]	[0.0024]	[0.0024]	*
$WorkExperienceFulltime$	0.0174	0.0173	0.0162	
	[0.0179]	[0.0179]	[0.0176]	
$WorkExperienceFull-time^2$	-0.0003	-0.0003	-0.0003	
	[0.0001]***	[0.0001]***	[0.0001]***	***
$WorkExperiencePart-time$	0.0264	0.029	0.0307	
	[0.0409]	[0.0409]	[0.0406]	
$WorkExperiencePart-time^2$	-0.0067	-0.0069	-0.0071	
	[0.0091]	[0.0091]	[0.0090]	
D: Recent Unemployment	-0.1567	-0.1569	-0.1563	
	[0.0292]***	[0.0294]***	[0.0288]***	***
D: ISCED High-Skilled	0.0435	0.1189	0.2452	
	[0.0297]	[0.1380]	[0.1661]	
D: ISCED Medium-Skilled	0.058	0.1099	0.0807	
	[0.0302]*	[0.0689]	[0.1004]	
Task: Interactivity Index	0.0187			
	[0.0710]			
Task: $InteractivityIndex \times High-Skilled$		-0.0444	-0.2693	
		[0.1420]	[0.1972]	
Task: $InteractivityIndex \times Medium-Skilled$		-0.0787	-0.1192	
		[0.1344]	[0.1708]	
Task: $InteractivityIndex \times Low-Skilled$		0.0556	-0.0624	
		[0.0801]	[0.0863]	
...				

Table 4: ...Continued

	(a)	(b)	(c)	Pairs-Cluster Bootstrapped-t
Production Value Y	-0.0005	-0.0004	-0.0005	
	[0.0006]	[0.0006]	[0.0007]	
$R\&D/Y$	-0.0107			
	[0.0066]			
$R\&D/Y \times High-Skilled$		-0.0176	-0.0173	
		[0.0087]*	[0.0083]*	*
$R\&D/Y \times Medium-Skilled$		-0.0079	-0.0068	
		[0.0079]	[0.0082]	
$R\&D/Y \times Low-Skilled$		-0.0093	-0.0083	
		[0.0078]	[0.0077]	
Cap_{Equ}/Y	0.0007	0.0007	0.0005	
	[0.0022]	[0.0022]	[0.0022]	
Cap_{Plant}/Y	0.0018	0.0018	0.0021	
	[0.0033]	[0.0033]	[0.0034]	
OS_{Narrow}	-0.001			
	[0.0018]			
$OS \times High-Skilled$		-0.0003	-0.0222	
		[0.0035]	[0.0135]	**
$OS \times Medium-Skilled$		0.0008	-0.0033	
		[0.0039]	[0.0082]	
$OS \times Low-Skilled$		-0.0023	-0.0117	
		[0.0025]	[0.0035]***	***
$OS \times Task\ Index \times High-Skilled$			0.0286	
			[0.0184]	**
$OS \times Task\ Index \times Medium-Skilled$			0.0076	
			[0.0100]	
$OS \times Task\ Index \times Low-Skilled$			0.0215	
			[0.0067]***	***
Constant	32.5901	30.7816	34.3588	
	[44.2775]	[43.8242]	[43.7532]	***
Observations	13189	13189	13189	
R^2	0.82	0.82	0.82	

Note: *, **, significant at 10%, 5% 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 as well as industry specific linear time trends.
Inverse sample probability weighted regression with cluster-robust standard errors.

Table 5: Industry-Level Offshoring: Classification based on Spitz-Oener (2006)

	(a)	Pairs-Cluster Bootstrapped-t	(b)	Pairs-Cluster Bootstrapped-t
	Interactive		Non-Routine	
Dependent variable: Log hourly wage				
D:Married	0.0187		0.019	
	[0.0147]		[0.0146]	
D: Has Children	0.007		0.0072	
	[0.0093]		[0.0092]	
D: $FirmSize < 20$	0.0029		0.0027	
	[0.0369]		[0.0370]	
D: $FirmSize 20-199$	-0.0415		-0.0417	
	[0.0220]*	**	[0.0221]*	**
D: $FirmSize 200-1999$	-0.0153		-0.0155	
	[0.0140]	*	[0.0139]	**
D: Public Firm	0.0016		0.0014	
	[0.0420]		[0.0420]	
D: Firm Owner not reported	0.0003		0.0003	
	[0.0528]		[0.0529]	
$Tenure$	0.0035		0.0034	
	[0.0023]	*	[0.0023]	*
$WorkExperienceFulltime$	0.0162		0.0161	
	[0.0176]		[0.0175]	
$WorkExperienceFull-time^2$	-0.0003		-0.0003	
	[0.0001]***	***	[0.0001]***	***
$WorkExperiencePart-time$	0.0295		0.0296	
	[0.0398]		[0.0397]	
$WorkExperiencePart-time^2$	-0.0071		-0.007	
	[0.0090]		[0.0090]	
D: Recent Unemployment	-0.1568		-0.1564	
	[0.0284]***	***	[0.0282]***	***
D: ISCED High-Skilled	0.0874		0.1185	
	[0.1555]		[0.1892]	
D: ISCED Medium-Skilled	0.052		0.0667	
	[0.0603]		[0.0752]	
Task: $InteractivityIndex \times High-Skilled$	0.0042		-0.0328	
	[0.2230]		[0.2432]	
Task: $InteractivityIndex \times Medium-Skilled$	0.0051		-0.0175	
	[0.1305]		[0.1387]	
Task: $InteractivityIndex \times Low-Skilled$	0.0278		0.0264	
	[0.0788]		[0.0800]	
...				

Table 5: ...Continued

	(a)	Pairs-Cluster Bootstrapped-t	(b)	Pairs-Cluster Bootstrapped-t
	Interactive		Non-Routine	
Production Value Y	-0.0005		-0.0005	
	[0.0007]		[0.0007]	
$R\&D/Y \times High-Skilled$	-0.0169		-0.0165	
	[0.0087]*	*	[0.0086]*	*
$R\&D/Y \times Medium-Skilled$	-0.0076		-0.0072	
	[0.0079]		[0.0079]	
$R\&D/Y \times Low-Skilled$	-0.0083		-0.0081	
	[0.0077]		[0.0078]	
Cap_{Equ}/Y	0.0009		0.0009	
	[0.0022]		[0.0022]	
Cap_{Plant}/Y	0.0011		0.0011	
	[0.0033]		[0.0034]	
$OS \times High-Skilled$	-0.0028		-0.0077	
	[0.0063]		[0.0082]	
$OS \times Medium-Skilled$	-0.0024		-0.0046	
	[0.0076]		[0.0090]	
$OS \times Low-Skilled$	-0.0067		-0.0083	
	[0.0040]		[0.0044]*	*
$OS \times Task\ Index \times High-Skilled$	0.0043		0.0107	
	[0.0117]		[0.0136]	
$OS \times Task\ Index \times Medium-Skilled$	0.0083		0.0111	
	[0.0133]		[0.0138]	
$OS \times Task\ Index \times Low-Skilled$	0.0146		0.0158	
	[0.0069]**	**	[0.0067]**	**
Constant	-27.498		-27.2169	
	[46.5312]		[45.5411]	
Observations	13189		13189	
R^2	0.82		0.82	

Note: *, **, significant at 10%, 5% 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 as well as industry specific linear time trends.
Inverse sample probability weighted regression with cluster-robust standard errors.

Table 6: 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=3.87**		**F=3.20**		F=0.66	
	p= 0.0380		**p=0.0624**		p=0.5254	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Interactive 10th percentile	**-0.32**	**-2.17**	**-0.38**	**-2.23**	0.15	0.57
Interactive 50th percentile	**-0.10**	**-0.66**	**0.07**	**0.41**	-0.09	-0.33
Interactive 90th percentile	**0.10**	**0.65**	**0.27**	**1.58**	-0.16	-0.60
Non-Routine Tasks						
Joint Significance of OS	**F=6.57**		F=0.44		F=1.40	
	p=0.0064		p=0.6525		p=0.2693	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro		in Euro	
Non-Routine 10th percentile	**-0.26**	**-1.73**	-0.05	-0.29	-0.32	-1.20
Non-Routine 50th percentile	**-0.12**	**-0.82**	0.04	0.21	0.15	0.58
Non-Routine 90th percentile	**0.15**	**1.04**	0.15	0.89	0.32	1.23
Task Classification based on Spitz-Oener (2006)						
Interactive Tasks						
Joint Significance of OS	F=2.23		F=0.34		F=0.10	
	p=0.1332		p=0.7136		p= 0.9087	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Interactive 10th percentile	-0.17	-1.15	-0.05	-0.32	-0.04	-0.16
Interactive 50th percentile	-0.13	-0.90	0.05	0.30	-0.01	-0.02
Interactive 90th percentile	0.03	0.18	0.18	1.08	0.06	0.22
Non-Routine Tasks						
Joint Significance of OS	**F= 2.85**		F=0.50		F=0.48	
	p= 0.0814		p=0.6143		p=0.6243	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Non-Routine 10th percentile	**-0.19**	**-1.29**	-0.10	-0.59	-0.06	-0.21
Non-Routine 50th percentile	**-0.11**	**-0.77**	0.06	0.36	0.01	0.04
Non-Routine 90th percentile	**0.05**	**0.37**	0.20	1.21	0.13	0.50

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

Table 7: Occupation-Specific Offshoring: Interactive Tasks, Becker et al. (2009)-Classification

	(a)	(b)	(c)
Dependent variable: Log hourly wage			
D:Married	0.0224	0.0217	0.0223
	[0.0154]	[0.0156]	[0.0155]
D: Has Children	0.0081	0.008	0.0071
	[0.0117]	[0.0118]	[0.0121]
D: $FirmSize < 20$	-0.0133	-0.0129	-0.0141
	[0.0398]	[0.0404]	[0.0406]
D: $FirmSize20-199$	-0.0573	-0.0572	-0.0584
	[0.0330]*	[0.0331]*	[0.0330]*
D: $FirmSize200-1999$	-0.0146	-0.0153	-0.0146
	[0.0137]	[0.0136]	[0.0134]
D: Public Firm	0.001	0.0019	0.0006
	[0.0408]	[0.0419]	[0.0420]
D: Firm Owner not reported	0.0217	0.0215	0.0227
	[0.0581]	[0.0581]	[0.0576]
$Tenure$	0.0015	0.0016	0.0014
	[0.0020]	[0.0019]	[0.0019]
$WorkExperienceFulltime$	0.0233	0.0238	0.0238
	[0.0183]	[0.0183]	[0.0181]
$WorkExperienceFull-time^2$	-0.0003	-0.0003	-0.0003
	[0.0001]***	[0.0001]***	[0.0001]***
$WorkExperiencePart-time$	0.025	0.0266	0.0261
	[0.0597]	[0.0606]	[0.0609]
$WorkExperiencePart-time^2$	-0.0083	-0.0085	-0.0081
	[0.0087]	[0.0089]	[0.0088]
D: Recent Unemployment	-0.1615	-0.1614	-0.1632
	[0.0278]***	[0.0277]***	[0.0275]***
D: ISCED High-Skilled	0.0571	0.0759	0.0279
	[0.0436]	[0.0973]	[0.0776]
D: ISCED Medium-Skilled	0.0616	0.0647	0.0646
	[0.0258]**	[0.0590]	[0.0599]
...			

Table 7: ...Continued

	(a)	(b)	(c)
Production Value Y	-0.001	-0.001	-0.0014
	[0.0021]	[0.0021]	[0.0023]
$R\&D/Y$	-1.2556		
	[2.2516]		
$R\&D/Y \times High-Skilled$		-2.5036	-0.2967
		[2.9936]	[3.2035]
$R\&D/Y \times Medium-Skilled$		0.3412	0.9456
		[2.6313]	[2.7934]
$R\&D/Y \times Low-Skilled$		-1.8342	-1.6931
		[2.2279]	[2.3887]
Cap_{Equ}/Y	0.1013	0.1147	-0.039
	[0.4286]	[0.4278]	[0.4853]
Cap_{Plant}/Y	-0.5201	-0.525	-0.4173
	[0.6537]	[0.6592]	[0.7125]
OS_{Narrow}	-0.0203		
	[0.0059]***		
$OS \times High-Skilled$		-0.0193	0.0117
		[0.0093]**	[0.0242]
$OS \times Medium-Skilled$		-0.0282	-0.0553
		[0.0081]***	[0.0193]***
$OS \times Low-Skilled$		-0.0193	-0.0517
		[0.0062]***	[0.0145]***
$OS \times Task\ Index \times High-Skilled$			-0.0522
			[0.0471]
$OS \times Task\ Index \times Medium-Skilled$			0.0639
			[0.0438]
$OS \times Task\ Index \times Low-Skilled$			0.0818
			[0.0365]**
Constant	122.7105	124.3848	120.6054
	[36.1652]***	[36.5883]***	[36.0719]***
Observations	13189	13189	13189
R^2	0.83	0.83	0.83

Note: *, **, significant at 10%, 5% 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 as well as occupation specific linear time trends.
Inverse sample probability weighted regression with cluster-robust standard errors.

Table 8: Occupation-Specific Offshoring: Non-Routine Tasks, Becker et al. (2009)-Classification

	(a)	(b)	(c)
Dependent variable: Log hourly wage			
D:Married	0.0224	0.0217	0.0221
	[0.0154]	[0.0156]	[0.0157]
D: Has Children	0.0081	0.008	0.0084
	[0.0117]	[0.0118]	[0.0118]
D: $FirmSize < 20$	-0.0133	-0.0129	-0.0126
	[0.0398]	[0.0404]	[0.0401]
D: $FirmSize 20 - 199$	-0.0573	-0.0572	-0.0573
	[0.0330]*	[0.0331]*	[0.0329]*
D: $FirmSize 200 - 1999$	-0.0146	-0.0153	-0.0148
	[0.0137]	[0.0136]	[0.0135]
D: Public Firm	0.001	0.0019	0.0025
	[0.0408]	[0.0419]	[0.0419]
D: Firm Owner not reported	0.0217	0.0215	0.0218
	[0.0581]	[0.0581]	[0.0577]
$Tenure$	0.0015	0.0016	0.0016
	[0.0020]	[0.0019]	[0.0019]
$WorkExperienceFulltime$	0.0233	0.0238	0.0243
	[0.0183]	[0.0183]	[0.0184]
$WorkExperienceFull-time^2$	-0.0003	-0.0003	-0.0003
	[0.0001]***	[0.0001]***	[0.0001]***
$WorkExperiencePart-time$	0.025	0.0266	0.0283
	[0.0597]	[0.0606]	[0.0610]
$WorkExperiencePart-time^2$	-0.0083	-0.0085	-0.0085
	[0.0087]	[0.0089]	[0.0089]
D: Recent Unemployment	-0.1615	-0.1614	-0.1614
	[0.0278]***	[0.0277]***	[0.0278]***
D: ISCED High-Skilled	0.0571	0.0759	0.0505
	[0.0436]	[0.0973]	[0.1061]
D: ISCED Medium-Skilled	0.0616	0.0647	0.0531
	[0.0258]**	[0.0590]	[0.0607]
...			

Table 8: ...Continued

	(a)	(b)	(c)
Production Value Y	-0.001	-0.001	-0.001
	[0.0021]	[0.0021]	[0.0021]
$R\&D/Y$	-1.2556		
	[2.2516]		
$R\&D/Y \times High-Skilled$		-2.5036	-1.0004
		[2.9936]	[3.1702]
$R\&D/Y \times Medium-Skilled$		0.3412	0.6691
		[2.6313]	[2.6838]
$R\&D/Y \times Low-Skilled$		-1.8342	-2.0011
		[2.2279]	[2.1995]
Cap_{Equ}/Y	0.1013	0.1147	0.1436
	[0.4286]	[0.4278]	[0.4320]
Cap_{Plant}/Y	-0.5201	-0.525	-0.4973
	[0.6537]	[0.6592]	[0.6805]
OS_{Narrow}	-0.0203		
	[0.0059]***		
$OS \times High-Skilled$		-0.0193	-0.0188
		[0.0093]**	[0.0260]
$OS \times Medium-Skilled$		-0.0282	-0.0381
		[0.0081]***	[0.0158]**
$OS \times Low-Skilled$		-0.0193	-0.039
		[0.0062]***	[0.0109]***
$OS \times Task\ Index \times High-Skilled$			0.0047
			[0.0301]
$OS \times Task\ Index \times Medium-Skilled$			0.0193
			[0.0232]
$OS \times Task\ Index \times Low-Skilled$			0.0372
			[0.0219]*
Constant	122.7105	124.3848	121.7589
	[36.1652]***	[36.5883]***	[36.6548]***
Observations	13189	13189	13189
R^2	0.83	0.83	0.83

Note: *, **, significant at 10%, 5% 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 as well as occupation specific linear time trends.
Inverse sample probability weighted regression with cluster-robust standard errors.

Table 9: Occupation-Specific Offshoring: Classification based on Spitz-Oener (2006)

	Interactive	Non-Routine
Dependent variable: Log hourly wage		
D:Married	0.0238	0.0233
	[0.0156]	[0.0156]
D: Has Children	0.0065	0.0068
	[0.0120]	[0.0121]
D: $FirmSize < 20$	-0.0138	-0.0135
	[0.0401]	[0.0403]
D: $FirmSize 20 - 199$	-0.0556	-0.0556
	[0.0333]*	[0.0333]
D: $FirmSize 200 - 1999$	-0.0135	-0.0135
	[0.0137]	[0.0137]
D: Public Firm	0.0027	0.0021
	[0.0423]	[0.0422]
D: Firm Owner not reported	0.0226	0.0219
	[0.0570]	[0.0568]
$Tenure$	0.0016	0.0016
	[0.0019]	[0.0019]
$WorkExperienceFulltime$	0.0244	0.0244
	[0.0182]	[0.0182]
$WorkExperienceFull - time^2$	-0.0003	-0.0003
	[0.0001]***	[0.0001]***
$WorkExperiencePart - time$	0.0255	0.0254
	[0.0607]	[0.0606]
$WorkExperiencePart - time^2$	-0.0081	-0.008
	[0.0088]	[0.0088]
D: Recent Unemployment	-0.1635	-0.1638
	[0.0277]***	[0.0277]***
D: ISCED High-Skilled	0.097	0.0639
	[0.0748]	[0.0789]
D: ISCED Medium-Skilled	0.0786	0.0756
	[0.0565]	[0.0563]
...		

Table 9: ...Continued

Production Value Y	-0.001	-0.0011
	[0.0021]	[0.0022]
$R\&D/Y$		
$R\&D/Y \times High-Skilled$	-0.5632	0.2332
	[3.1291]	[3.2618]
$R\&D/Y \times Medium-Skilled$	0.6758	0.781
	[2.7191]	[2.7581]
$R\&D/Y \times Low-Skilled$	-1.8265	-1.8757
	[2.1738]	[2.1953]
Cap_{Equ}/Y	0.1095	0.0721
	[0.4283]	[0.4412]
Cap_{Plant}/Y	-0.5381	-0.5143
	[0.6128]	[0.6154]
OS_{Narrow}		
$OS \times High-Skilled$	-0.0202	-0.0142
	[0.0133]	[0.0165]
$OS \times Medium-Skilled$	-0.0488	-0.0533
	[0.0101]***	[0.0125]***
$OS \times Low-Skilled$	-0.0398	-0.046
	[0.0064]***	[0.0081]***
$OS \times Task\ Index \times High-Skilled$	0.0188	0.0076
	[0.0215]	[0.0218]
$OS \times Task\ Index \times Medium-Skilled$	0.0622	0.0566
	[0.0195]***	[0.0207]***
$OS \times Task\ Index \times Low-Skilled$	0.0715	0.0674
	[0.0209]***	[0.0206]***
Constant	123.7121	122.2289
	[36.2078]***	[36.2237]***
Observations	13189	13188
R^2	0.83	0.83

Note: *, **, significant at 10%, 5% 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 as well as occupation specific linear time trends.
Inverse sample probability weighted regression with cluster-robust standard errors.

Table 10: 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=9.39**		**F=8.40**		F=1.89	
	p= 0.0003		**p=0.0006**		p=0.1595	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Interactive 10th percentile	**-1.31**	**-8.85**	**-1.64**	**-9.74**	-0.61	-2.32
Interactive 50th percentile	**-0.77**	**-5.17**	**-1.01**	**-6.01**	-0.92	-3.47
Interactive 90th percentile	**-0.29**	**-1.97**	**-0.73**	**-4.34**	-1.01	-3.82
Non-Routine Tasks						
Joint Significance of OS	**F=10.15**		**F= 5.49**		F=1.06	
	p=0.0002		**p= 0.0065**		p=0.3513	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro		in Euro	
Non-Routine 10th percentile	**-1.06**	**-7.14**	**-1.23**	**-7.30**	-0.94	-3.56
Non-Routine 50th percentile	**-0.83**	**-5.56**	**-1.01**	**-6.03**	-0.86	-3.26
Non-Routine 90th percentile	**-0.35**	**-2.32**	**-0.72**	**-4.31**	-0.83	-3.16
Task Classification based on Spitz-Oener (2006)						
Interactive Tasks						
Joint Significance of OS	**F=20.14**		**F=11.80**		F= 1.16	
	p=0.0000		**p=0.0000**		p=0.3209	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Interactive 10th percentile	**-1.06**	**-7.15**	**-1.56**	**-9.28**	-0.66	-2.49
Interactive 50th percentile	**-0.88**	**-5.92**	**-0.79**	**-4.68**	-0.50	-1.90
Interactive 90th percentile	**-0.09**	**-0.61**	**0.20**	**1.20**	-0.22	-0.85
Non-Routine Tasks						
Joint Significance of OS	**F=19.37**		**F=9.49**		F=0.50	
	p=0.0000		**p=0.0003**		p= 0.6101	
Cumulated OS effect 1991-2006	in Euro	in percent	in Euro	in percent	in Euro	in percent
Non-Routine 10th percentile	**-1.17**	**-7.86**	**-1.63**	**-9.68**	-0.55	-2.08
Non-Routine 50th percentile	**-0.84**	**-5.63**	**-0.82**	**-4.85**	-0.50	-1.91
Non-Routine 90th percentile	**-0.11**	**-0.76**	**-0.08**	**-0.50**	-0.42	-1.58

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

References

Antonczyk, Dirk, Bernd Fitzenberger, and Ute Leuschner, "Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure?," *Journal of Economics and Statistics*, 2009, *229* (2+3), 214–238.

Arellano, Manuel, "Computing Robust Standard Errors for Within-Group Estimators," *Oxford Bulletin of Economics and Statistics*, 1987, *49*, 431–434.

Autor, David H. and Michael J. Handel, "Putting Tasks to the Test: Human Capital, Job Tasks and Wages," Working Paper, MIT 2009.

—— **, Frank Levy, and Richard J. Murnane**, "The Skill Content of Recent Technological Change: An empirical exploration," *The Quarterly Journal of Economics*, 2003, *118* (4), 1279–1333.

Baumgarten, Daniel, "International Outsourcing, the Nature of Tasks, and Occupational Stability: Empirical Evidence for Germany," Ruhr Economic Papers 108 2009.

Beaudry, Paul and David A. Green, "Wages and employment in the United States and Germany: What explains the differences?," *American Economic Review*, 2003, *93* (3), 573–602.

Becker, Sascha O., Karolina Ekholm, and Marc-Andreas Muendler, "Offshoring and the Onshore Composition of Tasks and Skills," Discussion Paper 7391, CEPR 2009.

Berman, Eli, John Bound, and Stephen Machin, "Implications of Skill-Biased Technological Change: International Evidence," *Quarterly Journal of Economics*, 1998, *113* (4), 1245–1280.

Blinder, Alan S., "Offshoring: The Next Industrial Revolution?," *Foreign Affairs*, 2006, *85* (2), 113–128.

Borghans, Lex, Bas ter Weel, and Bruce A. Weinberg, "Interpersonal styles and labor market outcomes," *Journal of Human Resources*, 2008, *43* (4), 815–858.

Brown, Charles and James Medoff, "The Employer Size-Wage Effect," *Journal of Political Economy*, 1989, *97* (5), 1027–1059.

Cameron, Colin A., Jonah B. Gelbach, and Douglas L. Miller, "Bootstrap-Based Improvements for Inference with Clustered Errors," *Review of Economics and Statistics*, 2008, *90* (3), 414–427.

Crinò, Rosario, "Service Offshoring and White-Collar Employment," *Review of Economic Studies*, 2010, *forthcoming.*

DiNardo, John E. and Jörn-Steffen Pischke, "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?," *The Quarterly Journal of Economics*, 1997, *112* (1), 291–303.

Dustmann, Christian, Johannes Ludsteck, and Uta Schönberg, "Revisiting the German Wage Structure," *Quarterly Journal of Economics*, 2009, *124* (2), 843–881.

Ebenstein, Avraham, Ann E. Harrison, Margaret S. McMillan, and Shannon Phillips, "Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population surveys," Working Paper 15107, NBER 2009.

Feenstra, Robert C. and Gordon H. Hanson, "Globalization, Outsourcing, and Wage Inequality," *American Economic Review*, 1996, *86* (2), 240–245.

___ **and** ___ , "The impact of outsourcing and high-technology capital on wages: estimates for the United States, 1979-1990," *Quarterly Journal of Economics*, 1999, *114* (3), 907–940.

___ **and** ___ , "Global production sharing and rising inequality: A survey of trade and wages," Working Paper 8372, NBER 2001.

Frick, Joachim R. and Markus M. Grabka, "Imputation of Item-Non-Response on Income Questions in the SOEP 1984 to 2002," Research Notes 29, DIW 2003.

Gathmann, Christina and Uta Schönberg, "How General is Human Capital? A Task-Based Approach," *Journal of Labor Economics*, 2010, *28* (1), 1–50.

Geishecker, Ingo, "Does Outsourcing to Central and Eastern Europe really threaten manual workers' jobs in Germany?," *The World Economy*, 2006, *29* (5), 559–583.

___ **and Holger Görg**, "Winners and losers: A micro-level analysis of international outsourcing and wages," *Canadian Journal of Economics*, 2008, *41* (1), 243–270.

Grossman, Gene M. and Esteban Rossi-Hansberg, "Trading Tasks: A Simple Theory of Offshoring," *American Economic Review*, 2008, *98* (5), 1978–1997.

Haisken-DeNew, John P. and Markus Hahn, "PanelWhiz: A Flexible Modularized Stata Interface for Accessing Large Scale Panel Data Sets," mimeo (http://www.PanelWhiz.eu) 2006.

Leamer, Edward and Michael Storper, "The Economic Geography of the Internet Age," *Journal of International Business Studies*, 2001, *32* (4), 641–665.

Levy, Frank and Richard Murnane, *The New Division of Labor*, Princeton: Princeton University Press, 2004.

Liu, Runjuan and Daniel Trefler, "Much Ado About Nothing: American Jobs and the Rise of Service Outsourcing to China and India," Working Paper 14061, NBER 2008.

Mincer, Jacob, *Schooling, Experience and Earnings*, New York: National Bureau of Economic Research, 1974.

Moulton, Brent R., "Random Group Effects and the Precision of Regression Estimates," *Journal of Econometrics*, 1986, *32* (3), 385–397.

Prasad, Eswar S., "The unbearable stability of the German wage structure: Evidence and interpretation," *IMF Staff Papers*, 2004, *51* (2), 354–386.

Schmidt, Christoph M. and Klaus F. Zimmermann, "Work Characteristics, Firm Size and Wages," *Review of Economics and Statistics*, 1991, *73* (4), 705–710.

Spitz-Oener, Alexandra, "Technical Change, Job Tasks and Rising Educational Demands: Looking Outside the Wage Structure," *Journal of Labor Economics*, 2006, *24* (2), 235–270.

Statistisches Bundesamt, *Klassifizierung der Berufe – Systematisches und alphabetisches Verzeichnis der Berufsbenennungen*, Stuttgart: Metzler-Poeschel, 1992.

White, Halbert, "A Heteroskedasticity Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica*, 1980, *48* (4), 817–838.

Appendix 1: 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.

Appendix 2: Exogeneity

For simplicity assume a reduced version of Equation 6

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

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}.

Table A2: Exogeneity Tests of Offshoring

	Interactive Column a, Table 3	Non-Routine Column a, Table 4
First Stage F-test		
OS	$F = 23.83$	$F = 23.86$
	$p = 0.0000$	$p = 0.0000$
Kleibergen-Paap rank LM statistic of underidentification		
	$Chi^2 = 21.32$	$Chi^2) = 21.36$
	$p = 0.0000$	$p = 0.0000$
Hansen J statistic for excluded instruments		
	$Chi^2 = 0.001$	$Chi^2 = 0.000$
	$p = 0.9778$	$p = 0.9861$
C-test of Endogeneity		
	$Chi^2 = 0.959$	$Chi^2 = 0.989$
	$p = 0.3275$	$p = 0.3200$

Excluded Instruments: OS_{t-1}, OS_{t-2}