Offshoring, tasks, and the skill-wage pattern

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Abstract

The paper investigates the relationship between offshoring, wages, and the occupational task profile using rich individual-level panel data. Our main results suggest that, when only considering within- industry changes in offshoring, we identify a moderate wage reduction due to offshoring for low-skilled workers, though wage effects in relation to the task profile of occupations are not estimated with sufficient precision. However, when allowing for cross-industry effects of offshoring, i.e. allowing for labor mobility across industries, negative wage effects of offshoring are quite substantial and depend strongly on the task profile of workers' occupations. A higher degree of interactivity and, in particular, non-routine content effectively shields workers against the negative wage impact of offshoring.

Keywords: Tasks, Offshoring, Outsourcing, Skills, Wages
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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 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.

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 (which according to the literature should make jobs less offshorable) are not necessarily identical with higher educational attainment. Blinder and Krueger (2012), for example, find that the proportion of "offshorable jobs" appears to be higher among workers with a college degree compared to those without. But all educational groups show significant percentages of jobs that may be offshorable. Jensen and Kletzer (2010) come to a similar conclusion – there is a positive correlation between skills and tasks (that define offshorability), but this is far from perfect. By contrast, Blinder (2006) finds no clear correlation between skills and "offshorability". Our data description also shows substantial heterogeneity between skills and tasks, although there is a tendency that high-skilled workers are more likely to hold jobs that use tasks that are less offshorable.

Traditionally, the literature has concluded that offshoring from newly 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; Biscourp and Kramarz, 2007). However, when considering tasks as well as skills, the conclusions may be more subtle. This is what we investigate in this paper.

By using rich individual-level panel data, we are able to measure in detail wages, skills, and occupations of individuals. Importantly, we are able to construct various measures of the task content of occupations which we can link to the individual data via the occupational code. The individual-level data is combined with data on offshoring activities at the level of the industry.[1] The use of individual-level data allows us also to control in our empirical analysis for a host of observable and unobservable characteristics at the individual level avoiding aggregation and selection bias.

We use these data to model empirically the impact of offshoring on wages and focus on how offshoring affects individuals with particular skill levels and task characteristics differently. More specifically, we study the interaction between skill levels and tasks and investigate whether within skill groups, the nature of tasks carried out by an individual matters for the effect of offshoring on wages. Our working hypothesis is that, in the absence of a one-to-one relationship between tasks and skills, taking account of tasks as an aspect of individual heterogeneity matters. Our empirical results support this hypothesis.[2]

Why should task content matter in addition to skills? As we show below, tasks and skills are not synonymous concepts, hence allowing for task differences in the wage effect captures one additional aspect of individual heterogeneity. This is an important aspect in this context, as a number of papers have established that there is a strong correlation between tasks and offshorability - jobs or occupations with certain task profiles are more easily offshorable than others.With regards to our empirical analysis, we should reiterate Blinder and Krueger's (2012) important point that "offshorability" is a different concept than offshoring. The first is a job or occupation characteristic, the second is the observable action of relocating production abroad. One difficulty when measuring offshoring is that data are fairly aggregate, that is in general there is no direct information on the concrete skill requirement or task content of offshored activities. However, when looking at aggregate offshoring activities, they may constitute a stronger threat for offshorable occupations than for non-offshorable occupations. Hence, actual measured aggregate offshoring may be expected to have larger negative wage effects on workers carrying out easily offshorable tasks.

Summarizing the literature on offshoring and tasks (as we do in Section 2), it is

[1]We measure offshoring as imported intermediates, both from foreign subsidiaries and independent suppliers. This approach dates back to Feenstra and Hanson (1999). More recent applications are Liu and Trefler (2008) or Geishecker and Görg (2008).

[2]The model by Grossman and Rossi-Hansberg (2008) is frequently alluded to in discussions of tasks and offshoring. Another theoretical model focusing on offshoring and tasks is Kohler and Wrona (2010). While we recognize these papers, we do not test the models explicitly. The main reason for this is that in the models, offshoring costs are task-specific, while our data do not allow us to measure task-specific offshoring, or offshoring costs. Rather, as in Becker et al. (2012) and Hummels et al. (2011), we are able to measure the task content of occupations and see whether this matters, in conjunction with skills, for the link between offshoring and individual wages. Our analysis therefore relates particularly to the recent empirical work by Blinder and Krueger (2012), who not only describe task content (i.e., offshorability) but also the implications of differences in tasks for labor market outcomes of individuals.

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 use two strategies for identifying a link between offshoring and wages. The first is to use within-industry changes in offshoring intensity and wages. The assumption is that only offshoring activity in the same industry affects individual wages, while any wage effects that occur indirectly through offshoring in other industries are ruled out.[3] This is a very limiting assumption. In order to relax this, we propose a second identification strategy based on the idea that 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.[4]

An important challenge in this literature (including our paper) is to isolate fully the effect of offshoring. This is not an easy task, as other unobserved variables may be confounding the effects and, hence, lead to endogeneity of the offshoring measure. One example would be reverse causality: offshoring decisions may be related to the wage level in the industry, with high wage industries being more likely to offshore. To investigate and deal with the potential endogeneity of offshoring, we implement instrumental variables regressions, where we predict industry or occupation level offshoring in the first stage regressions using various trade cost measures and world export supply as instruments. In the choice of instruments, we follow the recent paper by Hummels et al. (2011). We discuss and test for instrument relevance and validity, and we present tests of the hypothesis that our offshoring measures are exogenous in the individual-level wage regressions.

To further aid identification, we – depending on the identification strategy – also include industry or occupation fixed effects or even industry-specific time effects to

[3] This essentially confines the analysis to the short run, assuming that labor is immobile between industries. 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.

[4] Note that actual movement of workers is not required to generate these cross- industry effects: the potential for movement is sufficient.

capture unobserved time (in)variant industry or occupation characteristics that may be related to the offshoring decision. Furthermore, we also include a host of observable industry or occupation characteristics that may determine both wages and the offshoring decision.

Based on these identification strategies, we find pure industry-level offshoring to have a very moderate effect on wages. However, when allowing for cross industry effects, our empirical results show that wage effects of offshoring are substantial and very heterogeneous within skill groups, strongly depending on the degree of interactivity or non-routine content of the respective tasks of workers. Thus, offshorability of tasks matters over and above skills and the more traditional dichotomy between high-skilled and low-skilled workers may need to be revised, taking the nature of tasks into account.

In the next section, we provide a brief review of the related literature 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 short-run, 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 discusses robustness checks, while Section 8 concludes the analysis.

2 Related literature

In the growing literature on offshoring and tasks our paper mainly relates to and expands on Becker, Ekholm and Muendler (2012), Ebenstein, Harrison, McMillan and Phillips (2012) and Hummels, Jorgensen, Munch and Xiang (2011).[5]

Becker et al. (2012) 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 enterprises in manufacturing and service industries alike is related to onshore skill-upgrading. Moreover, offshore employment is related to demand shifts away from routine and non-interactive

[5] Other studies analyzing task specific offshoring effects include Crinò (2010) who uses aggregate data to look at the impact of services offshoring on demand for skilled workers while differentiating between "tradable" and "non-tradable" occupations and Baumgarten (2009) who uses similar data to ours to investigate the relationship between offshoring, tasks, and employment stability.

job tasks, suggesting that indeed offshorability is inversely related to the non- routine content and interactivity of job tasks. Our paper differs from Becker et al. (2012) in three main respects. First, while they look at plant-level wage-bill shares, thus mixing employment and wages, we focus on task-specific absolute wage gains and losses associated with offshoring. Second, by using individual-level data, we are able to control for individual-level observed and unobserved heterogeneity. Moreover, we take into account cross-plant effects of offshoring. Third, while Becker et al. (2012) consider the skill-upgrading effect of offshoring conditional on plant's changing task composition, we conversely investigate to what extent the task-specific effects of offshoring on labor demand go beyond any potential education-related heterogeneity in the offshoring effect.

Ebenstein et al. (2012) 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. (2012), 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 the most routine. They argue that these tasks are most easily offshorable and, hence, should be the most affected by actual offshoring activity. What, furthermore, separates the paper of Ebenstein et al. (2012) from earlier micro-level studies (e.g., Liu and Trefler, 2008 and Geishecker and Görg, 2008) is that they allow for cross-industry effects of offshoring, resulting in considerably larger wage effects of offshoring than in pure within- industry studies. Ebenstein et al. (2012), however, do not analyze the interaction of job tasks and educational attainment, that is, occupational task-specific effects of offshoring and education-specific effects are potentially confounded. Furthermore, due to data limitations, Ebenstein et al. (2012) cannot control for unobserved individual heterogeneity and the associated selection of individuals into specific industries.

Another related paper is by Hummels et al. (2011) who use matched employer-employee data for Denmark to investigate wage effects of offshoring in individual firms. They measure offshoring as imported intermediate inputs at the firm level. While they focus on effects by different skill levels, they, in an extension, also look at the interaction of skills and occupational task measures, similar to our approach. They find, as we do, that such an interaction is important. A limitation of their approach is the measure of offshoring at the level of the firm, as in Becker et al. (2012). While this provides important new information, it does assume that the relevant labor market is firm-specific. Hence workers are affected only by their own firm's offshoring activities, not by others in the same industry or occupation. We expand on this by assuming either industry or occupation specific labor markets taking into account these important between firm effects.

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. Specifically, we use data from the German Socio-Economic Panel (SOEP), a representative longitudinal survey of private households in Germany, for the years 1991– 2006.[6] 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 utilize retrospectively collected yearly individual labor earnings and yearly individual work hours from the Cross-National Equivalent files (CNEF), which are part of the standard SOEP data package. Gross wages include payments from bonuses, overtime, and profit-sharing. Annual work hours in the CNEF are constructed by combining information on average number of hours per week and calendar information on employment status, full- and part-time work.[7] Excluding observations with missing or imputed wage information, this yields 13,695 observations for 2129 individuals.[8,9]

[6]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.

[7]A detailed description of the CNEF files is provided in Grabka (2012).

[8]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. Accordingly, individuals with imputed wage data are excluded from the analysis.

[9]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. Fourth, in

In order to obtain measures of the task content of occupations, 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. (2012).[10]

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.[11]

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. (2012) propose a mapping of tasks into occupations.

In the first step, each of the 81 tools identified in the survey is connected with a task, which is classified as (i) routine or non-routine and (ii) interactive or non-interactive, where the first grouping refers to non-repetitive tasks and the second 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).[12]

In a next step, we calculate the average number of non-routine and interactive tasks for each occupation. A higher number implies a more intensive use of the associated

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the SOEP information on educational attainment is more complete and precise.

[10]We also use a different mapping based on Spitz-Oener (2006), which we describe below, as a robustness check. The German Qualification and Career Survey was previously used, for example, by DiNardo and Pischke (1997). Like Becker et al. (2012), we rely on the most recent wave as it follows a comparable occupational classification (KldB92).

[11]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).

[12]We use the authors' preferred strict classification, where only a few tasks are coded as interactive (non-routine). As a robustness check, we also use the authors' lenient classification instead. The results stay virtually the same. These results are not reported here but can be obtained upon request.

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:

$$TASK_{zk} = \frac{\text{Average number of } z\text{-tasks in occupation } k}{\text{Maximum number of } z\text{-tasks in any occupation}}, \tag{1}$$

where k denotes the occupation and $z \in \{$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.

For the definition of skill groups we utilize the International Standard Classification of Education (ISCED) and rely on the highest degree attained taking into account general schooling, vocational, and university education. Low-skilled workers are workers without any degree, a lower secondary degree (Elementary School), basic vocational training, or a higher secondary degree (High School) without any vocational training (OECD, 1999: ISCED-1997, 1-3). High-skilled workers have basic vocational training combined with a higher secondary degree, higher vocational training, or a university degree (OECD, 1999: ISCED-1997, 4-6).

To what extent non-routine and interactive tasks and skills, measured in terms of educational attainment, are related is summarized in Table 1.[13] 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. These are tasks that should make a job less offshorable (Blinder and Krueger, 2012). However, from Figures 1 and 2, it also becomes clear that there is a significant heterogeneity within skill groups.

This finding is somewhat in contrast to the results by Blinder and Krueger (2012) and Jensen and Kletzer (2010). Using data for the US, both of these studies find that there is a positive correlation between skills and offshorability of tasks, although they also show that low skilled workers have a significant share of offshorable tasks. Our evidence suggests that, in our German data, low-skilled workers are those who,

[13]Table 1 also reports on alternative task measures which are used for later robustness tests.

on balance, tend to have occupations with a task profile that makes them easier to offshore.

Still, while higher skills and non-routine or more interactive tasks, respectively, 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. Hence, the task profile may add an important aspect of worker heterogeneity in a wage regression.

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.

"Engineers" are the most frequently encountered occupational group among the very high-skilled, followed by "technicians". Both occupations are characterized by high degrees of non-routine and interactive tasks. However, there is still heterogeneity. For example, "computer scientists" are characterized by a high non-routine content but are less intensive in interactive tasks.

4 Empirical approach: Baseline analysis of within-industry offshoring

The challenge for the econometric analysis is to establish 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. In addition to that, it is challenging to determine whether the occupational task content matters (i) over and above the level of education and (ii) differently for workers with different levels of education. To investigate these issues, we first proceed by assuming that workers' wages are affected by offshoring activity in the industry in which the worker is employed. In Section 6 we relax this assumption and consider cross-industry effects of offshoring.

In order to implement the first 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 report imported intermediate inputs separately industry by industry.[14] 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). 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., 2012) since i) affiliate employment also reflects horizontal MNE activities and ii) not all offshoring takes place through foreign direct investment.[15]

Formally we can denote offshoring as:

$$OS_{jt} = \frac{IMP_{jjt}}{Y_{jt}} \tag{2}$$

with IMP_{jjt} denoting intermediate inputs used in industry j that are imported from the same industry abroad. Imports are reported in input-output tables. Y_{jt} is 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.

As pointed out above, data for the costs or the level of offshoring are not separately available for different skill-groups, let alone for different occupational tasks. We therefore look at the differential wage impact of overall industry- level offshoring across occupational tasks reflecting differential changes in the true offshoring exposure generating heterogeneous wage pressure for (yet non-offshored) workers.[16] Accordingly, we assess whether the wage effects of offshoring are indeed in line with hypothesized differences in the offshorability of tasks as predicted in e.g., Blinder and Krueger (2012).

To do so, while conditioning on observed and unobserved heterogeneity, we estimate variants of the following Mincer wage equation separately for low- and high-

[14] See e.g., Statistisches Bundesamt (2009), Table 1.2.

[15] On the other hand, we acknowledge that our offshoring measure might omit potentially unobserved service trade flows that are not tied to observed merchandize trade but reflected in foreign capital holdings or employment within multinationals. Also, we acknowledge that not all imported intermediates (even if they are from the same industry) necessarily substitute for domestic production.

[16] Note that we cannot rule out that even a uniform across-the-board change in offshoring of a particular industry could have differential task-specific wage effects if it is, e.g. associated with a differential (future) relocation threat for workers carrying out different tasks.

skilled workers:[17]

$$
\begin{aligned}
\ln WAGE_{ijkt} &= \alpha + \beta\, DEMOG_{it} + \gamma\, WORK_{it} \qquad (3)\\
&+ \delta\, TASK_k + \lambda\, OS_{jt} + \nu\, OS_{jt} \times TASK_k\\
&+ \theta\, IND_{jt} + \rho\, R\&D/Y_{jt} + \tau_j + \mu_t + \iota_i + \epsilon_{ijkt}
\end{aligned}
$$

where $WAGE_{ijt}$ denotes individual i's hourly wage at time t in industry j and occupation k.[18]

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. $DEMOG$ denotes the demographic control variables for marital status, children, and geographic region.[19] The second set of control variables ($WORK$) refers to workplace-related characteristics such as firm size, firm ownership and 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 ($R\&D/Y_{jt}$) 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 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_{ijkt}.[20,21]

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

[18] The specification allows for within-individual variation in the task measure $TASK_k$ – as described in Equation 1 – if individuals change the occupation.

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

[20] 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.

[21] 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).

We control for the nature of job tasks of individuals by including our constructed interactivity and non-routine indices, respectively. By splitting the sample between low- and high-skilled workers we allow for heterogeneous task effects across skill groups. To capture the potentially heterogeneous wage pressure from offshoring across skill groups and tasks, we interact offshoring with the typical task content of workers' occupations ($OS \times TASK$) and estimate the model for the split samples of low- and high-skilled workers respectively.

Accordingly, the marginal effect of offshoring for the different groups of low- and high-skilled workers can be denoted as:

$$\left(\frac{\partial \ln WAGE_{ijkt}}{\partial OS_{jt}}\right) = \lambda + \nu \times TASK_k. \tag{4}$$

Hence, we allow for heterogeneous effects of offshoring within skill groups depending on the corresponding non-routine or interactivity index. This captures the idea that actual measured offshoring may be expected to have stronger effects on workers carrying out tasks that are more easily offshorable, even within a given skill group. By splitting the sample between high- and low-skilled workers, 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, Liu and Trefler (2008), Hummels et al. (2011)).

One particular concern with our empirical analysis is that offshoring may be endogenous to wages.[22] This would be the case if, for example, offshoring took place in high-wage industries in order to exploit the potential for cost savings abroad. As argued in e.g., Ebenstein et al. (2012), simultaneity of industry-level offshoring and individual wages may be less of a problem as it seems less likely that industry aggregates are determined by individual labor market outcomes. However, depending on the within-industry correlation of wages, simultaneity may still persist.

[22]Another possible concern about endogeneity is the potential endogeneity of individuals' tasks (as stressed by Autor and Handel, forthcoming) since workers may readily switch between different sets of tasks depending on associated wages. However, in contrast to Autor and Handel (forthcoming), 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 470 year to year occupation changes (of 13,695 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.

Another source of endogeneity is an exogenous shock that affects both wages and offshoring simultaneously.[23] In order to deal with such unobservable shocks, we control for observed and unobserved industry-specific effects using time-varying observable characteristics (industry size, capital intensity, research and development intensity), industry fixed effects, and in some specifications industry-specific time effects. Our identifying assumption is then that the unobservable shock would be correlated with these variables.[24] Still, this might not be enough to rule out all endogeneity concerns.

We therefore explicitly test the hypothesis that offshoring is exogenous to wages in our setting. In order to do so, we implement an instrumental variables estimation. In the first stage estimation we regress the offshoring measure as dependent variable on individual and industry characteristics included in the empirical model, as well as a number of excluded instruments that determine offshoring but not individual-level wages in Germany. In the choice of instruments, we follow recent work by Hummels et al. (2011) and use industry-specific measures of trade costs and world export supply.[25]

Hence, these variables capture shocks to transport costs and world-wide export supply, which are important determinants of offshoring but which, arguably, are exogenous to German workers. Hence, while both types of variables should be strongly correlated with offshoring activity, they are not correlated directly with the residual in the wage regression. In other words, they are likely to be relevant as well as valid instruments.

Table 3 shows the first stage regression results for the excluded instruments and reports test results of instrument strength and orthogonality.[26] The regression is run for the full sample and separately for the sub samples of low- and high-skilled workers. Given that we have individual-level data, a sample split between low- and high-skilled

[23] For example, think of final product demand shocks that affect industries and that thus translate into differential skill demands and revenues. If offshoring involves fixed costs, then higher revenues may translate into more offshoring and a simultaneous skill and task demand shift.

[24] One potential problem that remains (not only in our paper but in all of the literature) is that the exogenous shock may be specific to certain products within particular industries, i.e., there may be within-industry heterogeneity in the shock. We cannot address this issue with either our covariates or an instrumental variables approach, which are both based on industry-specific variables. This potential shortcoming should be kept in mind in the interpretation of results.

[25] Ad valorem and unit transport costs are obtained from the OECD Maritime Transport Costs data base (OECD, 2011) at the two-digit level of the Harmonized System (HS2) and refer to container shipments. We subsequently map transport costs to two-digit industries using Eurostat's concordance table and calculate the weighted two-digit industry averages with 1991 HS2 import values as weights. Clearly, maritime transport costs cannot capture costs of other transport modes such as air traffic. Nevertheless, their explanatory power for offshoring appears to be high. World export supply is calculated on the basis of data from UN Comtrade and then mapped to two digit industries utilizing concordances between five-digit SITC and two-digit industry codes (ISIC, rev.3).

[26] We only report coefficients of excluded instruments in order to save space. Full first stage estimation results are relegated to a separate Appendix to this paper.

workers implies that the resulting industry structure differs between the sub samples. Accordingly, in the low(high)-skill sample offshoring activities of low(high)-skill intensive industries are over-represented, making necessary different sets of excluded instruments. Starting from the full set of available instruments (ad valorem and unit trade costs for exports and imports to/from USA, China, and Japan, as well as world export supply), we subsequently simplify the "first stage" model in order to maximize overall predictive power of excluded instruments while maintaining orthogonality.

Irrespective of whether we pool over all observations or split the sample between low- and high-skilled workers, F-statistics for the joint significance of the excluded instruments are always above 10, hence, problems of weak instruments are unlikely to be present (see Staiger and Stock, 1997). Instrument relevance is further indicated by the individual significance of the coefficients. This indicates that our instruments are important determinants of offshoring activity. The estimated coefficients also have the expected signs: world export supply is positively correlated with offshoring, while trade costs are generally negatively related. There is one exception, though, which is the cost of exports to Japan as a determinant of offshoring in the low-skill sample. In this particular instance, this may indicate that transport costs are in turn themselves determined by the level of offshoring, with high levels of offshoring to Japan or other countries in East Asia raising transport costs to East Asia.[27]

Based on these instruments, we can test the hypothesis of exogeneity of our offshoring measures in the second stage regression. Note from the Durbin-Wu-Hausman test that for the pooled sample we are unable to reject the H_0 of exogeneity within reasonable confidence bounds. The same holds true for the sample of high skilled workers. This implies that in these cases the OLS estimation is more efficient and, hence, preferable to the IV estimation. However, for the subsample of low- skilled workers we have to reject exogeneity of offshoring. In other words, while our empirical approach appears powerful enough to control for potential unobserved industry-specific shocks and while individual within-industry wage variation appears to be large enough to counter potential simultaneity in the sample of high-skilled workers (in which high skilled intensive industries are over- represented), this is not the case for the sample of low-skilled workers. Hence, in what follows we therefore always split the sample between low- and high-skilled workers and use different estimation techniques for the

[27]The fact that offshoring and trade costs are jointly determined does not invalidate their use as instruments for our purposes. What is important in our context is that the instruments are exogenous to individual-level wages, conditional on other covariates in the model.

two samples.

5 Within industry offshoring: Estimation results

We now turn to the results of estimating various specifications of Equation 3 for different task definitions. The main estimation results are presented in Table 4 for the interactivity and non-routine task index following the methodology proposed by Becker et al. (2012).

All specifications are estimated conditional on a large set of controls for observed individual heterogeneity as well as individual fixed effects and industry, region, and time fixed effects.[28] The results presented in Column (a) refer to a baseline specification for low-skilled workers, where potential endogeneity is ignored. In order to deal with potential endogeneity, we implement two approaches. Firstly, the specification in Column (b) includes industry- specific time dummies in order to capture time-varying unobserved shocks that may be correlated with offshoring. This specification is more robust to omitted variable bias as one potential source of endogeneity. Clearly, by including interacted industry-time dummies, all industry-level variables, including offshoring, are rendered collinear. However, one can still identify the parameter of the offshoring-task interaction, ν, in Equation 3 as this only requires within industry-year variation of the task content. Comparing estimates of ν between Column (a) and (b) of Table 4 shows that both estimates are very similar. Accordingly, for the identification of the task-specific offshoring effect, unobserved industry-specific shocks do not seem to play an important role. Rather, we suspect simultaneity of low-skilled workers wages and offshoring to be of relevance.

We therefore further address the endogenity concern in a second approach by instrumenting for offshoring and the associated task-related interaction term. Our choice of excluded instruments is similar to the one employed for the exogeneity tests reported in Table 3. However, to instrument the task-related interaction term, we interact world export supply and one trade cost measure with the respective task index under consideration. As indicated by the Angrist-Pischke F-tests reported in Column (c-iv) of Table 4, our set of excluded instruments has sufficient predictive power in the two "first stages" and the test of the associated overidentifying restrictions does not indicate any violation of the orthogonality assumption.[29]

[28] Coefficients on individual-level covariates take on the expected sign and are of the expected magnitude. To save space, coefficients are not reported but are relegated to a separate Appendix to this paper.

[29] Angrist and Pischke (2009) show how one can obtain modified first stage F-tests as the conventional

Both, the simple model specification that ignores endogeneity reported in Column (a) and the instrumental variables specification reported in Column(c-iv) of Table 4 show a similar pattern for the wage effect of offshoring albeit the overall negative wage effect is much more pronounced in the instrumental variables model. In both model specifications, low-skilled workers experience a wage reduction due to offshoring which, however, becomes less severe the more interactive or non-routine occupational tasks become.

However, precision of the instrumental variable estimator is fairly low as not only offshoring but also the task-related interaction term has to be instrumented, resulting in rather large confidence bands around the marginal effect of offshoring as indicated in Figure 4. Despite these complications, we find some support for our argument that tasks, in addition to skills, matter for the wage effect of offshoring. Thus, our results suggest that among the low-skilled, occupations with a high degree of interactive or non-routine tasks are somewhat shielded from the immediate negative wage impact of industry- level offshoring.

For high-skilled workers, however, as indicated in Column (d) of Table 4, we find no statistically significant wage effect of offshoring irrespective of the occupational task content of workers. Thus, although we observe high-skilled workers in occupations with low interactivity and low non-routine content we cannot identify any immediate wage impact of industry-level offshoring.

6 Cross-Industry Results

We now turn to our second identification strategy. This is based on the idea that industry-specific offshoring measures may be a poor predictor of individual wages if individuals can potentially move between industries. Instead, we now look at cross industry wage effects of offshoring. As discussed in Section 1, when allowing for worker mobility across industries, 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.[30]

One way of approximating these wage effects of offshoring is to use weighted cross-industry measures of offshoring. In order to implement this, we build on Ebenstein

ones are no longer appropriate if there are multiple endogenous variables.

[30]What is important is that no actual movement of workers is required to generate these cross-industry effects; the potential for movement suffices.

et al. (2012) and construct cross-industry offshoring by re-weighting industry-level offshoring measures (cf. Equation 2) with respect to industry employment within a given occupation L_{kj} as a share in total employment within the respective occupation L_k in 1991:

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

Thus, we allow for cross-industry effects of offshoring by making the identifying assumption that workers are reluctant or unable to change occupation k but readily switch between industries j. Accordingly, we re-estimate Equation 3 substituting OS_{kt} for OS_{jt}.

$$\begin{aligned} \ln WAGE_{ikt} &= \alpha + \beta\ DEMOG_{it} + \gamma\ WORK_{it} \\ &+ \lambda OS_{kt} + \nu OS_{kt} \times TASK_k \\ &+ +\theta\ OCC_{kt} + \rho R\&D/Y_{kt} + \tau_k + \mu_t + \iota_i + \epsilon_{ikt} \end{aligned} \tag{6}$$

where $WAGE_{ikt}$ denotes individual i's hourly wage in occupation k at time t.[31]

We now control for occupation-specific observable characteristics by including occupation-specific output and capital (OCC_{kt}) as well as 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 $TASK_k$ in our data, we have perfect collinearity between the two variable sets. Accordingly, our occupation dummies also capture the respective main effect of interactivity and non-routine content. The main difference with respect to the estimation strategy used in Section 4 is that offshoring from several industries is now aggregated according to occupations' representation in the respective industries to capture cross-industry spillovers. Importantly, the weighted cross-industry offshoring measure still does not incorporate any (non-available) information on concrete task or skill specific offshoring costs or levels. Accordingly, similar to Section 4, we essentially rely on aggregated industry-level data to assess whether differential wage effects across different degrees of interactivity of non-routine content follow a pattern consistent with the offshorability of activities as postulated in e.g. Blinder and Krueger (2012). Again, we need to

[31]We now have 61 clusters (occupations) instead of 21 (industries) in the previous analysis.

establish first whether occupation-level offshoring can indeed be considered exogenous to individual wages. Recalling the previous industry-level analysis, we established that endogeneity of offshoring seems to be mainly the result of simultaneity between offshoring and wages rather than that of industry-specific omitted variables. In the present cross-industry analysis we therefore expect less of an endogeneity problem as occupational level offshoring is constructed as a weighted average of industry-level offshoring intensities thereby introducing an extra layer between individual level wages and aggregate offshoring figures. Or put differently, even if certain industries may raise their offshoring activities in response to contemporaneous individual wage increases, as long as there is sufficient variation in wage trends across industries overall occupational-level offshoring will only respond by a fraction corresponding to the respective industries' occupational employment share.

To test for the exogeneity of offshoring, we again utilize measures of industry-level world export supply and industry-level trade costs and transform them into occupation-level variables applying the same weighting scheme as used in Equation 5. Table 5 reports on the choice of excluded instruments and their relevance and validity. For the pooled sample as well as for the low-skilled and high-skilled samples our excluded instruments have high predictive power both individually and jointly, and coefficients have the expected sign, indicating that offshoring increases as world export supply increases and decreases as trade costs rise. Furthermore, our test of overidentifying restrictions does not indicate any violation of the orthogonality assumptions. Accordingly, our excluded instruments are relevant and valid. On this basis we perform a Durbin-Wu- Hausman test of the exogeneity of offshoring and cannot reject exogeneity in any of our three samples. For their superior efficiency, we therefore prefer standard fixed effects estimations over instrumental variable techniques.

Table 6 reports the parameter estimates applying the task classification scheme of Becker et al. (2012). Again, all estimates are conditional on a large set of individual-level control variables (see Table 2), individual fixed effects, as well as time, region, and occupation fixed effects.[32] We find a pronounced negative wage effect of cross-industry offshoring that is inversely related to the interactivity and non- routine content of workers' occupations. We provide a graphical representation of the marginal wage effect of cross-industry offshoring in Figure 5. What becomes clear is that among low-skilled workers, occupations with low interactivity and low non-routine content

[32] Coefficients on individual-level covariates take on the expected sign and are of the expected magnitude. To save space, coefficients are not reported but are included in a separate Appendix to this paper.

experience significant wage cuts while occupations in the higher regions of interactivity and non-routine content are shielded from negative wage effects. Furthermore, after allowing for cross-industry effects of offshoring, we now also find statistically significant wage effects for high-skilled workers that are of similar magnitude and follow a similar pattern as those for low- skilled workers.

To sum up, we find evidence that offshoring mainly lowers wages for workers in occupations that are less interactive and have lower non- routine content. Moreover, this pattern is present for low-skilled and high-skilled workers alike. Our results suggest that indeed irrespective of the education, a high degree of occupational interactivity or non-routine content shields workers from negative wage effects.

How large are these negative wage effects and how discrepant are they between the different occupational tasks? From the regression Table 6 this is difficult to infer. Instead we engage in a thought experiment and ask by how much hourly wages would have decreased had offshoring remained constant at its 1991 value.[33] We do this separately for low- 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 occupational tasks. Table 7 presents the outcome of this exercise.

We find low-skilled workers in the bottom decile of interactivity to experience average cumulated wage cuts of 9 per cent which is equivalent to a 1.3 Euro reduction in hourly gross earnings as compared to average wages in 1991. In comparison, low-skilled workers at the median experience wage cuts of 6 per cent while low-skilled workers at the top decile of interactivity only experience wage cuts of less than 3.5 per cent. Similarly, low-skilled workers in the bottom decile of non-routine content experience wage cuts due to offshoring of about 10 percent while low-skilled workers in the top decile have no significant wage losses. High-skilled workers generally have no statistically significant wage losses due to offshoring, unless, they work in occupations belonging to the bottom decile of interactivity or non-routine content. For these high-skill occupations with very low interactivity and non-routine content we find wage losses from offshoring of around 12 percent.

To further corroborate the importance of the task dimension for the wage impact of offshoring, we run our model without the interaction of task and offshoring. Leaving this interaction term out and calculating the economic significance of offshoring allows

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

us to assess the relevance of the interactions. As the table shows, we find a statistically significant negative effect of 5.3 percent for low skilled workers, and no impact for high skilled workers. By construction, these effects are uniform across tasks. Comparing this to our previous estimates shows that including the task interactions does indeed add important information to our analysis.

In sum, offshoring matters economically and can significantly reduce workers' wages. The effect, however, is heterogenous within skill groups and crucially depends on the interactivity and non-routine content of occupational tasks.

7 Robustness Analysis

This section presents a number of robustness tests for the main cross-industry specification. For all of our tests we do not present the regression table here to save space. Instead, we proceed immediately to the calculation of economic significance, replicating Table 7 based on the new estimates.

In a first test, we expand Equation 6 and apply an alternative set of technology controls. More specifically, we include occupation-specific time trends in addition to all time-varying industry variables (reweighted to the level of the occupation) included in the model. In a further test we exclude all individuals who have changed occupation during the sample period in order to focus on pure within-occupation changes. The calculated wage effects presented in Table 8 are similar for those two specifications compared to the ones presented in Table 7.

We also re-consider our offshoring measure. This is calculated based on offshoring activity within the industry in which an individual works. The idea behind this is, as pointed out above, that such a measure is likely to be most closely related to the actual concept of offshore outsourcing, i.e., that the production was carried out in the home country first and then switches to a location abroad. In comparison, imported intermediates from other industries simply correspond to a switch from domestic to foreign suppliers. Still, we now also consider effects of imported intermediates from other industries by recalculating our offshoring measure using now the difference between imports from the own industry and imports of intermediates from other industries as an additional control variable.[34] In addition we add controls for overall import penetration and export intensity. The results from this exercise are reported in Table 8. We can see that the economic significance of our preferred offshoring measure is hardly

[34] This corresponds to the difference offshoring measure used by Feenstra and Hanson (1999).

affected.[35]

A further set of robustness checks focuses on our task measure. Our analysis thus far uses task indices as outlined in Section 3 based on the classification strategy used by Becker et al. (2012). We now investigate how sensitive our results are to the definition of these task measures. Descriptive statistics for the alternative definitions of tasks are provided in Table 1.

A first test uses an alternative task classification, where we classify tasks into interactive / non- interactive and routine / non-routine, respectively, based on a list of 13 job descriptions that is available in our data set. This is the same set of questions that was first used by Spitz-Oener (2006). The questions are given in Table A2 in Appendix A. We then calculate a task index as described in Equation 1 based on this classification.

Based on this alternative task measure, we re-estimate Equation 6. Results are presented in the top panel of Table 9. A look at the economic significance shows that the magnitude and pattern of the calculated wage effects is similar to our original results when applying this new task measures based on the alternative classification scheme based on Spitz-Oener (2006).

In a further robustness check we propose another alternative task index. Our definition of the task index in Equation 1 implies, as in Spitz-Oener (2006) and Becker et al. (2012), that interactivity and non-routine content increase in the number of interactive or non-routine occupational tools or tasks. However, as the total number of tools or tasks, interactive / non-routine or not, varies across occupations, the proposed classification scheme could be distorted. Consider truck drivers as an illustrating example. Trucks are classified as tools that correspond to an interactive task. However, based on the task index used thus far, truck driving occupations might not be classified as very interactive as truck drivers may use little other tools than a truck.

As an alternative, we therefore use the task classification of Becker et al. (2012) but normalize by the total number of tasks used in the occupation (instead of the maximum number of interactive / non-routine tasks in any occupation). Thus, we construct modified indexes of interactivity and non-routine content based on the share of interactive (non routine) tasks in total occupational tasks:

$$TASK_{zk}^{modified} = \text{Average}\left(\frac{\text{Number of } z\text{-tasks}}{\text{Number of total tasks}}\right) \text{ of occ. } k, \tag{7}$$

[35] Note that all additional globalization indicators including the difference between broadly and narrowly defined offshoring are rendered statistically insignificant for the sample of low- and high-skilled workers alike.

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

The bottom panel of Table 9 reports the predicted wage changes due to offshoring according to specifications relying on these alternative task indices. We first focus on the interactivity index. While results are broadly in line with our previous findings for high-skilled workers, the negative wage effect for low-skilled workers is now essentially uniform across different degrees of interactivity.

This suggests that the initial task intensity measures based on the absolute number of tasks do capture some within skill-group heterogeneity for low-skilled workers that the measures using the alternative normalization do not. In fact, the correlation coefficient between the alternative interactivity index and the one obtained following Becker et al. (2012) is only 0.563 for low skilled workers.[36]

What our results suggest is that the total number of interactive tasks matters rather than their share in the total number of tasks, casting some doubt on whether the within-skill heterogeneity of offshoring effects can indeed be attributed to different degrees of interactivity. What seems to be important and what is at least implicitly captured in the initial interactivity index is the complexity of occupations as approximated by the total number of (interactive) tasks (cf. Antonczyk et al., 2009).

In contrast, the choice of index does hardly matter for the results relying on the intensity of non-routine tasks. (see the top panel of Table 9). This can be explained by the fact that the correlation between the alternative task index and the one calculated according to Equation 1 based on Becker at al. (2012) is very large (correlation coefficient equals 0.90 for the low-skilled and 0.93 for the high-skilled). Thus, occupations will be classified very similarly according to their non-routine content irrespective of the classification scheme. Put differently, in occupations that use many non-routine tasks, that is in occupations that can, arguably, be described as rather complex, these non-routine tasks also account for a large share in the total number of tasks. Accordingly, we find the effects of offshoring to be very similar between the different classification methods for non- routine content.

Summarizing, we find the complexity of occupations as captured by the number of interactive or non-routine occupational tasks to play a mitigating role for the wage effect of offshoring. While the complexity of occupations is indistinguishable from the non-routine content (both are strongly correlated), our robustness analysis casts some

[36]For high- skilled workers for whom we find a wage effect that is smaller but at least weakly statistically significant when using the alternative interactivity index, the correlation coefficient between the two interactivity measures is 0.656 and thus significantly higher.

doubt on the importance of pure interactivity of occupations for mitigating the wage effects of offshoring.

8 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), Leamer and Storper (2001), Levy and Murnane (2004), and Blinder and Krueger (2012), 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 or on the extent to which personal interaction is needed on the job.

For the empirical analysis we combine individual-level data and industry- specific offshoring measures and classify occupations according to their degree of interactivity and non-routine content. In line with earlier research, we find the within-industry impact of offshoring on individual wages to be rather modest or non-existent. However, we find substantial negative cross-industry wage effects of offshoring for low- and high-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 non-routine content (which, arguably, are also the tasks that can most easily be offshored), increased offshoring between 1991 and 2006 accounts for a cumulative average yearly wage reduction of around 2400 euros (assuming 1500 annual work hours). For low-skilled workers with the highest degree of non-routine content, offshoring can merely explain an (insignificant) yearly wage reduction of about 15 euros.

Thus, in line with the arguments put forward in the literature a higher degree of interactivity and, in particular, non-routine content can indeed shield workers against the negative wage impact of offshoring. Furthermore, this effect is present even after conditioning on workers' education.

Figures and Tables

Table 1: Description of Task Indices

TASK	All	Low-Skilled	High-Skilled
Interactivity Index based on Becker et al. (2012)			
Mean μ	0.358	0.319	0.445
Standard Deviation	0.146	0.137	0.125
Mean Comparison Test		$H_0 : \mu_{Low-Skilled} = \mu_{High-Skilled}$ p=0.000	
Non-Routine Index based on Becker et al. (2012)			
Mean μ	0.492	0.407	0.682
Standard Deviation	0.237	0.186	0.229
Mean Comparison Test		$H_0 : \mu_{Low-Skilled} = \mu_{High-Skilled}$ p=0.000	
Interactivity Index based on Spitz-Oener (2006)			
Mean μ	0.343	0.268	0.512
Standard Deviation	0.230	0.189	0.224
Mean Comparison Test		$H_0 : \mu_{Low-Skilled} = \mu_{High-Skilled}$ p=0.000	
Non-Routine Index based on Spitz-Oener (2006)			
Mean μ	0.428	0.345	0.612
Standard Deviation	0.239	0.198	0.219
Mean Comparison Test		$H_0 : \mu_{Low-Skilled} = \mu_{High-Skilled}$ p=0.000	
Modified Interactivity Index			
Mean μ	0.095	0.092	0.101
Standard Deviation	0.041	0.045	0.030
Mean Comparison Test		$H_0 : \mu_{Low-Skilled} = \mu_{High-Skilled}$ p=0.000	
Modified Non-Routine Index			
Mean μ	0.215	0.189	0.275
Standard Deviation	0.076	0.061	0.072
Mean Comparison Test		$H_0 : \mu_{Low-Skilled} = \mu_{High-Skilled}$ p=0.000	
Observations	13,695	9,458	4,237

Figure 1: Distribution of Interactivity-Index by Skill (based on Becker et al., 2012)

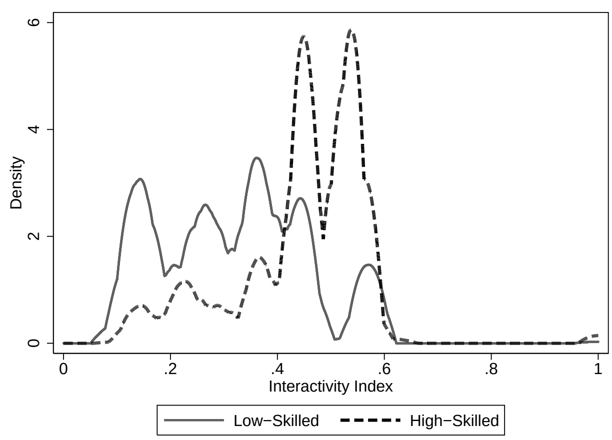


Figure 2: Distribution of Non-Routine-Index by Skill (based on Becker et al., 2012)

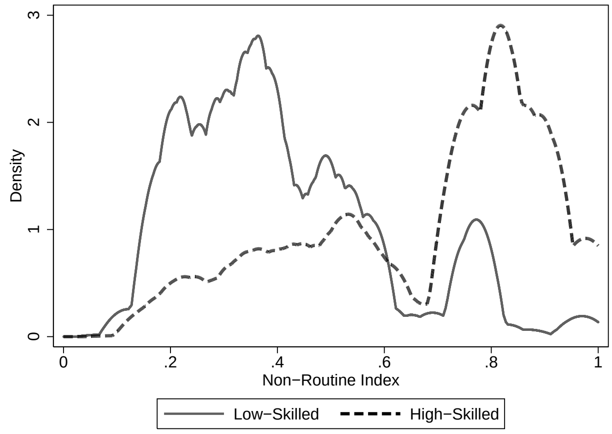
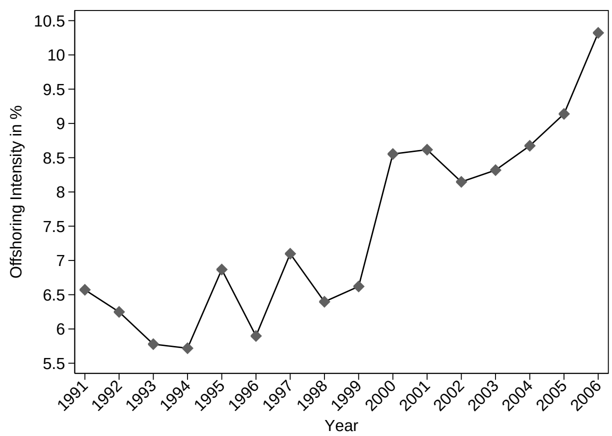


Figure 3: Offshoring in Manufacturing



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

Table 2: Descriptive Statistics

	Notes:	Low- and High-Skillled		Low-Skilled		High-Skilled	
		Mean	SD	Mean	SD	Mean	SD
WAGE	0/1	17.30	8.06	15.20	5.25	21.99	10.79
D: Married	0/1	0.76	0.43	0.74	0.44	0.79	0.41
D: Has Children	0/1	0.57	0.50	0.56	0.50	0.59	0.49
D: Firm Size < 20	0/1	0.01	0.11	0.01	0.10	0.01	0.12
D: Firm Size $20 - 199$	0/1	0.09	0.29	0.10	0.30	0.08	0.26
D: Firm Size $200 - 1999$	0/1	0.27	0.45	0.29	0.45	0.24	0.43
D: Public Firm	0/1	0.01	0.09	0.01	0.10	0.00	0.07
D: Firm Owner not reported	0/1	0.01	0.10	0.01	0.10	0.01	0.10
Tenure	in years	12.00	9.29	12.56	9.39	10.77	8.94
Work Experience Full-time	in years	18.41	10.34	19.19	10.61	16.65	9.48
Work Experience Part-time	in years	0.23	1.11	0.18	0.99	0.34	1.35
D: Recent Unemployment	0/1	0.02	0.13	0.02	0.14	0.01	0.11
D: High-Skilled	0/1	0.31	0.46				
Production Value Y	in billion euros	98.88	55.09	95.52	53.89	106.39	56.97
Cap_{Equ}/Y	in per cent	54.84	15.28	55.53	15.42	53.29	14.86
Cap_{Plant}/Y	in per cent	30.99	12.62	32.01	13.05	28.70	11.30
$R\&D/Y$	in per cent	2.32	2.46	2.10	2.36	2.81	2.61
OS	in per cent	6.53	5.11	6.29	5.16	7.09	4.94
Observations		13,695		9,458		4,237	

Table 3: Within-Industry Analysis: Exogeneity Tests

	Low- and High-Skilled Workers		
"First-Stage" coefficients of excl. instruments			
ln(World Export Supply)	2.046	(0.485)	***
Advalorem Trade Costs - Export to USA	-44.936	(4.926)	***
F-test	F=67.630	p=0.000	***
Hansen J-Statistic, overidentifying restrictions	χ^2=0.028	p=0.868	
Durbin-Wu-Hausman, H_0: Exogeneity	χ^2=0.756	p=0.385	
	Low-Skilled Workers		
"First-Stage" coefficients of excl. instruments			
ln(World Export Supply)	2.224	(0.524)	***
Advalorem Trade Costs - Export to USA	-45.578	(5.813)	***
Advalorem Trade Costs - Export to Japan	6.835	(1.757)	***
F-test	F=57.350	p=0.000	***
Hansen J-Statistic, overidentifying restrictions	χ^2=1.685	p=0.431	
Durbin-Wu-Hausman, H_0: Exogeneity	χ^2=4.099	p=0.043	**
	High-Skilled Workers		
"First-Stage" coefficients of excl. instruments			
ln(World Export Supply)	2.737	(1.032)	***
Unit Trade Costs - Export JPN	-0.645	(0.127)	***
F-test	F=13.610	p=0.000	***
Hansen J-Statistic, overidentifying restrictions	χ^2=0.447	p=0.504	
Durbin-Wu-Hausman, H_0: Exogeneity	χ^2=0.126	p=0.723	

Note: Standard errors in parentheses. *, **, *** significant at 10%, 5%, 1% error probability.

Table 4: Within-Industry Analysis – Becker et al. (2012) classification

	Interactive Tasks			
	Low-Skilled			High-Skilled
	(a)	(b)	(c-IV)	(d)
TASK	-0.0901		-0.0114	-0.0806
	[0.140]		[0.165]	[0.094]
Production Value Y	-0.0002		-0.0012*	0.0012**
	[0.000]		[0.001]	[0.001]
Cap_{Equ}/Y	0.0017		-0.0026	0.0049*
	[0.002]		[0.003]	[0.002]
Cap_{Plant}/Y	-0.0045		-0.0018	-0.0066
	[0.004]		[0.003]	[0.005]
$R\&D/Y$	0.0096		-0.0043	0.0034
	[0.006]		[0.009]	[0.006]
OS	-0.0112*		-0.0369**	0.002
	[0.006]		[0.017]	[0.008]
$OS \times TASK$	0.0216*	0.0230***	0.0046	-0.0005
	[0.011]	[0.009]	[0.020]	[0.018]
Observations	9,458	9,458	9,458	4,237
R^2	0.77	0.78	0.73	0.84
Industry-time effects	No	Yes	No	No
Angrist-Pischke F-test			F=31.83, F=64.09	
Hansen test of overidentifying restrictions			χ^2=3.352	
			p=0.340	
Durbin-Wu-Hausman test of exogeneity			χ^2=5.401	
			p= 0.067	
Excluded Instruments in Column (c-IV):			Adv. TradeC osts:Export USA, JPN	
			Adv.Trade Costs:Export JPN $\times TASK$	
			ln(World Export Supply),ln(World Export Supply)$\times TASK$	

	Non-Routine Tasks			
	Low-Skilled			High-Skilled
	(a)	(b)	(c-IV)	(d)
TASK	-0.0424		-0.1454	-0.1639
	[0.108]		[0.131]	[0.150]
Production Value Y	-0.0002		-0.0011*	0.0012**
	[0.000]		[0.001]	[0.001]
Cap_{Equ}/Y	0.0018		-0.0025	0.0048*
	[0.002]		[0.002]	[0.002]
Cap_{Plant}/Y	-0.0048		-0.0015	-0.0065
	[0.004]		[0.003]	[0.005]
$R\&D/Y$	0.0095		-0.0028	0.0043
	[0.006]		[0.009]	[0.006]
OS	-0.0093**		-0.0456**	-0.0056
	[0.004]		[0.019]	[0.005]
$OS \times TASK$	0.0123	0.0156**	0.0278	0.0102
	[0.008]	[0.008]	[0.018]	[0.007]
Observations	9,458	9,458	9,458	4,237
R^2	0.77	0.78	0.73	0.84
Industry-time effects	No	Yes	No	No
Angrist-Pischke F-test			F=22.49 , F=47.22	
Hansen test of overidentifying restrictions			χ^2=3.677	
			p=0.299	
Durbin-Wu-Hausman test of exogeneity			χ^2=4.695	
			p=0.096	
Excluded Instruments in Column (c-IV):			Adv. Trade Costs:Export USA, CHN	
			Adv.Trade Costs:Export CHN $\times TASK$	
			ln(World Export Supply), ln(World Export Supply)$\times TASK$	

Note: Standard errors in parentheses. *, **, *** significant at 10%, 5%, 1% error probability. Regressions contain full set of individual-level control variables as described in Table 2. All models with full set of individual and region, (interacted) time and industry fixed effects.

Figure 4: Marginal Effect of Industry-Specific Offshoring with Confidence Band: Becker et al. (2012) classification

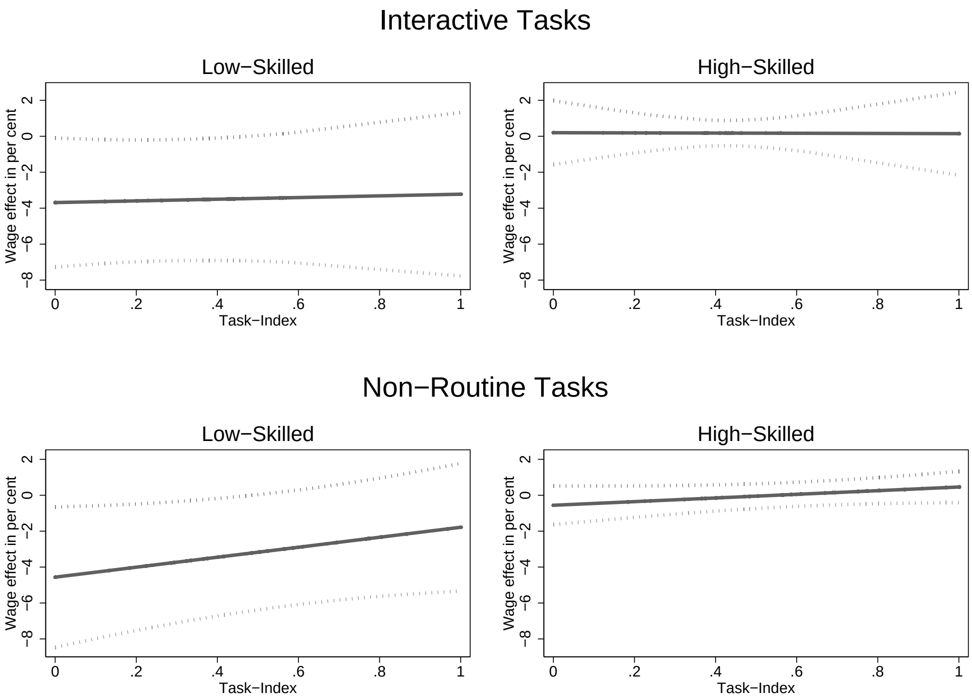


Table 5: Cross-Industry Analysis: Exogeneity Tests

	Low- and High-Skilled Workers pooled		
"First-Stage" coefficients of excl. instruments			
ln(World Export Supply)	2.9575	(0.3953)	***
Advalorem Trade Costs - Export to USA	-35.1334	(5.5191)	***
F-test	F= 57.47	p=0.000	***
Hansen J-Statistic, overidentifying restrictions	χ^2=1.721	p=0.190	
Durbin-Wu-Hausman, H_0: Exogeneity	χ^2=0.803	p=0.370	
	Low-Skilled Workers		
"First-Stage" coefficients of excl. instruments			
ln(World Export Supply)	3.459	(0.478)	***
Advalorem Trade Costs - Export to USA	-38.268	(5.668)	***
Advalorem Trade Costs - Export to China	-2.209	(0.651)	***
F-test	F=45.43	p=0.000	***
Hansen test of overidentifying restrictions	χ^2=2.711	p=0.258	
Durbin-Wu-Hausman, H_0: Exogeneity	χ^2=0.524	p=0.469	
	High-Skilled Workers		
"First-Stage" coefficients of excl. instruments			
Unit Trade Costs - Import USA	-0.634	(0.132)	***
Unit Trade Costs - Import JPN	-1.052	(0.414)	**
F-test	F=13.93	p=0.000	***
Hansen test of overidentifying restrictions	χ^2=0.771	p= 0.380	
Durbin-Wu-Hausman, H_0: Exogeneity	χ^2=0.118	p=0.731	

Note: Standard errors in parentheses. *, **, *** significant at 10%, 5%, 1% error probability.

Table 6: Cross-Industry Analysis – Becker et al. (2012) classification

	Interactive Tasks			**Non-Routine Tasks**	
	Low-Skilled (a)	High-Skilled (b)		Low-Skilled (c)	High- Skilled (d)
Production Value Y	0.0004	-0.0018		0.0006	- 0.0013
	[0.001]	[0.004]		[0.001]	[0.004]
Cap_{Equ}/Y	0.002	0.0053		0.0031	0.0037
	[0.004]	[0.009]		[0.003]	[0.008]
Cap_{Plant}/Y	-0.0036	-0.0209		-0.0034	- 0.0162
	[0.004]	[0.017]		[0.004]	[0.017]
$R\&D/Y$	-0.0098	0.0439***		-0.0062	0.0460***
	[0.018]	[0.016]		[0.018]	[0.016]
OS	-0.0279***	-0.0531***		-0.0380***	- 0.0471**
	[0.010]	[0.020]		[0.010]	[0.020]
$OS \times TASK$	0.0358	0.0805**		0.0494**	0.0407*
	[0.022]	[0.040]		[0.019]	[0.022]
Observations	9,458	4,237		9,458	4,237
R^2	0.77	0.84		0.77	0.84
Joint significance $OS, OS \times TASK$	F = 7.34 p = 0.002	F = 3.72 p = 0.032	F =9.11 p = 0.000	F = 2.86 p = 0.067	

Note: Standard errors in parentheses. *, **, *** significant at 10%, 5%, 1% error probability. Regressions contain full set of individual-level control variables as described in Table 2. All models contain a full set of individual, time, occupation and region fixed effects.

Figure 5: Marginal Effect of Occupation-Specific Offshoring with Confidence Band: Becker et al. (2012) classification

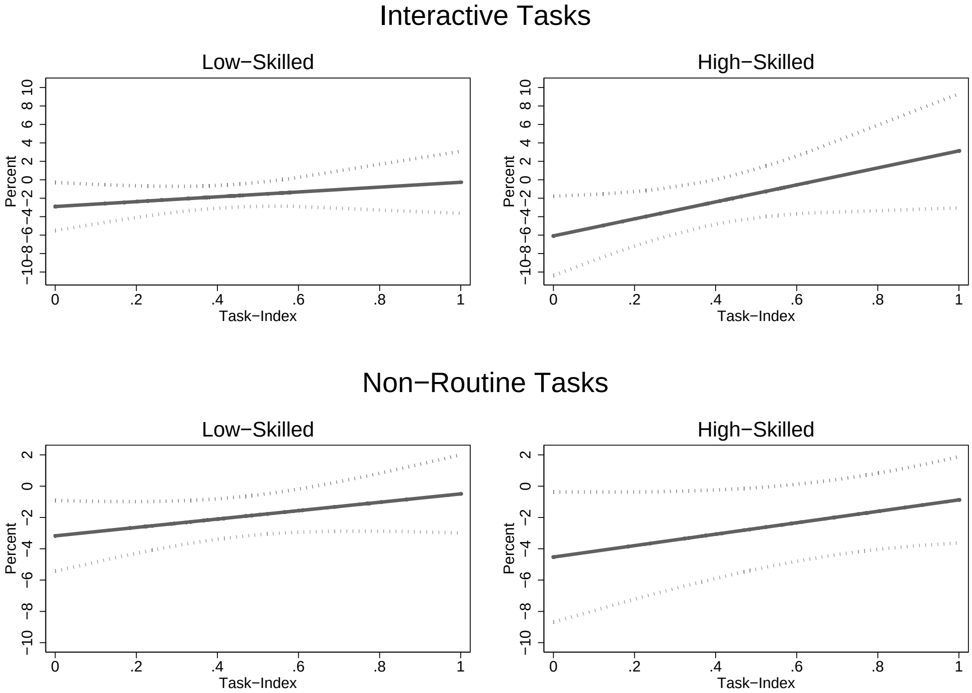


Table 7: Cross-Industry Analysis – Economic Significance Calculations

	Low-Skilled			High-Skilled		
Average hourly wage in 1991	15.00			21.00		
Interactive Tasks						
	Percent		Euro	Percent		Euro
10th percentile	-8.52	(2.55)***	-1.28	- 12.60	(4.91)**	-2.65
50th percentile	-5.79	(1.53)***	-0.87	- 5.94	(4.43)	-1.25
90th percentile	-3.42	(1.80)**	-0.51	- 3.01	(4.95)	-0.63
Joint significance	$F = 7.34$			$F = 3.72$		
OS,$OS \times TASK$	$p = 0.002$			$p = 0.032$		
Non-Routine Tasks						
	Percent		Euro	Percent		Euro
10th percentile	-10.87	(2.64)***	-1.63	- 12.10	(5.22)**	-2.54
50th percentile	-7.32	(1.77)***	-1.10	- 5.90	(4.20)	-1.24
90th percentile	-0.05	(2.74)	-0.01	- 2.90	(4.58)	-0.61
Joint significance	$F = 9.11$			$F = 2.86$		
OS,$OS \times TASK$	$p = 0.000$			$p = 0.067$		
Model without Task interaction						
	Percent		Euro	Percent		Euro
	-5.31	(1.57)***	-0.80	-6.80	(4.53)	-1.43

Note: Standard errors in parentheses. *, **, *** significant at 10%, 5%, 1% error probability.

Table 8: Alternative Specifications – Economic Significance Calculations

	Low-Skilled			High-Skilled		
	Percent		Euro	Percent		Euro
Industry-Specific Time Trends						
Interactive Tasks						
10th percentile	-8.72	(3.39)**	-1.31	-14.03	(5.05)***	- 2.95
50th percentile	-5.96	(1.98)***	-0.89	-6.11	(4.52)	-1.28
90th percentile	-3.56	(2.30)	-0.53	-2.62	(5.27)	-0.55
Joint significance	$F = 4.60$			$F = 4.11$		
OS,$OS \times TASK$	$p = 0.014$			$p = 0.023$		
Non-Routine Tasks						
10th percentile	-9.03	(3.11)***	-1.36	-9.72	(6.07)	-2.04
50th percentile	-6.75	(2.05)***	-1.01	-6.65	(4.14)	-1.40
90th percentile	-2.06	(3.37)	-0.31	-5.16	(4.52)	-1.08
Joint significance	$F = 5.42$			$F = 1.49$		
OS,$OS \times TASK$	$p = 0.007$			$p = 0.235$		
Reduced sample without occupation switchers						
Interactive Tasks						
10th percentile	-9.44	(3.64)***	-1.42	-14.43	(5.13)***	- 3.03
50th percentile	-7.44	(2.42)***	-1.12	-6.82	(4.71)	-1.43
90th percentile	-5.70	(2.51)**	-0.85	-3.46	(5.43)	-0.73
Joint significance	$F = 4.74$			$F = 4.24$		
OS,$OS \times TASK$	$p = 0.013$			$p = 0.020$		
Non-Routine Tasks						
10th percentile	-10.05	(3.17)***	-1.51	-12.01	(5.44)**	- 2.52
50th percentile	-8.13	(2.46)***	-1.22	-6.49	(4.50)	-1.36
90th percentile	-4.19	(3.29)	-0.63	-3.81	(5.00)	-0.80
Joint significance	$F = 5.56$			$F = 2.49$		
OS,$OS \times TASK$	$p = 0.006$			$p = 0.094$		
Additional Globalization Controls						
Interactive Tasks						
10th percentile	-7.62	(2.42)***	-1.14	-13.85	(4.57)***	- 2.91
50th percentile	-4.84	(1.65)***	-0.73	-6.61	(4.09)	-1.39
90th percentile	-2.42	(1.98)	-0.36	-3.42	(4.73)	-0.72
Joint significance	$F = 5.29$			$F = 4.82$		
OS,$OS \times TASK$	$p = 0.008$			$p = 0.013$		
Non-Routine Tasks						
10th percentile	-9.96	(2.68)***	-1.49	-11.88	(4.79)***	- 2.49
50th percentile	-6.12	(1.86)***	-0.92	-6.28	(3.88)	-1.32
90th percentile	1.75	(2.68)	0.26	-3.57	(4.64)	-0.75
Joint significance	$F = 6.93$			$F = 3.08$		
OS,$OS \times TASK$	$p = 0.002$			$p = 0.055$		

Note: Standard errors in parentheses. *, **, *** significant at 10%, 5%, 1% error probability.

Table 9: Alternative Task Indices – Economic Significance Calculations

	Low-Skilled			High-Skilled		
	Percent		Euro	Percent		Euro
Task Classification based on Spitz-Oener (2006)						
Interactive Tasks						
	Percent		Euro	Percent		Euro
10th percentile	-8.60	(1.78)***	-1.29	-11.74	(5.35)**	- 2.46
50th percentile	-7.11	(1.34)***	-1.07	-3.33	(4.37)	- 0.70
90th percentile	-0.65	(2.68)	-0.10	2.43	(5.62)	0.51
Joint significance	$F = 14.11$			$F = 2.85$		
OS,$OS \times TASK$	$p = 0.000$			$p = 0.068$		
Non-Routine Tasks						
	Percent		Euro	Percent		Euro
10th percentile	-9.44	(2.01)***	-1.42	-11.47	(5.60)**	- 2.41
50th percentile	-6.74	(1.32)***	-1.01	-3.32	(4.22)	- 0.70
90th percentile	-0.85	(2.45)	-0.13	0.39	(4.92)	0.08
Joint significance	$F = 13.30$			$F = 2.33$		
OS,$OS \times TASK$	$p = 0.000$			$p = 0.108$		
Modified Task Classification, Equation: 7						
Interactive Tasks						
10th percentile	-5.20	(2.14)**	-0.78	-8.71	(4.71)*	- 1.83
50th percentile	-5.35	(1.49)***	-0.80	-5.55	(4.72)	- 1.17
90th percentile	-5.45	(2.14)***	-0.82	-1.39	(5.42)	- 0.29
Joint significance	$F = 6.58$			$F = 3.39$		
OS,$OS \times TASK$	$p = 0.003$			$p = 0.042$		
Non-Routine Tasks						
10th percentile	-10.17	(2.47)***	-1.53	-13.96	(5.24)**	- 2.93
50th percentile	-7.67	(1.72)***	-1.15	-2.80	(4.50)	- 0.59
90th percentile	0.48	(3.04)	0.07	-1.17	(4.70)	-0.25
Joint significance	$F = 9.92$			$F = 4.55$		
OS,$OS \times TASK$	$p = 0.000$			$p = 0.016$		

Note: Standard errors in parentheses. *, **, *** significant at 10%, 5%, 1% error probability.

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Appendix A: Task Classification

Table A1: Classification of tasks following Becker et al. (2012)

	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. (2012). 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

Note: Items refer to the list of surveyed job descriptions in the German Qualification and Career Survey 1998/99. Whereas Spitz-Oener (2006) follows Autor et al. (2003) and creates five task categories, we aggregate them to measures of non-routineness and interactivity in order to ensure comparability with the Becker et al. (2012) mapping.