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Complementary Tasks and the Limits to the Division of Labour*

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Abstract: During the recent decades, multitasking has become a more and more common phenomenon at workplaces. Rather than specializing in a job task, workers perform bundles of tasks. Bundling occurs when tasks are complements. Using individual-level data about job tasks, we analyze which tasks are complements. Such intrapersonal task complementarities limit the division of labour as complementary tasks can only be unbundled at a cost (productivity loss). To illustrate this point, we apply our findings to the debate about the offshorability of jobs and show that the number of potentially offshorable jobs is significantly lower when task complementarities are accounted for. We also advance the current literature on offshorability by introducing an indicator at the task-level, rather than the occupation-level.

Keywords: tasks, complementarities, offshoring, offshorability, division of labor

JEL classification: F16, L23, J22

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1. Introduction

Ever since Adam Smith's famous description of a pin factory, economists have suggested that workers should specialize in tasks in order to enhance their productivity through learning by doing. Yet, during the last decades, the organization of work has changed significantly with multitasking (as opposed to task specialization) becoming a more and more prominent phenomenon (NUTEK, 1999; OECD, 1999; Osterman, 2000; Caroli & van Reenen, 2001). Moreover, many authors acknowledge that jobs, rather than being made up of just one specialized task, are in fact bundles of tasks, even though some jobs certainly consist of larger bundles than others (e.g. Autor & Handel, 2009).

There is an obvious reason why we observe multitasking at workplaces: if two tasks are complements, combining them increases total productivity. Performing both tasks gives rise to intertask learning, where a worker's performance in a particular task is increased when he or she can apply knowledge and experience from performing another task (cf. Lindbeck & Snower, 2000). Consequently, complementary tasks can better be performed by one worker rather than two or more. Rising levels of multitasking can be explained by an increasing exploitation of complementarities between tasks, which has been significantly eased by improvements in ICT capital, more versatile machines, and the broadening of human capital across skills (Milgrom & Roberts, 1990; Lindbeck & Snower, 1996, 2000; Gibbs, Levenson & Zoghi, 2010).

The presence of task complementarities has important implications for the division of labour. Since combining complementary tasks increases a worker's productivity, unbundling these tasks comes at a cost: productivity declines. Consequently, gains from unbundling (e.g. wage savings) should be at least as large as the productivity loss in order for unbundling to occur. Thus, intrapersonal task complementarities limit the division of labour. This holds both for a division at the local shop-floor level, as well as for an international division of labour through offshoring or trade in tasks. If a complementary task pair involves both an offshorable and a non-offshorable task, the fact that they are complements makes unbundling them more costly. If the strength of a complementarity is higher than the wage savings that can be achieved by offshoring, the offshorable task will still be produced domestically.

In this paper, we ask *which* tasks are complementary. Using person-level data including detailed information about job tasks performed at work, we identify tasks, which are frequently combined by workers and can thereby infer which tasks are complements. We call these intrapersonal task complementarities. Examples are "operating machines" and "repairing", or "selling and buying" and "consulting". In order to show to what extent complementarities limit the offshorability of jobs (i.e. the feasibility that a job is offshored), we first classify tasks as offshorable or non-offshorable. Then, we take out those complementary pairs that involve an offshorable and a non-offshorable task and calculate what fraction of workers in high-offshoring-risk occupations performs them. We find that, on average, 59% of the workers in these high-risk occupations perform at least one such complementary offshorable/non-offshorable task pair. Hence, the potential international division of labour is severely limited by the presence of intrapersonal task complementarities.

This article contributes to current research in three respects. First, we present empirical evidence on intrapersonal task complementarities and task bundling. Task bundles are characterized by gender, education, and earnings groups. Second, we offer an indicator for offshorability at task- rather than occupation-level (unlike, e.g., Blinder, 2007; Goos, Manning & Salomons, 2010). Third, we show and quantify how task complementarities can limit the international division of labour by reducing the potential to unbundle a job's task portfolio.

The plan of the paper is as follows. Section 2 discusses previous literature about the division of labour and the role of job tasks. Section 3 outlines our empirical approach for identifying complementary tasks. Section 4 describes the data and construction of variables. Results on complementary tasks are presented in section 5. In section 6, we apply our findings to the debate about the offshorability of jobs, preceded by a short literature overview on the subject and the classification of offshorable tasks. Section 7 concludes.

2. Previous Literature

The idea of this paper follows from theoretical considerations by Lindbeck and Snower (1996, 2000). They seek to explain the increasing spread of multitasking by looking at *intra*personal task coordination and specialization, in contrast to an *inter*personal perspective as in other studies discussed below. Lindbeck and Snower observe that many firms have restructured from Tayloristic towards holistic organizations, where the former is characterized by a strong degree of task specialization and the latter by multitasking of workers. They argue that improvement in computerized information and communication systems, new flexible machine tools, a widening of human capital, and changes in workers' preferences towards their working environment all favour holistic organizational forms (i.e. multitasking) over Tayloristic firms because they facilitate intertask learning: productivity in one task is increased when the worker is also involved in another, complementary task.[1] Dividing

[1] Consider how the emergence of flexible machine tools increased the versatility of machines across tasks: the quick retooling, which was then possible, allowed fast reactions to changing customer demands, hence making strong complementarities between sales and production tasks arise.

complementary tasks between workers would impede intertask learning and, thus, implies a cost to the firm.

Besides this, there is a large body of theoretical literature discussing how tasks should be allocated between workers in a firm. Most of these focus on the limits of task specialization. In these models, several tasks have to be combined to produce output and these can be split among workers each specializing in a particular task within the required spectrum. Adam Smith (1776) has argued that task specialization is only limited by market size. More recent studies have argued, however, that particularly coordination costs are an important limit to specialization. Becker and Murphy (1992) mention principal-agent conflicts, hold-up problems and breakdowns in supply and communication as examples of coordination costs, but it can more generally be seen as the challenge to arrive at a harmonious output when each worker provides a different specialized inputs.

The model by Becker and Murphy (1992) suggests that lower communication costs, e.g. due to computers, make specialization more likely (see also Borghans & ter Weel, 2006). Yet, recent years have rather been characterized by increases in multitasking and, hence, a lower degree of specialization. Borghans and ter Weel explain this development by arguing that computer technology has made workers more productive in many tasks, so that the relative gains from learning-by-doing for a specialized task have decreased. Dessein and Santos (2006) highlight that organizations need to adapt to a changing environment and that worker-specific information may be required to do so. It may, hence, makes sense for a firm to allow their employees more flexibility to arrange their work, rather than assigning them fixed specialized tasks. Essentially, this implies that the workers perform a wider range of tasks (higher levels of multitasking). Using a principal-agent framework, Holmstrom and Milgrom (1991) show that multitasking is also affected by remuneration schemes and the measurability of employee performance.[2]

Coordination costs and intrapersonal task complementarities are not rival explanations for the limits to the division of labour. Coordinating specialized workers is only costly if the tasks are complements, i.e. if they are linked in some productive way. The amount of the costs could even be positively related to the strength of the complementarity. In principle, all papers mentioned above, use complementarities between tasks for their arguments. For example, in Dessein and Santos (2006), workers are multitasking because they tailor their work to maximally use local information, i.e. they exploit complementarities between tasks.

A recent empirical literature has started to look into task profiles of occupations (rather than individuals as we do in this study) by using detailed information about tasks performed by the

[2] See also Zhang (2003), Itoh (1994), Schöttner (2008), Kaarboe & Olsen (2006), or Corts (2007) for more work in this spirit.

workers. Using earlier waves of the German survey employed in this study, Spitz-Oener (2006) analyzed changes in occupational skill requirements by investigating how many workers performed nonroutine analytical, nonroutine interactive, routine manual, routine cognitive and nonroutine manual tasks. Her results show that occupations are undergoing significant changes in task inputs over time and that they require increasingly complex skills. A similar result emerged from the work by Autor, Levy and Murnane (2003) for the US. Analyzing the polarization of employment, Goos and Manning (2007), and Goos et al. (2010) also use the task content of occupations to make sense of the decline of middle-income jobs.[3]

With the exception of Spitz-Oener (2006), previous studies did not or could not employ within-occupation information about task assignment for their analyses. Yet, Autor and Handel (2009) show that individual differences in task portfolios might be important in explaining wages. Controlling for occupation fixed effects, human capital and demographic characteristics of the worker, they include three (aggregate) task measures into an otherwise standard wage regression: Data, People, Things, which represent cognitive job demands, face-to-face interactions, and physical and routine job tasks, respectively.[4] They find that variation in individual task input accounts for a significant fraction of the variation in earnings. Accordingly, it is important to analyze tasks at a worker rather than occupation level.

3. Empirical Approach

Generally, complementarity can be investigated using the partial elasticities of factor prices from a wage regression. Assume that a worker produces output by performing one or several tasks, $Y = f(X_1, X_2, \ldots, X_N)$, where X_n designates the task. These tasks may be complements in production. Assuming that wages equal the marginal product, two tasks are complements when the partial elasticity $\partial \ln w_n / \partial \ln X_m > 0$, i.e. an increase in the quantity of task *m* raises the marginal product and hence the return to task *n*. An illustrative example is the combination of repairing and manufacturing tasks. If a worker is performing both tasks there is likely to be strong *intertask* learning, i.e. productivity in repairing is increased when the worker is also involved in manufacturing. Taking this argument to the empirical exercise, it would be possible to recover complementary tasks by extending a standard Mincerian wage

[3] They argue that middle-income jobs, i.e. those in the middle of the earnings distribution, are intensive in routine tasks which can more easily be replaced by computers.

[4] The tasks are captured by questions such as the length of the longest document typically read on the job, the use of maths or problem-solving, interactions with customers or colleagues, or the proportion of the day spent standing, operating machines or fixing things by hand.

equation and regressing wages on tasks and all the possible interactions between tasks. A significantly positive coefficient of a task pair would indicate that the two are complements.

However, this approach is not appropriate in our case. Theoretical work based on a task framework suggests that the results of a regression of wages on task inputs may not be interpretable (Acemoglu & Autor, 2010). In their model, production factors – skills (labour), technology (capital), or trade (offshoring) – are assigned to accomplish a particular task. However, this assignment is endogenous and depends on cost (the market value of the task and factor costs) and comparative advantage. Hence, tasks are not fixed worker attributes (unlike, e.g., education), so that there is no economy-wide return to a task, either (see also Autor & Handel, 2009).

Moreover, some task may be more valuable in one occupation than in another (Firpo, Fortin & Lemieux, 2010). A wage regression on the pooled sample, including the whole universe of occupations, would consequently not be able to produce any sensible task returns. Estimating task returns within occupations would essentially show whether performing a certain task results in a deviation from the occupation's average pay. That said, a regression coefficient near zero (or insignificant) does not necessarily imply that performing the task is not rewarded in an occupation. It could simply be the case that all workers perform it and there is no variation in task input which can be used to explain wage differences. Lastly, due to the limited sample size of most occupations at a reasonable level of disaggregation, such an exercise is not possible.

Hence, we will abstain from using wage regressions to identify task complementarities, but rely on revealed complementarity and analyze frequent task combinations. To that end, we assume that the economy is in equilibrium and all tasks are allocated optimally. If, in equilibrium, a worker combines two tasks, the two are complements. This approach would, hence, assume that the combinations of tasks, which we observe in the data, are indeed complements. There are two important drawbacks to this approach. First, simply analyzing unconditional correlations between tasks may include effects resulting from the occupational composition in the economy. In other words, task combinations may simply occur more frequently because a particular occupation is large. Hence, controlling for occupations is important. Second, small firms may lack the personnel to divide tasks optimally so that one person is performing tasks which are not complements. We try to control for this effect by including a firm size measure into the estimations in section 5.2.

4. Data and Variables

This study uses the Employment Survey 2006 by the German *Federal Institute for Vocational Education and Training*. The goal of the survey is to shed light on structural change in the

German labour market, and to document how it affects working conditions, work pressure, and individual mobility. For that purpose, it collects detailed data on issues, such as qualification and career profiles of the workforce, and organizational and technological conditions at the workplace.[5] Earlier waves of the Qualification and Career Survey have already served a large number of academic studies (e.g. DiNardo & Pischke, 1997; Spitz-Oener, 2006). The survey contains 20,000 observations of employed persons aged between 16 and 65.

A particular feature of the data is detailed information on job tasks carried out by workers. Respondents of the survey are directly asked about the tasks they perform at work: "Please think about your job. I name several selected tasks now. Please tell me how often these tasks occur during your work (often, sometimes, never)". The possible response options are listed in table 1 (details of this table will be explained in the following section). Respondents can choose among 17 tasks and multiple answers are possible. In addition, respondents were asked whether any important task has been forgotten, but the question was negated almost unanimously.

This survey is particularly interesting for our purpose because data on job tasks are collected at the individual level. As mentioned, other studies in this field have to rely on third party information about typical job tasks of an occupation and then match the task profile to a worker based on her occupation. In contrast, individual-level data allows us to use variation in task profiles within occupations for the determination of intrapersonal task complementarities.

It is useful at this point to take note of the differences between our task variables and those used in other papers. Typical tasks in other papers are cognitive tasks (measured e.g. by the length of the longest document read, or the frequency of problem-solving tasks), interpersonal tasks (measured e.g. by information on interaction with others), or physical tasks (measured e.g. by the proportion of time spent standing).[6] Unfortunately, comparisons with other papers are difficult because our measures of tasks are rather plastic descriptions of work activities, while other authors' task variables are closely related to skills. An adequate allocation of our tasks to those broader categories is not possible. Nevertheless, we consider our tasks to be sufficiently broad descriptions of activities, which may appear in many different occupations, and can thus be used to uncover relationships that are frequent on an economy-wide level (and not only within specific occupations).

Instead of presenting summary statistics for the entire aggregate sample, we illustrate the task inputs of four reasonably large 3-digit occupations: sales persons, secondary school teachers,

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[5] The Qualification and Career Survey has also been conducted in the years 1979, 1986, 1992, and 1999. We do not employ these earlier surveys in this study because of problems with the comparability of the task measures.

[6] Cf. Autor & Handel (2009).

accountants, and computer (IT) experts. Table 1 shows the share of workers performing a particular task. Looking at the sales personnel first, a large percentage performs “consulting, advising, informing” and “selling, buying” tasks. Further tasks that are frequently combined with these are “measuring, quality control”, “transporting, packing, shipping”, and “cleaning, recycling”. This set of tasks seems to describe a sales person’s work rather well. Nevertheless, there is also a small, but non-negligible fraction of workers (around 27%) who perform tasks such as teaching and training other, operating and monitoring machines, or serving, accommodating and cooking. The spectrum of tasks, which sales persons perform is thus wide.

The same applies for teachers, who uniformly carry out “teaching, training”, “collecting data, documenting”, and “consulting, advising”. A large fraction also combines these with e.g. organizing and coordinating tasks. Yet, also all the other tasks belong to the task bundles of some teachers in the sample. Similarly, accountants and computer experts show heterogeneous task inputs across people. Accordingly, it emerges as a side result, that studies basing occupational task inputs on secondary sources such as the Dictionary of Occupational Titles are unable to capture this important heterogeneity and aggregate occupational statistics may be biased (see Autor et al., 2003; Goos & Manning, 2007; Blinder, 2007 for studies relying on secondary occupational task inputs).

5. Results

Relying on revealed complementarity, complementary task pairs can be identified by calculating correlations between tasks. We first calculate unconditional correlations between tasks in section 5.1. Then, we estimate conditional correlations using logit regressions, including occupation fixed effects and a firm size measure. Then, we characterize the complementary task pairs in terms of gender, educational attainment, and earnings. Unfortunately, the analysis of correlations does not allow to make any judgement about the strength of the complementarities because we essentially only estimate the probability that two tasks are performed jointly. Therefore, we define threshold values of the correlation size beyond which we consider tasks as complements. Working with such thresholds vastly simplifies the combination of the results on complementarities with those on offshorability in section 6.3.[7]

[7] Correlations can only identify task *pairs*, but it is likely that entire *sets* of tasks are complements. Such bundles of several tasks can be identified from a principal components analysis. The results can be found in Appendix I.

5.1. Correlations

A simple way to find common task combinations is to calculate correlations between the tasks. Since our task indicators are only available as dummy variables, we calculate phi coefficients, which is a measure of association between two binary variables. In principle, the phi coefficient is identical to the common Pearson correlation coefficient and can, hence, vary between 0 (no correlation) and |1| (perfect correlation). However, this only holds when the margins in a 2x2 table, which is used for its calculation, are identical. Otherwise, the maximum coefficient can be smaller than |1|, so that the calculated coefficient appears smaller than it truly is. Moreover, phi coefficients are not comparable across different variable pairs when the margins of the corresponding 2x2 tables differ. Liu (1980) suggested a simple method to correct the phi coefficient in order to make it comparable between variables and account for a maximum value lower than |1|. The approach rests on an iterative standardization of the margins across 2x2 tables. We also follow this approach here.

The corrected phi coefficients are presented in table 2. Strong correlations ($\varphi > .4$) are printed in bold. Moderate correlations ($.3 < \varphi < .4$) are underlined. For example, "collecting data and documenting" (*dat*) is strongly correlated with "consulting, informing, and advising" (*con*, $\varphi = .540$). "Operating and monitoring machines" (*ope*) is frequently combined with "repairing and reconstructing" (*rep*, $\varphi = .421$). Note that this aggregate analysis does not tell us anything about specific occupations, where observed task combinations might be completely different.

5.2. Logistic Regressions

The phi coefficients above only describe the unconditional correlation between tasks. In order to arrive at associations between tasks that are conditional upon the worker's performance of other tasks, her occupation and firm size, we estimate logistic regressions for each of the 17 tasks, where all the other tasks enter as explanatory variables:

$$X^n = \alpha + \sum_m \beta_{nm} X^m + \sum_j \gamma_{nj} occ_j + \eta_n \text{firmsize} + \varepsilon \,,\ n,m \in \{1,2,\ldots,17\} \wedge n \neq m \,.$$

X^n corresponds to task n, occ_j is a dummy for occupation j. The results in terms of the odds ratios are summarized in table 3.[8] The interpretation of odds ratios is straightforward: suppose that, in a regression of task i on all the other tasks, task j carries an odds ratio of 2. This means that, given the worker's task portfolio, a worker who performs task j is twice as likely to perform task i than a worker who does not perform task j. For example, among those workers who perform repairing tasks, the chance that a worker is also doing operating tasks is three times higher than among workers who do *not* perform repairing tasks.

[8] Conditional correlations could also be obtained from running a series of probit regressions and calculating average marginal effects (AME). An odds ratio of 2 approximately corresponds to an AME of .13 in our sample.

Both the correlation and the logistic (odds ratio) approach to identifying task complementarities result in a continuous metric for the probability that the tasks are performed jointly, i.e. that they are complements. Yet, for summary purposes and for the analysis of offshorability in section 6, we would like to draw upon a well-defined list of complementary tasks. Consequently, we define – admittedly arbitrary – threshold values for both approaches, beyond which we consider two tasks as complements: these are $\varphi > .3$ for correlations and an odds ratio $OR > 2$ for the logistic approach. The sets of complementary task pairs resulting from the two approaches overlap to a large extent. In drawing up the final list of complements, we take a conservative stance and include only those task pairs, which passed the thresholds of both approaches (see table 4).

5.3. Characteristics of complementary tasks

In table 4, we characterize the complementary tasks selected above in terms of their employment share. The first column shows the overall employment share of the task pair, i.e. the share of workers performing it. Shares range from 6% of the workforce carrying out both "research" and "programming", to 75% carrying out "data collection" and "consulting". The average share of workers performing any of the complementary task pairs is 29%. In columns 2 and 3, we calculate employment shares by gender. As one would expect, some task pairs show large gender differences: measuring and operating machines is a task combination in which men dominate, while women dominate task combinations such as serving and nursing. On average, 32% of the male workforce performs a complementary task pair, while this holds for only 27% of the female workforce.

Taking a look at employment shares by educational level in columns 4 to 6 reveals that performing a complementary task pairs is much more common among workers with tertiary education (33%) than among workers with primary and secondary education (21% and 28%, respectively). In general, the number of tasks a worker performs is positively correlated with educational level, which may be due to the fact that better educated workers are either more capable of multitasking, or they work in jobs where more complementarities between tasks arise (cf. Görlich & Snower, 2010).

In table 5, we show the employment shares separately by earnings quartile. The conclusions are similar to the educational level: Among workers with high earnings (4th quartile), 32% perform at least one complementary task pair, while among workers with low earnings (1st quartile), only 25% do so. The last two columns show the average hourly wage and the average wage percentile of workers performing the respective task pair. Not surprisingly, task pairs such as cleaning and transporting, and cleaning and serving others are paid the lowest wages, while research and programming, and research and data collection is paid the highest wages.

6. An Application: The Offshorability Debate

We now apply our findings on complementary tasks to the debate about the offshorability of jobs. A number of recent papers discuss the possibility of an international trade in *tasks* and argue that globalisation has reached much further into the stages of the production process: now even certain tasks necessary in the production of an intermediate good may be offshored (e.g. Grossman & Rossi-Hansberg, 2008). Baldwin (2006) aptly calls this "globalisation at a finer resolution". These new perspectives on offshoring and the public debate which took place alongside the academic one, have spurred an interest in identifying potentially offshorable tasks in order to obtain a number for potentially offshorable jobs and the workers at risk of losing their jobs due to offshoring (e.g. van Welsum & Vickery, 2005; Blinder, 2007; Blinder & Krueger, forthcoming).

Offshoring is essentially a breaking up of production stages. Understanding offshoring thus also requires understanding the "glue" that keeps production stages and tasks together (Baldwin, 2006). Estimating intrapersonal task complementarities is a first step into that direction as it analyzes which complementary tasks make up a job and whether offshoring is a suitable option, given this additional information. Consequently, we are now interested in those complementary task bundles that involve an offshorable and a non-offshorable task. Unbundling the tasks and offshoring some of them would result in a productivity loss due to the complementarity. The gains from offshoring (e.g. wage savings) need to be at least as large as the productivity loss in order for unbundling and offshoring to be efficient.

6.1. Previous Literature

Papers discussing the topic of offshorability have usually concentrated on identifying potentially offshorable occupations. They merely refer to the technological feasibility of offshoring a job rather than to whether it actually happens. This is also why the papers pay no attention to productivity and wage differentials between sending and host countries. The wage differential (i.e. the wage savings) should of course be larger than the productivity differential (i.e. the potential productivity loss due to lower labour productivity abroad) in order to make offshoring attractive to a firm.

The identification of offshorable occupations has been done in various ways. Van Welsum and Vickery (2005) selected occupations "by hand" (at the 3-digit ISCO88 level), based on the following three criteria: (i) workers in the occupation make intensive use of ICTs. The authors argue that also the output of such occupations is likely to be "digital" and hence electronically transmittable. (ii) The work has high explicit information or codified knowledge content; and (iii) the work does not require face-to-face contact to customers or colleagues. The selected occupations represent 19.2% of total employment in the European Union.

Using detailed occupational descriptions from the US-based O*Net data base, Blinder (2007) tried to characterize occupations by their main work task and whether this main task needs to performed at a specific domestic location and requires face-to-face contact with customer or colleagues. If not, he argues, the task could potentially done anywhere and the output is likely to be deliverable over long distances without degradation in quality. Blinder puts no emphasis on whether the task is routine or codifiable because he considers this feature as less important for the question of offshorability. His list of occupations represents between 22% and 29% of total US employment, depending on the conservativeness of the selection process. In an identical exercise for the German labour market, Schrader and Laaser (2009) calculated that 45% of jobs are potentially offshorable. Moreover, both studies conclude that an offshoring risk is present across all educational levels.

In a more recent paper, Blinder and Krueger (forthcoming) use worker-level survey instruments to find out more about potential offshorability of occupations. The survey allows them to ask respondents directly whether they think that their job can be performed by someone abroad. Moreover, respondents are asked about certain characteristics of their jobs that allow the researchers and professional coders to assess the offshorability potential themselves. All measures arrive at the conclusion that roughly 25% of all jobs are potentially offshorable.[9]

Most other authors looking at the issue of offshorability have suggested similar attributes of affected tasks. Snower, Brown and Merkl (2009) suggest that physical delivery tasks (e.g. sales personnel, waiters), non-codifiable tasks (e.g. creative and leadership tasks), and personal relationship tasks (e.g. psychotherapists, nurses) are shielded from international competition. Bardhan and Kroll (2003) use the same criteria as van Welsum and Vickery (2005), but add high wage differentials with similar occupations in the offshore market, low setup barriers and low social networking requirements to the list. They estimate that 11% of US jobs are potentially offshorable. Employing an approach based upon the geographical concentration of occupations, Jensen and Kletzer (2006) estimate that 38% of US jobs are tradable.

In the wider context of the effects of offshoring on domestic employment and wages, Geishecker and Görg (2008) estimate the wage impact of outsourcing for Germany and find that a 1% increase in industry-level outsourcing reduces the wage of low-skilled workers by 1.5%. At the same time, wages of high-skilled workers increase. Ebenstein et al. (2009)

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[9] The authors also add another criterion for a non-offshorable job: cultural sensitivity, which for example is important for a news anchorman.

distinguish by offshore location and find that relations with high-wage countries raise domestic manufacturing employment, while relations with low-wage countries decrease it. Wage declines are found mostly for workers who leave manufacturing and go on to take jobs in agriculture or services instead. In summary, it appears that offshoring has negative wage effects for displaced workers. Therefore, it is useful to know more about who could potentially be affected by offshoring in the future.

6.2. Classifying offshorable tasks

In order to determine the degree of offshorability of a task, we take into account four of the criteria mentioned above: (i) necessity of face-to-face contact to customer or colleague, or necessity of proximity to the object being processed;[10] (ii) the computer intensity of the task (iii) the codifiability of the task; and (iv) the "routineness" of the task. However, before discussing the details of our classification, a word of caution is in order. Our classification necessarily relies on a large degree of subjective judgements. Even the more objective measures (ii-iv) may suffer from significant measurement error and are therefore approximate. Yet, these problems are a disease of all studies on this issue and cannot truly be resolved given the rather vague concept of offshorability, the forward-looking nature of the exercise and the current data situation.

In order to assess the face-to-face characteristic of a task, we asked whether the task necessitates face-to-face interactions with customers or colleagues, whether proximity to the processed object is required and whether delivery over internet without degradation in quality is possible. As already noted by Blinder (2007), the necessity of face-to-face contact is not measurable so that we also have to rely on a subjective assessment of this characteristic. Our assessments are shown in column 3 of table 6. In cases where we considered it as obvious that face-to-face contact is necessary, we assigned the value of -1 (a minus because it *limits* offshorability). Nursing, treating and healing others is a natural example of such a task. In cases where we thought that physical presence of the worker is not necessary, we assigned a value of +1; for example collecting and documenting data. In cases where the question could not be answered clearly, we assigned a value of 0. This was done when the task definitions included a number of ambiguous "subtasks" so that a clear judgment could not be made (e.g. transporting, packing, shipping). In addition, sometimes it was simply not possible to judge whether the task required physical presence, e.g. for "selling and buying": this could easily be done over the internet or phone and hence not require face-to-face contact. Yet, if the person were a shop assistant, the task *would* require face-to-face contact.

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[10] Alan Blinder (2007) would distinguish personal and impersonal services here. Snower et al. (2009) make a distinction between physical delivery and personal relationship tasks, where the latter involves necessity of a longer-term relationship. We try to subsume both of these under the heading face-to-face interactions.

As mentioned, the assigned scores are subjective assessments and one may disagree with our classification. Yet, our assessment is only meant to adequately capture broad trends. This is also reflected in our restriction to only three possible values (-1, 0, 1), which truly cannot do more than indicating a broad trend into one direction or the other direction.

The further three characteristics, computer intensity, codifiability, and “routineness” of a task, can be assessed more objectively using our data. In order to capture computer intensity, we use the question “How often do you use a computer during work?” (often, sometimes, or never). Codifiability is captured using the question “How often is your work process defined in all its particulars?” (often, sometimes, seldom, or never). Routineness is captured by the question “How often does your work process repeat itself in all its particulars?” (often, sometimes, seldom, or never). From these, we create dummy variables for the three criteria, which is equal to 1 if the person answered “often” or “sometimes”.

Initially, the dummies we created are available at the person level, not at the task level. We thus need to create a mapping of the values onto the tasks. Table 7 shows the share of workers using a computer among those who perform a particular task. In other words, we restrict the sample to workers performing e.g. “installing, constructing, manufacturing” and calculate the mean values of the computer use dummy variable. Similarly, table 7 shows the share of workers who claimed that their job is codifiable or routine. Note that this mapping might be subject to some error because an individual might perform several tasks, so that it is not guaranteed that the information “I use a computer” relates to the task under examination. We nevertheless rely on this mapping assuming that, on average, it conveys the information we want.

Knowing the shares of people using a computer for each task is not directly helpful because we do not have an idea about which level is *normal* and for which tasks computer usage is particularly intensive. Hence, the shares are standardized in order to learn about the deviation from the mean. Based on these standard scores, we then assign the values for our offshorability score: tasks with a computer intensity of more than 0.5 standard deviations below the mean are assigned the value -1, tasks with a computer intensity of 0.5 standard deviation above the mean are assigned the value 1, and the rest obtains a 0. The values for codifiablility and routineness are assigned in an analogous fashion.

We acknowledge that the assessment based on deviations from the mean shares does not come without problems because it only reflects whether a task is e.g. computer-intensive relative to the other tasks. One could argue that the absolute share and not its deviation from the mean is what should really matter for determining whether a task is computer-intensive. Consider for example the task “installing, constructing, manufacturing”: after all, almost 75% of workers performing this task use a computer. Even though this is a rather large share, we assign it the value of -1 and thus claim that it is not computer-intensive because 75% is low relative to computer use in the other tasks. Nevertheless, we think that looking at relative intensity is adequate, since it gives us an idea about which tasks are most likely to be contestable internationally. Moreover, it makes measures for all four criteria comparable in terms of scale.

Having assigned values for each offshorability criterion, we create a final offshorability score for each task by simply calculating the (weighted) sum over all criteria. As discussed in the previous section, the opinions about which criteria are relevant for determining offshorability diverge slightly. We take account of these controversies by applying two different weighting schemes when summing up. In the first scheme, we give all four criteria an equal weight (similar to van Welsum & Vickery, 2005). The offshorability score is shown in column 5 of table 8. Keeping in mind that the face-to-face criterion is the most relevant (cf. Blinder, 2007), we also apply a second weighting scheme, giving face-to-face contact a weight of 3 and a weight of 1 to the other criteria (column 3).[11]

The resulting offshorability score is essentially a continuous measure for the task's degree of offshorability. However, for simplicity and in order to link the offshorability measure to the complementary tasks, we strictly classify a task as offshorable or non-offshorable. Since none of the tasks "fulfils" all four offshorability criteria, we assume that half the maximum score reached by any of the tasks is sufficient to indicate offshorability (after all, the score could also be negative). Accordingly, in the 1-1-1-1 weighting, we mark tasks with an offshorability score of 1 or greater as offshorable, because the maximum score reached is 2. In the 3-1-1-1 weighting, we mark tasks with a score of 2 or greater as offshorable because the maximum score reached by any of the tasks is 4.

Comparing the two weighting schemes, we think that the 3-1-1-1 weighting produces a much more plausible classification. Consequently, we proceed with the following six offshorable tasks: operating and monitoring machines; marketing, PR and advertising; organizing, planning and coordinating; research and engineering; collecting data and documenting; programming.[12] Note – again – that our approach rests on subjective assessments and cannot give more than a tendency for the degree of offshorability.

6.3. Complementary tasks and (non-)offshorability

In section 5, we drew up a list of 17 complementary task pairs, based upon their passing of a threshold value for the unconditional and conditional correlations. Out of these 17 task pairs,

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[11] Instead of giving a high weight to the face-to-face criterion, one could also limit the range of tasks for which the other three criteria are inspected to those having a 1 (or at least a zero) for face-to-face contact.

[12] We acknowledge that some tasks may only partly be offshorable depending on which subtask is done by the worker.

six pairs involve an offshorable and a non-offshorable task. The complementarity between such tasks implies that offshoring the offshorable part may be very costly, since one would break apart a productivity-enhancing combination. In fact, the stronger the complementarity between an offshorable and a non-offshorable task, the larger the gains from offshoring need to be in order for offshoring to occur. Task complementarities may hence put a strong limit on offshorability, depending on how strong the complementarity is.

In tables 9 and 10, we repeat the exercise from section 5.3 and characterize the six complementary offshorable/non-offshorable task combinations in terms of employment share (overall, by gender, and by educational level). On average, 40 per cent of the workers in the sample perform at least one such complementary task bundle consisting of an offshorable and a non-offshorable job. For these jobs, relocating the production of the offshorable task abroad may be extremely costly, depending on how strong the complementarity is. As a consequence, the number of potentially offshorable jobs is sizeably reduced when intrapersonal task complementarities are taken into account. The numbers in tables 10 and 11 also suggest that men, higher educated workers, and workers in the upper regions of the wage distribution perform more complementary offshorable/non-offshorable task bundles than their respective counterparts. This implies that, apparently, these workers are better shielded from international competition.

We now also take a closer look at task complementarities in those occupations in Germany, which have been claimed to be "easily offshorable" (see Schrader and Laaser, 2009).[13] To begin with, we calculate the average share of offshorable tasks in the task portfolio of "easily offshorable" occupations and find that only 44 per cent of the occupations' average task portfolio is offshorable under our classification. Even though this number does not say anything about complementarity between tasks, it reveals that the majority of tasks typically performed in these occupations can be considered non-offshorable.

For each "easily offshorable" occupation, we also calculate its share of workers performing the six complementary offshorable/non-offshorable task pairs (table 11). The second to last column displays, for each occupation, the highest calculated share. This number can be interpreted as the occupation's share of workers who perform at least one complementary offshorable/non-offshorable task pair.[14] Across the occupations, numbers range from 26 to 100 per cent, but the outcomes are driven by the extremely large shares of workers performing data collection and consulting tasks (not reported). Leaving out this particular task

[13] Schrader and Laaser (2009) use the same methodology as Blinder (2007), but applied it to German data. Nevertheless, it is likely that the identified occupations are similar to those of Blinder. Our result would hence also hold for Blinder's analysis.

[14] It is, of course, possible that a worker carries out more than one complementary offshorable/non-offshorable task pair.

combination shows that, e.g. among typists, 6.7% perform at least one complementary offshorable/non-offshorable task pair (teaching and data collection).[15] Among sales agents, 91.5% of the workers perform a complementary offshorable/non-offshorable pair (marketing and consulting). For all other high-risk occupations, the share lies in between. On average, 58% of the workers in high-risk occupations perform a complementary offshorable/non-offshorable pair.

For illustration purposes, we take a closer look at IT professionals. About 52 per cent of IT professionals perform operating and monitoring tasks in combination with measuring and testing tasks, which is a complementary task combination according to our definition in section 5. According to our classification of offshorable tasks, operating and monitoring tasks can potentially be offshored, but measuring and testing tasks cannot. Moving operating and monitoring abroad and thus splitting these two complementary tasks would result in productivity losses, so that unbundling them may in fact be very costly. Hence, in some cases, the "ease" of offshoring a task is severely limited by intrapersonal task complementarities. In this case, at least 52 per cent of IT professional jobs are affected by this limitation.

Note that we only analyse task *pairs* in this study in order to avoid complexity. Yet, workers often perform a whole range of tasks.. Consequently, it is likely that not only task pairs are complementary, but also entire sets of tasks (see also Appendix I). This would clearly increase the probability that offshorable and non-offshorable tasks are jointly appearing in such a complementary set, and hence limit offshorability further.

7. Conclusion

During the recent decades, workplaces have been characterized more and more by multitasking. Workers have come to perform bundles of diverse tasks, rather than specializing in specific tasks. Such bundling occurs when tasks are complements. In this case, a worker's performance in one task is increased when he or she can use knowledge and experience from another task. An intuitive example is a machine operator who can use experience from his primary task (operating the machine) for repairing the machine. In this paper, we analyse empirically which job tasks are complements, using detailed individual-level data about job tasks. Intrapersonal task complementarities have an impact on the division of labour. In particular, they limit the possibilities for unbundling an occupation's task portfolio because this can only be done at a productivity loss and is, hence, costly. In an application, we illustrate the consequences of task complementarities for the offshorability of jobs. We show that the number of potentially offshorable jobs is significantly reduced when

[15] We only report the results without the data collection/consulting bundle.

complementarities are accounted for. In this domain, we also advance the current literature by introducing an offshorability indicator at the task-, rather than the occupation-level.

Some comments on the precision of our results are certainly warranted at this place. First, when identifying complements, we rely on revealed complementarity, i.e. we argue that only complementarities can explain why certain tasks are bundled within one worker. Nevertheless, inefficiencies may of course exist and cannot be accounted for by our analysis. Second, we look at the aggregate picture and do not identify occupation-specific task complementarities. Hence, the complementarities we identify are present at an economy-wide level, but may differ strongly between occupations. Moreover, some of the task pairs may not be complements in certain occupations. Third, we only investigate our questions at one point in time, but complementarities are likely to change over time due to technological progress and human capital formation. Fourth, the classification of offshorable tasks necessarily relies on subjective evaluations of job tasks, which is, however, a problem that the entire literature on this subject has to deal with. Moreover, the mapping of computer usage, routineness, and codifiability on tasks is imprecise. Hence, we would like to remind the reader to keep these limitations in mind and treat results with great care.

In order to understand offshoring practices and which jobs are at risk to be offshored in the future, it is essential to better understand the "glue" that binds occupations together (Baldwin, 2006). In this article, we take a first step towards understanding the glue by looking at *intra*personal task complementarities. Yet, *inter*personal task complementarities are also important. This involves questions such as: why are some jobs done together in one plant? Which jobs and functions are complementary? Which impact does technology have on these complementarities?

Moreover, the influence of task complementarities on the division of labour is likely to change over time. Since complementarities are likely to be positively influenced by progress in technology and human capital formation, also the feasibility of a specific division of labour is subject to change. Yet, the direction is ambiguous. On the one hand, technological innovations increase possibilities for offshoring; on the other hand, they increase complementarities between tasks, making an unbundling of offshorable and non-offshorable tasks more and more costly. Future research should take on these questions.

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Appendix I

A.1 Principal Components Analysis

A third method to investigate commonly observed task combinations is a principal component analysis. It allows us to identify sets of tasks performed jointly, rather than just frequent bivariate relationships. The rotated component loadings are shown in table A1. The highest loading of each task is printed bold. Based on the eigenvalues of the principal component analysis, we retain four principal components: manual manufacturing (with tasks such as operating, monitoring machines or repairing and reconstructing), abstract (with tasks such as organizing, planning, coordinating, consulting, advising, informing, or collecting data), physical delivery services (with tasks such as serving other, accommodating, cooking, cleaning and recycling), and interactive services (with tasks such as selling, buying, marketing, and transporting). Cleaning tasks load rather highly on more than one component, suggesting that it is also part of other task bundles (see underlined loadings in table A1). The analysis makes clear that workers perform bundles of tasks, rather than just specialized tasks.

A comparison to Autor and Handel (2009), who did a similar exercise with US data, shows that our data unveil slightly different task clusters. While their analysis retains the three principal components Data, People, and Things, representing cognitive tasks, face-to-face interactions, and physical and routine job tasks, respectively, our factor analysis suggests different dimensions. While we also find components representing Data (abstract) and Things (manual manufacturing) tasks, our other two components cut through the three dimensions suggested by Autor and Handel: physical delivery services have both a Things and People dimension, and interactive services can most probably be placed into the Data and People dimensions. Autor and Handel thus seem to miss an important personal relationship component of these jobs.

Table 1 – Summary statistics of tasks for four large occupations

		sales person		teacher		accountant		IT expert	
Key	Description of task	share	freq	share	freq	share	freq	share	freq
ins	installing, constructing, manufacturing	0.227	155	0.078	20	0.023	7	0.214	136
mea	measuring, testing, quality control	0.720	491	0.824	210	0.313	94	0.785	499
ope	operating, monitoring machines/processes	0.274	187	0.176	45	0.120	36	0.619	394
rep	repairing, reconstructing	0.302	206	0.369	94	0.080	24	0.561	357
sel	selling, buying	0.870	593	0.490	125	0.337	101	0.426	271
tra	transporting, packing, shipping	0.672	458	0.310	79	0.320	96	0.278	177
mar	marketing, PR, advertising	0.421	287	0.635	162	0.277	83	0.376	239
org	organizing, planning, coordinating	0.512	349	0.875	223	0.570	171	0.789	502
res	research, engineering	0.107	73	0.710	181	0.140	42	0.818	520
tea	teaching, training other	0.293	200	1.000	255	0.473	142	0.601	382
dat	collecting data, documenting	0.537	366	1.000	255	0.870	261	0.978	622
con	consulting, advising, informing	0.957	653	0.992	253	0.853	256	0.954	607
ser	serving others, accommodating, cooking	0.277	189	0.184	47	0.133	40	0.047	30
nur	nursing, treating, healing others	0.125	85	0.459	117	0.050	15	0.101	64
sec	securing, guarding	0.277	189	0.545	139	0.177	53	0.291	185
cle	cleaning, recycling	0.796	543	0.376	96	0.180	54	0.131	83
ins	installing, constructing, manufacturing	0.016	11	0.071	18	0.073	22	0.769	489
	observations	682		255		300		636	

Table 2 – Phi coefficients of correlations between tasks

	ins	mea	ope	rep	sel	tra	mar	org	res	tea	dat	con	ser	nur	sec	cle	pro
ins	-																
mea	**0.436**	-															
ope	0.383	0.399	-														
rep	0.346	0.343	**0.421**	-													
sel	0.058	0.126	0.021	0.139	-												
tra	0.198	0.217	0.242	0.282	0.204	-											
mar	-0.071	0.068	-0.089	-0.029	0.313	0.045	-										
org	0.037	0.221	0.106	0.097	0.220	0.064	0.256	-									
res	0.197	0.331	0.179	0.184	0.140	0.011	0.200	0.317	-								
tea	0.005	0.177	0.071	0.079	0.108	-0.011	0.217	0.309	0.271	-							
dat	-0.112	0.153	0.021	-0.009	0.197	-0.013	**0.415**	0.368	**0.430**	0.374	-						
con	-0.151	0.140	-0.028	-0.010	0.362	0.018	**0.530**	0.391	0.328	**0.402**	**0.540**	-					
ser	0.067	0.066	0.033	0.069	0.298	0.157	0.173	0.155	0.054	0.117	0.106	0.183	-				
nur	-0.032	0.150	0.094	0.131	0.149	0.105	0.135	0.182	0.132	0.265	0.248	0.288	0.367	-			
sec	0.086	0.251	0.278	0.241	0.083	0.186	0.053	0.175	0.147	0.194	0.182	0.164	0.193	0.329	-		
cle	0.279	0.235	0.277	0.370	0.161	0.336	-0.063	-0.015	-0.024	-0.021	-0.194	-0.129	0.332	0.266	0.239	-	
pro	0.017	0.193	0.188	0.112	0.018	-0.130	0.092	0.267	0.429	0.153	**0.514**	0.339	-0.183	-0.132	-0.004	-0.257	-

Note: Phi coefficients are corrected using the method suggested by Liu (1980)

Table 3 – Conditional correlations between tasks: Odds ratios of logistic regressions

	(1) ins	(2) mea	(3) ope	(4) rep	(5) sel	(6) tra	(7) mar	(8) org	(9) res	(10) tea	(11) dat	(12) con	(13) ser	(14) nur	(15) sec	(16) cle	(17) pro
ins		2.253***	1.979***	1.267***	1.357***	1.259***	0.955	1.120*	2.056***	1.075	0.868*	0.741***	1.539***	0.937	0.873**	1.466***	0.939
		(11.65)	(13.35)	(4.43)	(5.70)	(4.63)	(-0.87)	(2.07)	(13.60)	(1.42)	(-2.04)	(-3.83)	(6.53)	(-1.00)	(-2.73)	(7.04)	(-0.74)
mea	2.282***		2.130***	1.398***	1.149**	1.619***	1.167***	1.598***	2.089***	1.324***	1.621***	1.315***	0.883*	1.175**	1.576***	1.482***	1.331***
	(11.97)		(15.58)	(6.92)	(3.12)	(11.36)	(3.57)	(11.03)	(15.14)	(6.54)	(8.04)	(3.91)	(-2.14)	(2.71)	(9.83)	(8.15)	(3.35)
ope	1.978***	2.132***		2.527***	0.963	1.489***	0.820***	1.295***	1.362***	1.142**	1.290***	1.080	1.068	1.084	2.179***	1.514***	1.954***
	(13.38)	(15.53)		(21.55)	(-0.84)	(9.43)	(-4.50)	(5.68)	(6.72)	(3.07)	(4.18)	(1.10)	(1.16)	(1.42)	(18.42)	(8.86)	(8.92)
rep	1.354***	1.386***	2.504***		1.728***	1.749***	0.949	1.209***	1.468***	1.316***	1.128	1.125	0.962	1.255***	1.318***	2.494***	1.804***
	(5.72)	(6.70)	(21.33)		(11.96)	(13.24)	(-1.16)	(4.09)	(8.25)	(6.15)	(1.93)	(1.62)	(-0.69)	(4.03)	(6.44)	(20.01)	(7.66)
sel	1.366***	1.156**	0.990	1.715***		1.874***	2.238***	1.682***	1.234***	1.123**	1.374***	1.710***	1.962***	1.074	0.998	1.554***	0.866*
	(5.82)	(3.25)	(-0.23)	(11.87)		(15.91)	(20.63)	(12.35)	(4.86)	(2.84)	(5.29)	(7.46)	(12.44)	(1.33)	(-0.06)	(9.65)	(-2.03)
tra	1.252***	1.669***	1.501***	1.783***	1.875***		1.238***	1.137**	0.920	0.930	1.146*	1.091	1.324***	1.156**	1.347***	2.492***	0.802**
	(4.48)	(12.01)	(9.61)	(13.66)	(15.79)		(5.30)	(3.19)	(-1.93)	(-1.85)	(2.53)	(1.40)	(5.36)	(2.74)	(7.44)	(22.01)	(-3.08)
mar	0.991	1.152**	0.822***	0.944	2.202***	1.213***		1.532***	1.668***	1.598***	2.701***	3.327***	1.451***	1.179**	1.007	0.866**	1.223**
	(-0.17)	(3.26)	(-4.45)	(-1.28)	(20.21)	(4.85)		(10.40)	(12.09)	(11.81)	(16.08)	(13.70)	(7.19)	(3.17)	(0.17)	(-3.15)	(2.84)
org	1.106	1.612***	1.302***	1.221***	1.656***	1.141**	1.534***		1.727***	1.800***	1.676***	1.787***	1.273***	1.153*	1.299***	0.872**	1.603***
	(1.83)	(11.16)	(5.77)	(4.28)	(12.01)	(3.28)	(10.31)		(11.98)	(15.25)	(10.29)	(9.88)	(4.21)	(2.53)	(6.14)	(-3.00)	(5.48)
res	2.001***	2.101***	1.382***	1.503***	1.279***	0.939	1.694***	1.735***		1.484***	2.495***	1.272**	1.090	1.224***	1.234***	0.788***	3.274***
	(13.27)	(15.09)	(7.06)	(8.73)	(5.72)	(-1.49)	(12.48)	(12.10)		(9.28)	(12.75)	(3.01)	(1.56)	(3.75)	(4.97)	(-4.95)	(16.11)
tea	1.056	1.349***	1.145**	1.317***	1.141**	0.915*	1.580***	1.794***	1.474***		1.567***	2.067***	0.987	1.405***	1.357***	0.917	1.125
	(1.07)	(6.87)	(3.11)	(6.08)	(3.22)	(-2.26)	(11.50)	(15.16)	(9.09)		(8.50)	(11.38)	(-0.23)	(6.26)	(7.50)	(-1.93)	(1.65)
dat	0.832**	1.593***	1.249***	1.136*	1.391***	1.189**	2.644***	1.658***	2.589***	1.576***		3.446***	1.128	1.175*	1.484***	0.664***	2.727***
	(-2.73)	(7.88)	(3.74)	(2.10)	(5.68)	(3.26)	(15.88)	(10.22)	(13.53)	(8.79)		(19.95)	(1.52)	(2.16)	(6.98)	(-7.07)	(5.81)
con	0.672***	1.361***	1.084	1.094	1.800***	1.114	3.252***	1.791***	1.369***	2.087***	3.451***		1.184	1.705***	1.288***	0.967	1.600**
	(-5.24)	(4.44)	(1.19)	(1.30)	(8.45)	(1.78)	(13.40)	(10.08)	(4.00)	(11.68)	(20.04)		(1.66)	(5.61)	(3.88)	(-0.50)	(2.85)
ser	1.652***	0.882*	1.081	1.038	1.948***	1.303***	1.426***	1.280***	1.102	0.974	1.130	1.073		2.115***	1.367***	2.705***	0.824
	(7.67)	(-2.18)	(1.38)	(0.68)	(12.28)	(5.10)	(6.88)	(4.33)	(1.78)	(-0.50)	(1.50)	(0.66)		(12.22)	(6.05)	(17.65)	(-1.90)
nur	0.986	1.181**	1.092	1.272***	1.086	1.154**	1.175**	1.173**	1.223***	1.392***	1.185*	1.704***	2.026***		2.476***	1.504***	0.914
	(-0.23)	(2.74)	(1.54)	(4.25)	(1.54)	(2.72)	(3.10)	(2.84)	(3.71)	(6.10)	(2.20)	(5.47)	(11.46)		(18.19)	(7.24)	(-0.97)
sec	0.885*	1.571***	2.187***	1.321***	0.983	1.348***	1.016	1.316***	1.225***	1.373***	1.520***	1.264***	1.368***	2.495***		1.674***	0.896
	(-2.45)	(9.62)	(18.45)	(6.43)	(-0.42)	(7.47)	(0.37)	(6.44)	(4.75)	(7.81)	(7.22)	(3.51)	(5.99)	(18.34)		(11.74)	(-1.52)
cle	1.505***	1.542***	1.516***	2.517***	1.524***	2.441***	0.864**	0.871**	0.778***	0.931	0.648***	0.870*	2.801***	1.516***	1.645***		0.565***
	(7.52)	(8.83)	(8.90)	(20.17)	(9.17)	(21.56)	(-3.18)	(-3.01)	(-5.19)	(-1.59)	(-7.27)	(-2.01)	(18.00)	(7.35)	(11.37)		(-6.99)
pro	1.044	1.343***	2.097***	1.909***	0.879	0.716***	1.133	1.564***	3.375***	1.042	2.548***	1.380*	0.757**	0.954	0.868*	0.523***	
	(0.53)	(3.51)	(10.23)	(8.65)	(-1.86)	(-4.84)	(1.83)	(5.36)	(16.71)	(0.59)	(5.39)	(2.01)	(-2.73)	(-0.52)	(-2.01)	(-7.97)	
pseudo R-sq	0.333	0.277	0.312	0.336	0.261	0.207	0.234	0.191	0.272	0.225	0.368	0.358	0.306	0.386	0.204	0.355	0.292
N	19057	19028	19028	19084	19064	19083	19005	19085	19083	19079	19085	19069	18943	19041	19082	19082	18626

Exponentiated coefficients; Standard errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001; regression includes occupation dummies (2-digit) and firm size

Table 4 – Employment shares of complementary task bundles (by gender, education) and example occupations

	Overall	Gender		Educational level			Example occupation
	Share	Male	Female	primary	secondary	tertiary	
dat con	0.75	0.76	0.74	0.45	0.70	0.94	manager
mar con	0.42	0.41	0.43	0.22	0.36	0.60	pastor, publisher
dat pro	0.08	0.12	0.03	0.03	0.06	0.14	IT specialist
ins mea	0.20	0.27	0.13	0.21	0.23	0.14	baker
res dat	0.33	0.39	0.27	0.14	0.26	0.53	engineer
res pro	0.06	0.09	0.02	0.02	0.04	0.11	IT specialist
ope rep	0.27	0.39	0.15	0.27	0.32	0.16	machine operator
mar dat	0.40	0.40	0.41	0.18	0.34	0.60	publisher, librarian
tea con	0.52	0.54	0.50	0.25	0.47	0.70	teacher
mea ope	0.35	0.46	0.24	0.32	0.40	0.25	tool maker, cook
rep cle	0.30	0.37	0.22	0.34	0.35	0.16	carpenter, interior decorator
ser nur	0.10	0.05	0.16	0.10	0.10	0.09	caring prof., housekeeper
tra cle	0.34	0.36	0.31	0.42	0.40	0.17	farmer
ser cle	0.14	0.07	0.22	0.20	0.16	0.09	cook
mea res	0.30	0.37	0.22	0.14	0.24	0.45	engineer
nur sec	0.15	0.11	0.20	0.13	0.15	0.16	health worker
sel mar	0.28	0.27	0.29	0.15	0.26	0.36	sales personnel
Average	0.29	0.32	0.27	0.21	0.28	0.33	

Table 5 – Employment shares of complementary task bundles (by wage quartile) and wage level

	Wage quartiles				Average	Avg wage
	1	2	3	4	wage	percentile
dat con	0.55	0.73	0.83	0.91	16.58	55
mar con	0.34	0.39	0.43	0.52	16.65	55
dat pro	0.04	0.05	0.08	0.15	19.32	66
ins mea	0.21	0.22	0.22	0.17	14.75	48
res dat	0.19	0.27	0.38	0.48	17.89	60
res pro	0.02	0.03	0.06	0.12	19.75	68
ope rep	0.24	0.31	0.31	0.23	14.95	50
mar dat	0.30	0.37	0.42	0.51	16.90	56
tea con	0.33	0.49	0.60	0.67	17.07	57
mea ope	0.32	0.38	0.40	0.33	15.32	51
rep cle	0.34	0.35	0.30	0.19	13.72	44
ser nur	0.11	0.11	0.10	0.07	13.92	45
tra cle	0.45	0.40	0.31	0.18	13.15	41
ser cle	0.22	0.16	0.12	0.08	12.59	39
mea res	0.18	0.25	0.34	0.41	17.53	59
nur sec	0.14	0.17	0.17	0.13	14.87	50
sel mar	0.26	0.27	0.28	0.31	15.99	52
Average	0.25	0.29	0.31	0.32		

Table 6 – Scores for offshorability criteria, by tasks

		Criteria			
Code	Description	impersonal	computer	codifiable	routine
ins	installing, constructing, manufacturing	0	-1	1	1
mea	measuring, testing, quality control	0	0	0	0
ope	operating, monitoring machines/processes	0	0	1	1
rep	repairing, reconstructing	-1	-1	1	0
sel	selling, buying	0	0	-1	0
tra	transporting, packing, shipping	0	-1	1	1
mar	marketing, PR, advertising	1	1	-1	-1
org	organizing, planning, coordinating	1	1	0	0
res	research, engineering	1	1	-1	-1
tea	teaching, training other	-1	1	0	0
dat	collecting data, documenting	1	1	0	0
con	consulting, advising, informing	0	0	0	0
ser	serving others, accommodating, cooking	-1	-1	0	1
nur	nursing, treating, healing others	-1	0	0	0
sec	securing, guarding	-1	0	1	1
cle	cleaning, recycling	-1	-1	1	1
pro	Programming	1	1	-1	-1

Table 7 – Mapping of dummies for computer use, codifiability and routineness on tasks

	computer			codifiable			routine		
Task	Share	Std. score	Offsh. score	Share	Std. score	Offsh. score	Share	Std. score	Offsh. score
ins	0.747	-1.31	-1	0.525	1.19	1	0.727	0.84	1
mea	0.831	-0.16	0	0.473	0.32	0	0.677	0.11	0
ope	0.810	-0.44	0	0.533	1.33	1	0.731	0.90	1
rep	0.781	-0.84	-1	0.497	0.72	1	0.702	0.48	0
sel	0.853	0.14	0	0.406	-0.79	-1	0.664	-0.07	0
tra	0.800	-0.57	-1	0.506	0.88	1	0.743	1.06	1
mar	0.916	1.01	1	0.390	-1.05	-1	0.612	-0.82	-1
org	0.882	0.55	1	0.434	-0.32	0	0.649	-0.29	0
res	0.920	1.06	1	0.386	-1.11	-1	0.566	-1.49	-1
tea	0.898	0.76	1	0.427	-0.44	0	0.635	-0.49	0
dat	0.900	0.80	1	0.433	-0.33	0	0.652	-0.25	0
con	0.863	0.28	0	0.442	-0.19	0	0.666	-0.05	0
ser	0.763	-1.08	-1	0.452	-0.01	0	0.723	0.78	1
nur	0.821	-0.29	0	0.467	0.24	0	0.679	0.15	0
sec	0.822	-0.28	0	0.507	0.89	1	0.707	0.54	1
cle	0.711	-1.80	-1	0.520	1.11	1	0.758	1.28	1
pro	1.000	2.17	1	0.306	-2.44	-1	0.483	-2.69	-1
MEAN	0.842			0.453			0.669		
SD	0.073			0.060			0.069		

Note: std. score <= -.5 → -1
-.5 > std. score > .5 → 0
std. score >= .5 → 1

Table 8 – Offshorabilty scores by task

		3-1-1-1		1-1-1-1	
		score	indicator	score	indicator
ins	installing, constructing, manufacturing	1		1	x
mea	measuring, testing, quality control	0		0	
ope	operating, monitoring machines/processes	2	x	2	x
rep	repairing, reconstructing	-3		-1	
sel	selling, buying	-1		-1	
tra	transporting, packing, shipping	1		1	x
mar	marketing, PR, advertising	2	x	0	
org	organizing, planning, coordinating	4	x	2	x
res	research, engineering	2	x	0	
tea	teaching, training other	-2		0	
dat	collecting data, documenting	4	x	2	x
con	consulting, advising, informing	0		0	
ser	serving others, accommodating, cooking	-3		-1	
nur	nursing, treating, healing others	-3		-1	
sec	securing, guarding	-1		1	x
cle	cleaning, recycling	-2		0	
pro	programming	2	x	0	
	Min. score to be marked as offshorable	2		1	

Table 9 – Employment share of complementary offshorable/non-offshorable task bundles

	Overall	Gender		Educational level		
	Share	Male	Female	primary	secondary	tertiary
dat con	0.75	0.76	0.74	0.45	0.70	0.94
mar con	0.42	0.41	0.43	0.22	0.36	0.60
ope rep	0.27	0.39	0.15	0.27	0.32	0.16
mea ope	0.35	0.46	0.24	0.32	0.40	0.25
sel mar	0.28	0.27	0.29	0.15	0.26	0.36
mea res	0.30	0.37	0.22	0.14	0.24	0.45
Average	0.40	0.44	0.34	0.26	0.38	0.46

Table 10 – Employment share of complementary offshorable/non-offshorable task bundles and average wage level

	Wage quartiles				Average	Avg wage
	1	2	3	4	wage	percentile
dat con	0.55	0.73	0.83	0.91	16.58	55
mar con	0.34	0.39	0.43	0.52	16.65	55
ope rep	0.24	0.31	0.31	0.23	14.95	50
mea ope	0.32	0.38	0.40	0.33	15.32	51
tea dat	0.29	0.46	0.58	0.66	17.32	58
sel mar	0.26	0.27	0.28	0.31	15.99	52
mea res	0.18	0.25	0.34	0.41	17.53	59
Average	0.32	0.39	0.43	0.45		

Table 11 – Employment share of complementary offsh./non-offsh. task bundles within “easily offshorable” occupations

	mar con	ope rep	mea ope	sel mar	mea res	Max. (1) - (9)	Obs.
Typesetter	0.680	0.080	0.280	0.320	0.440	0.680	25
Printing plate producer	0.273	0.364	0.818	0.182	0.455	0.818	11
Other engineer	0.567	0.280	0.459	0.357	0.548	0.567	157
Physicist, mathematician	0.500	0.333	0.333	0.333	0.750	0.750	12
Draftsman	0.154	0.026	0.128	0.051	0.462	0.462	39
Sales agent	0.915	0.109	0.152	0.752	0.248	**0.915**	165
Telephone operator	0.495	0.054	0.063	0.225	0.081	0.495	111
Accountant (low level)	0.375	0.104	0.208	0.313	0.271	0.375	48
Accountant (high level)	0.270	0.027	0.073	0.177	0.103	0.270	300
IT professional	0.374	0.421	0.520	0.242	0.673	0.673	636
Clerk, office professionals	0.412	0.067	0.120	0.270	0.095	0.412	1844
Typist I	0.469	0.038	0.063	0.364	0.071	0.469	239
Typist II	0.000	0.000	0.067	0.000	0.000	**0.067**	15
Office assistant	0.323	0.097	0.032	0.161	0.000	0.323	31
Publisher	0.743	0.050	0.114	0.236	0.250	0.743	140
Translator, interpreter	0.500	0.000	0.000	0.275	0.125	0.500	40
Graphic artist	0.808	0.205	0.370	0.534	0.644	0.808	73
Decorator, sign painter	0.643	0.786	0.714	0.571	0.571	0.786	14
Economist, social scientist	0.704	0.049	0.111	0.259	0.469	0.704	81
Humanist	0.696	0.130	0.130	0.174	0.478	0.696	23
Natural scientist	0.538	0.192	0.423	0.385	0.654	0.654	26
Average	0.497	0.163	0.247	0.294	0.352	0.579	

Table A1 – Loadings of Principal Component Analysis, orthogonal rotation

	Components				
	1	2	3	4	unexplained
ins	**0.4206**	-0.0514	-0.1695	0.0586	0.5671
mea	**0.3819**	0.1523	0.0107	0.0211	0.5595
ope	**0.4642**	0.0428	0.053	-0.1386	0.4432
rep	**0.436**	-0.0338	0.0358	0.0465	0.4911
sel	0.0247	-0.0141	-0.0696	**0.6365**	0.3683
tra	0.2495	-0.2019	0.0171	**0.3472**	0.5617
mar	-0.1162	0.2002	-0.0451	**0.4635**	0.489
org	0.061	**0.3289**	0.0728	0.149	0.6105
res	0.2256	**0.384**	-0.06	0.0002	0.5413
tea	0.0008	**0.3491**	0.2762	-0.0772	0.5625
dat	-0.0714	**0.4163**	0.0987	0.0944	0.4998
con	-0.1043	**0.3267**	0.0822	0.2213	0.5592
ser	-0.0718	-0.137	**0.3718**	0.2746	0.5673
nur	-0.0568	0.0176	**0.6063**	-0.0515	0.3988
sec	0.1501	0.069	**0.4813**	-0.1717	0.4927
cle	**0.2633**	-0.3125	**0.2605**	0.1666	0.4
pro	0.1565	**0.3334**	-0.23	-0.1131	0.6609