Offshoring and the Onshore Composition of Tasks and Skills*

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Abstract

Using plant data that distinguish between occupations, tasks, and workforce skills, this paper investigates the relationship between offshoring and the onshore workforce composition at German multinational enterprises (MNEs) in manufacturing and services. We find that the proportion of non-routine and interactive tasks increases with offshoring, especially at services MNEs. Furthermore, we find that in excess of what is implied by changes in either the occupational or task composition, offshoring predicts an increase in the wage-bill share of highly educated workers. While the relationships between offshoring and composition of tasks and skills are statistically significant, the economic effect of offshoring is estimated to be small.

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1 Introduction

There is considerable agreement among economists that an increased fragmentation of production, involving offshoring of certain production stages, likely affects employment and wages across countries. However, there is disagreement as to the direction of these effects. If offshoring mainly involves tasks carried out by low-skilled labor, the relative demand for low-skilled labor might decline, contributing to a widening wage gap between skilled and unskilled labor (Feenstra and Hanson 1996, 1999). Nevertheless, because offshoring is associated with cost reductions, the low-skilled workers may benefit in absolute terms from an increase in their real wages. However, if the associated cost reductions are particularly strong in sectors using low-skilled labor relatively intensively, offshoring might actually reduce the wage gap between skilled and unskilled labor as resources are reallocated across sectors in general equilibrium (Jones and Kierzkowski 2001, Grossman and Rossi-Hansberg 2006).[1]

Moreover, it has been argued that the nature of tasks performed on the job may be more relevant for a job's propensity to be offshored than the skill level of the worker. Several authors have argued that current offshoring in fact involves many tasks carried out by high-skilled workers and perhaps even affect high-skilled workers more than low-skilled workers (see e.g. Markusen 2006, Blinder 2006). Several important characterizations of the nature of tasks being offshored have been proposed: the prevalence of routine tasks, especially if they can be summarized in deductive rules (Levy and Murnane 2004); the prevalence of codifiable rather than tacit information to perform the job (Leamer and Storper 2001); or the job's lacking requirement of physical contact and geographic proximity (Blinder 2006). Whereas the nature of tasks could perfectly correlate with the skill-intensity of the occupation, there is no *a priori* reason for this to be the case. Medical diagnostics of computer-tomography images or X-rays, for instance, typically require education at the upper-secondary level, but can easily move offshore.[2] Maintenance work, on the other hand, need not require secondary schooling, but can typically not relocate because proximity to the maintained facilities is indispensable.

We use plant-level data for German multinational enterprises (MNEs) to examine the relationship between in-house offshoring and the composition of workers and tasks in the German plants. We consider all types of foreign activities by German MNEs, i.e. affiliate activities that might be characterized as "horizontal" as well

[1] See also the treatments in Baldwin and Robert-Nicoud (2007) and Kohler (2008)

[2] This business practice has become known as *tele-radiology* and, for the United States and Europe, is typically performed by U.S. or EU trained doctors living in South Asia or Australia.

as "vertical", but we distinguish between activities located in high-income and low-income countries to take into account that activities located in low-income countries probably capture more closely the concept of in-house offshoring, if by that we mean a transfer of activities within firms motivated by cost differentials.[3]

The data cover activities in manufacturing as well as services and link information on MNEs' offshore activities to their onshore (i.e. German) plant workforces. The data allow us to infer information on the skills of workers and contain information about occupation. We follow Autor, Levy and Murnane (2003), and related research by Spitz-Oener (2006), in that we link occupations to the involved share of routine versus non-routine tasks. In addition, we link occupations to the prevalence of personal interaction with co-workers or customers for the involved tasks. To classify tasks, we codify information from a German work survey on workplace-tool use.[4] We then use the survey's information on workplace-tool use by occupation to map our task content measures into occupations. The prevalence of non-routine tasks in an occupation typically relates to a lack of deductive rules and codifiable information, while the prevalence of interactive tasks relates to the potential importance of physical contact and geographic proximity.

Throughout we use binary definitions of occupations, tasks and skills so that we can collapse the relative demand for onshore labor into a single reduced-form equation, similar to cost function estimation. We estimate the equation for composition of skills as well as tasks. We find that offshoring is consistently associated with skill upgrading at the German plants. This is the case even when we control for the composition of tasks at plant level. The task-based measures have a statistically significant relationship to offshoring in the direction theory leads us to expect: parent-firm workers perform more non-routine and more interactive tasks at MNEs with more offshoring. But the predicted economic effect of offshoring on the task composition is minor.

Our findings are thus consistent with the more traditional view that offshored tasks tend to be carried out by low-skilled rather than high-skilled workers. They also suggest that skills measured by educational attainment is a more important workforce dimension than whether tasks are non-routine or interactive when assessing the consequences of offshoring for the workforce structure. The predicted economic effect of offshoring on the educational composition of onshore workforces is nevertheless relatively modest. Our estimates translate into a contribution of off-

[3]We do not condition on affiliate output being used as input by the German firm, but allow for local or third country sales of the output.

[4]For earlier studies on the German work survey see, for instance, Acemoglu and Pischke (1998) or Spitz-Oener (2006).

shoring to changes in the wage-bill share of workers with upper-secondary education in the order of 10 percent – a modest effect compared to the 15-40 percent contribution of overall imports to the change in the wage-bill share of non-production workers in the U.S. (Feenstra and Hanson 1999).

Several interpretations are consistent with our finding that in-house offshoring predicts only small shifts in onshore demand for highly educated workers and only a small recomposition towards non-routine and interactive tasks. An empirical reason for the small predicted shifts is that we base our estimates on the wage-bill variation within plants over time, conditioning on plant-fixed and time effects. Time indicators are highly significant predictors of the workforce composition, however, and suggest that common shocks across firms are important elements of workforce changes. Whether these common shocks are related to offshoring, technical change, or a combination of these and other factors, is an open question for future research.

The paper has five more sections. In Section 2, we review the literature on offshoring and labor demand. We lay out our estimation strategy in Section 3. Section 4 discusses the data and offers descriptive statistics. Section 5 presents the results and discusses interpretations. Section 6 concludes.

2 Offshoring and Onshore Labor Demand

In industrialized countries, offshoring has typically been expected to increase the demand for skilled labor both because of a specialization in skill-intensive production stages and because of a shift towards more capital-intensive production, which tends to favor complementary skills. Feenstra and Hanson (1999) estimate that the effect of offshoring among U.S. industries, including both outsourced offshoring across firms and offshoring within MNEs, can explain 15 to 40 percent of the increase in the wage-bill share of white-collar workers.[5]

MNEs are behind an important part of overall offshoring. Offshore affiliates of MNEs ship a third of world exports, and the estimated share of value added at MNE affiliates in world output was 10.1 percent in 2005, up from 6.7 percent in 1990 (UNCTAD 2006). Several studies of foreign direct investment (FDI), however, report small or negligible effects on the relative demand for skills. Using industry data for the U.S. manufacturing sector, Slaughter (2000) finds that the industry's share of foreign affiliate production has no clear effect on the relative demand for non-

[5]Hijzen, Gorg and Hine (2005) use a similar concept of offshoring for the U.K. but education-based measures of skills.

production workers.[6] Using data for Japanese manufacturing MNEs, Head and Ries (2002) conduct a similar analysis at the firm level and find a statistically significant effect of the share of foreign affiliate employment on the wage-bill share of non-production workers at Japanese parent firms, but increased offshore employment explains less than 10 percent of the observed occupational recomposition.[7]

One possible explanation for these small effects is that a large part of the offshore activities relate to so-called "horizontal" rather than "vertical" FDI, implying that they are mainly motivated by the desire to get better access to markets rather than to cheap inputs (Carr, Markusen and Maskus 2003) Horizontal FDI is likely to result in operations with similar skill intensities as parent firm activities and may therefore have only small effects on the relative demand for skills at the parent firms. Hansson (2005) presents results lending some support to this view. Using data on Swedish manufacturing MNEs and measuring skills by educational attainment, he finds a statistically significant effect of offshoring to non-OECD countries on the wage-bill share of workers with post-secondary education, but no effect of offshoring to OECD countries.[8]

Several models of offshoring have been developed in the literature. A seminal contribution was made by Jones and Kierzkowski (1990), while more recent contributions include Kohler (2004), Grossman and Rossi-Hansberg (2006) and Baldwin and Robert-Nicoud (2007). A common feature is that offshoring reduces production costs for offshoring firms, thereby creating general equlibrium effects similar to technological progress.[9] This implies that there is a presumption for welfare gains in terms of increased real income. That the factor benefiting the most from offshoring may be the one whose services are being offshored was shown by Jones and Kierzkowski (2001) in a setting where offshoring occurs in one sector, implying that it works like sector-biased technological progress. In the absence of changes in relative goods prices, the effect on relative wages between skilled and unskilled workers

[6]Slaughter (2000) estimates the relationship between MNE production transfers and within-industry shifts in occupational composition, assuming capital to be a quasi-fixed factor.

[7]Head and Ries (2002) employ a 25-year panel data set and, similar to Slaughter (2000), use the non-production wage-bill share along with firm-average wages as proxies for skill intensity.

[8]Hansson (2005) does not report how much changes in offshoring to non-OECD countries contribute to explaining changes in the wage-bill share of highly educated workers. However, his point estimates suggest that a one percentage point increase in the share of non-OECD affiliate employment is associated with a .3 percentage point increase in the wage-bill share of workers with post-secondary education. Another Studies using education-based measures include Hansson (2005) and Hijzen et al. (2005)

[9]For a pedagogical discussion of this effect, see Baldwin and Robert-Nicoud (2007) and Kohler (2008)

depends crucially on the sector bias of the cost-savings generated by offshoring.[10] For relatively balanced offshoring across sector, both skilled and unskilled are likely to benefit in terms of increased real wages.

A particular feature of the analysis of Grossman and Rossi-Hansberg (2006) is that it treats offshoring as trade in tasks rather than trade in intermediate inputs. Grossman and Rossi-Hansberg (2006) show that if goods prices can change, the increase in the relative supply of the good intensive in offshorable tasks will reduce its relative price, which would then produce a Stolper-Samuelson effect hurting the factor carrying out offshorable tasks.[11]

Very few papers have studied empirically the nature of tasks being offshored and the extent to which offshored tasks involve high-skilled and low-skilled labor. Jensen and Kletzer (2007) use information on tasks to assess the offshorability of different services occupations in the U.S. They compare the outcome with what they get using a measure of offshorability based on the geographical concentration of services within the U.S., finding a considerable overlap.[12] They also find a positive correlation between their task-based measure of offshorability and skills measured by educational attainment, i.e. occupations with a greater share of highly educated workers are by them more highly ranked as offshorable.

Several recent studies have investigated the effect of technological change on the relative demand for skills, paying particular attention to tasks and their substitutability with information technology. Autor et al. (2003) develop a framework for the changing task composition of occupations and classify tasks into five skill-related categories: *routine cognitive* tasks, *routine manual* tasks, *nonroutine analytical* tasks, *nonroutine interactive* tasks, and *nonroutine manual* tasks. Routine tasks can be expressed as rules, implying that routine tasks are easily programmable and thus susceptible to execution by computers or robots. Nonroutine tasks, on the other side, are not easily codified. Analytical and interactive tasks among the nonroutine activities can be considered complementary to information technology.

To clarify how offshoring of certain tasks might affect the skill intensity at home, we build on Grossman and Rossi-Hansberg (2006) and assume that skilled and

[10] Baldwin and Robert-Nicoud (2007) provide necessary and sufficient conditions for changes in factor prices based on a two-factor, two-sector model.

[11] Moreover, the return to the factor whose tasks are being offshored could be negatively affected because offshoring frees up labor that then needs to be put to work carrying out other tasks. This effect, which Grossman and Rossi-Hansberg (2006) call a labor supply effect, does not generally arise in the even case with as many factors as goods, but when the number of factors exceeds the number of goods.

[12] The measure based on geographical concentration is developed in Jensen and Kletzer (2006)

unskilled workers (denoted S and L, respectively) carry out tasks, indexed by i_h, $h = S, L$, $i_h \in [0, 1]$, that vary by offshoring cost. This cost includes a task-specific component, $t(i_h)$, and a general component, β. Tasks are ranked according to $t(i_h)$, implying that for a particular β there will be a cut-off point $t(I_h)$ where all tasks with a lower t are offshored. A reduction in β leads to an increase in the range of offshored tasks by shifting the cut-off point, thereby making the average t of the tasks remaining onshore higher.

Let us use $\tilde{\theta_S}$ to denote the average wage bill share of skilled workers onshore of a firm that is a price taker in the factor market:

$$\tilde{\theta_S} := \frac{w_S \int_{I_S}^1 a_S(i_S) f(i_S) di_S}{w_S \int_{I_S}^1 a_S(i_S) f(i_S) di_S + w_L \int_{I_L}^1 a_L(i_L) f(i_L) di_L}, \tag{1}$$

where $f(i_h)$ is the amount of task i carried out by factor h required per unit of output and we normalize so that $\int_0^1 f(i_h) di_h = 1$, $a_h(i_h)$ is the per unit factor input coefficient and w_h the given factor price. The per unit factor requirement coefficient may vary with tasks, but a common assumption in the literature is that $a_h(i_h) = a_h$ (see e.g. Kohler 2008). If that is the case, (7) reduces to

$$\tilde{\theta_S} = \frac{w_S a_S \int_{I_S}^1 f(i_S) di_S}{w_S a_S \int_{I_S}^1 f(i_S) di_S + w_L a_L \int_{I_L}^1 f(i_L) di_L}. \tag{2}$$

It is easily realized that an increase in I_S, i.e. an increase in the range of skilled tasks that are performed offshore, leads to a reduction in $\tilde{\theta_S}$, while the opposite holds true for an increase in I_L. Formally, differentiation of (2) with respect to I_S and I_L yields:

$$d\tilde{\theta_S} = \Psi \left[\frac{f(I_L) dI_L}{\int_{I_L}^1 f(i_L) di_L} - \frac{f(I_S) dI_S}{\int_{I_S}^1 f(i_S) di_S} \right], \tag{3}$$

where

$$\Psi := \frac{w_S a_S w_L a_L}{\int_{I_S}^1 f(i_S) di_S \int_{I_L}^1 f(i_L) di_L (w_S a_S \int_{I_S}^1 f(i_S) di_S + w_L a_L \int_{I_L}^1 f(i_L) di_L)^2} > 0. \tag{4}$$

This expression makes clear that $\tilde{\theta_S}$ increases only if the expression within brackets is positive, i.e. if:

$$\frac{f(I_L)dI_L}{\int_{I_L}^{1} f(i_L)di_L} > \frac{f(I_S)dI_S}{\int_{I_S}^{1} f(i_S)di_S}. \tag{5}$$

The left hand side of this inequality shows the change in unskilled tasks taking their importance in production into account relative to the importance-weighted range of unskilled tasks remaining onshore. The right hand side shows the corresponding measure for skilled tasks. If the increase in the range of offshored unskilled tasks is considerably larger than the increase in the range of offshored skilled tasks, or if the shifted unskilled tasks are considerably more important in the production process than the shifted skilled tasks relative to the tasks that remain onshore, we expect the wage-bill share of skilled workers to increase.

The relative size of the changes in I_S and I_L depends on how task-specific offshoring costs vary across tasks. The cut-off level I_h is determined by the first-order condition that the onshore and offshore per unit cost of performing the marginal task is equal, which requires:

$$w_h = \beta t(I_h) w_h^*, \tag{6}$$

where w_h^* is the foreign price of factor h. How much I_h has to increase in response to a decrease in the general component of offshoring costs, β, in order to satisfy the first-order condition depends on how responsive the function $t(i_h)$ is to changes in i_h. If offshoring costs vary little across different tasks, the range of offshored tasks must increase more to maintain the first-order condition. For firms with similar offshoring costs for unskilled tasks but varying offshoring costs for skilled tasks, we would thus expect a large shift in the range of unskilled tasks and a small shift in the range of skilled tasks in response to decreased offshoring costs.

In this setup tasks with different offshoring costs differ in terms of skill-intensity. The assumption that offshorability of tasks is unrelated to their skill content may be captured by setting $i_S = i_L$, in which case the wage-bill share of skilled workers is unaffected by a change in the range of offshored tasks.

We might adopt the view more closely related to the arguments made by e.g. Blinder (2006) that the nature of the tasks carried out affect how offshorable they are. A way to capture this notion is to assume that the task-specific offshoring cost, $t(i)$, is related to the nature of task i. Suppose, for instance, that non-routine tasks are always more costly to offshore than routine tasks. This would imply that there is a cut-off level of i where tasks with a lower i are all routine tasks while tasks with a higher i are all non-routine tasks. Define this level as I^T. Assuming that some routine tasks remain onshore, we can then express the wage-bill share of non-routine tasks as

$$\tilde{\theta_N} := \frac{w_N \int_{I^T}^{1} f(i)di}{w_R \int_{I^O}^{I^T} f(i)di + w_N \int_{I^T}^{1} f(i)di}, \tag{7}$$

where w_N and w_R are given prices of non-routine and routine tasks, respectively, and I^O denotes the cut-off level for offshored tasks. As is evident from this expression, a shock that increases the range of tasks being offshored (i.e. increases I^O) will in this case always increase the wage-bill share of non-routine tasks.

There are thus different ways of looking at how offshoring may affect the onshore workforce composition at the level of the firm. This paper will provide empirical evidence based on German MNEs on whether it tends to shift it in the direction of high-skilled workers and in the direction of tasks that might be thought of as less offshorable. As noted above, however, the policy-relevant effects of offshoring on welfare and income distribution depend crucially on general equilibrium effects, which involve the sector-bias of offshoring and any resulting terms-of-trade changes. This paper will not have much to say about such effects. However, it will present evidence against the view that offshored tasks tend to be skill-intensive or neutral with respect to the skill-intensity. It will also present descriptive evidence that in-house offshoring is positively correlated with the skill-intensity of firms, suggesting that, if anything, the sectoral bias seems to be in the direction of the skill-intensive sector.

3 Estimation Strategy

We seek to estimate the contribution of an MNE's offshore expansion to the relative onshore demand for skills or tasks.

Main specification. We follow the prior literature and consider a reduced-form equation to predict the relative demand for work type i at an onshore plant j of MNE $k(j)$ with offshore employment (OE) at location $\ell(k)$ in year t:[13]

$$\theta_{ijt} = \alpha_j + \beta_K \ln \tfrac{K_{kt}}{Y_{kt}} + \beta_Y \ln Y_{jt} + \beta_w \ln \tfrac{w_{ijt}}{w_{-ijt}} + \textstyle\sum_\ell \gamma_\ell \, OE_{k\ell t} + \delta_t + \varepsilon_{ijt}, \tag{8}$$

[13] Equation (8) is the common model in related prior research (Slaughter 2000, Head and Ries 2002, Hansson 2005).

where θ_{ijt} is the share of factor input i in the total wage bill at plant j, α_j is a plant-fixed effect, K_{kt}/Y_{kt} is the parent-level capital-output ratio at MNE k, Y_{jt} is real value added at plant j, w_{ijt} is the wage of work type i at plant j, w_{-ijst} is the composite wage of the complementary work type not in i, δ_t is a year effect, and ε_{ijt} an additive error term.

Equation (8) specifies a reduced-form relationship for relative onshore labor demand, given activities at offshore locations, captured by the variable *OE*. Several adjustments to a conventional factor-demand system are required to arrive at (8). The specification collapses offshore activities into a scalar sum of *OE* measures by location: $\sum_\ell \gamma_\ell \, OE_{k\ell t}$.[14] This measure is introduced as a variable that can affect the relative productivity of different work types at home, much like factor-biased technical change.[15] An implicit identifying assumption is that MNEs decide on their offshore activities $OE_{k\ell t}$ prior to determining the composition of their onshore work force. Plausible rationales for the sequential choice are fixed coordination costs or sunk investment costs associated with offshore activities. The wage ratio accounts for variation in the wage-bill share θ_{ijt} that is explained by relative factor prices and restricts the own- and composite cross-wage coefficients to be equal in absolute value.[16] Capital enters as a quasi-fixed factor. The capital-output ratio captures unobserved user costs of capital at the parent level and accounts for variation in θ_{ijt} due to capital deepening. Time dummies control for changes in the workforce composition that are common to all plants. The plant-fixed effect conditions out unobserved time-invariant plant heterogeneity.

The coefficients of foremost interest are γ_ℓ. We wish to test whether a γ_ℓ coefficient is statistically significantly different from zero. We are also interested in the economic importance of the predicted relationship between $OE_{k\ell t}$ and the wage-bill variation across workforce characteristics. We focus on the task and skill composition by considering the nature of performed tasks (non-routine or interactive i and routine or non-interactive $-i$) and workers' educational attainment (upper-secondary schooling i or less schooling $-i$).For comparison, we also consider the composition of white-collar and blue-collar workers (white-collar i and blue-collar $-i$), as this has been a widely used proxy for skills in the previous literature.

[14]This strategy is similar to Hansson (2005). An alternative specification would be to interact the *OE* measure with the per-capita income of the host country (see Head and Ries (2002) for a discussion).

[15]A conventional factor-demand system would involve specifying factor cost share equations for offshore locations as well and estimation of a system of equations.

[16]This is tantamount to assuming the short-run cost function for onshore activities to be linearly homogenous in the wages of the different work types entering the cost function.

Simultaneity problems may affect equation (8). If offshore employment at ℓ and onshore demand for work type i are simultaneously determined γ_ℓ may be biased. Instrumenting for OE might solve this problem if a sufficiently good instrument for offshore employment could be found. We report results from estimations using the two-year lag of OE as instrument. This variable is not an ideal instrument, but we argue that it is a valid one.[17]

A second source of potential bias arises from the presence of the term $\ln w_{it}/w_{-it}$ because wages also enter the dependent wage-bill share variable. We follow Slaughter (2000) and Head and Ries (2002), who omit $\ln w_{it}/w_{-it}$. To check robustness, we also include the relative wage term, and find results to be similar. Note that sector-level collective bargaining in Germany, and our use of plant data, mitigate the concern that the joint determination of plant employment and economy-wide wages affects estimates. We also run regressions with employment shares rather than wage-bill shares as left-hand side variables.

We estimate several variants of specification (8) to assess robustness. We drop plant size weights, and we include a number of additional controls at the industry level: the ratio between imported intermediates and output (a variable arguably capturing offshoring of intermediate inputs more generally), import penetration, R&D intensity and the average wage-bill share of work type i in plants belonging to non-MNEs. The latter variable should control for secular trends in the wage-bill shares affecting all firms within a sector. We are particularly concerned about a general increase in the education level of the population, which will lead to an increased proportion of workers with upper secondary education in our data. By including the wage-bill shares of non-MNE firms within the same sector, we control for such potential supply effects (the time dummies will capture any secular trends that affect all sectors in the same way). We also try several different alternative measures of non-routine and interactive tasks.

When estimating (8) for the wage-bill share of highly educated workers we also control directly for the task composition at the level of the plant. This may be important since shifts in a workforce's task composition alone may account for shifts in its educational profile. A significant a positive estimate of γ_ℓ with this control included would indicate that offshoring is associated with educational upgrading in excess of what can be explained by changes in the task composition. A similar exercise for the composition of white-collar versus blue-collar workers allow us to

[17]We have tried a number of industry-level variables as instruments, such as offshore employment by Swedish MNEs and exports and imports by Germany's trading partners. However, neither of them have turned out to be valid instruments.

examine whether offshoring predicts educational upgrading in excess of what can explained by a shift in the share of white-collar workers.

4 Data and Descriptive Statistics

Our data derive from the combination of four micro-data sources, assembled at Deutsche Bundesbank in Frankfurt. The unit of analysis in this paper is an onshore plant of a German MNE.[18]

4.1 Data sources

Onshore plant information comes from confidential quarterly social-security records of the German Federal Labor Agency (Bundesagentur für Arbeit BA), our first data source. The raw BA data are at the worker-job level and cover the universe of workers registered in the social insurance system over the years 1998-2006, representing around 80 percent of the formally employed German workforce.[19] The records contain worker and job characteristics including worker age, education, occupation and the monthly wage. Wages in the German social security data are top-coded at the ceiling for old-age insurance, which is annually adjusted for nominal wage changes, but there is no censoring from below.[20] We aggregate the worker-job information to the plant level and compute wage-bill shares for individual occupations, tasks, and education levels by plant.

Second, confidential information on German MNEs and their offshore activities comes from the combined MIDI-USTAN database at Deutsche Bundesbank (BuBa); see Lipponer (2003) for a documentation of MIDI (MIcro database Direct Investment, formerly DIREK) and Bundesbank (1998) for a documentation of USTAN (which

[18]A German MNE is an MNE, headquartered in Germany, with reported outward FDI, or a firm in Germany, with reported outward FDI, whose ultimate parents are headquartered elsewhere.

[19]Covered are full- and part-time workers at private enterprises, apprentices, and other trainees, as well as temporarily suspended employment relationships. Civil servants, student workers, and self-employed individuals are excluded and make up the remaining 20 percent of the formal-sector labor force. Plants within the same municipality may report workforce information using a single plant identifier. Although our data derive from the pristine BA source, Bender, Haas and Klose's (2000) description of a random sample also applies to our universal BA records.

[20]We use the average monthly wage during the second quarter, when records are considered most representative, for the year. Top-coding is binding only for a minor fraction of workers (Bender et al. 2000). Workers with an annual income below 3,865 EUR (in 2001) are not subject to social security contributions, but are part of our estimation sample.

reports parent-level operations of German MNEs). The outward FDI data cover all offshore affiliates of German MNEs according to minimal reporting thresholds.[21] For the present paper, we retain MNEs in manufacturing, services (including utilities and construction), and commerce. We extract affiliate-level information on employment and ownership (from MIDI) and parent-level information on fixed assets and value added (from USTAN). We allocate parent-level value added to the plant according to the plant's employment share in parent employment. We deflate nominal variables to the December-31 1998 value.[22]

Third, we use the commercial database MARKUS (from Verband der Vereine Creditreform) on German corporate ownership to combine the preceding two data sources. MARKUS allows us to identify all onshore affiliates of MIDI-USTAN firms, to which we then link BA plants. Multinational enterprises are also multi-firm enterprises in the home economy so that outward FDI affects workers beyond the individual FDI-reporting firm's workforce. Moreover, many German enterprises bundle the management of their offshore affiliates into legally separate firms (mostly limited liability *GmbHs*) for tax and liability reasons. Those bundling firms then report FDI to MIDI as required by German law. The economic impact of the reporting firm's FDI, however, goes beyond the firm's formal legal boundary in that jobs throughout the corporate group may be affected. We consider all firms within a corporate group (an enterprise) as *potential* FDI firms if at least one firm in the group reports outward FDI activities.[23]

The resulting matched sample allows us to discern between German plants that belong to German MNEs and plants that belong to non-MNEs. We compare descriptive statistics for MNEs and non-MNEs below and use information for the non-MNEs to control for secular trends in wage-bill shares at the industry level. In Section 5, we report results from an MNE sample that excludes parent firms with

[21]In 1999 through 2001, reporting is mandatory for all offshore affiliates with either a balance sheet total of more than EUR 5 million and at least a ten-percent ownership share of the German parent or with a balance sheet total of more than EUR 0.5 million and at least a 50-percent ownership. In 1998, reporting was mandatory for offshore affiliates with a balance sheet total of more than EUR 0.5 million and at least a twenty-percent ownership share. We keep balanced panels to prevent attrition due to reporting thresholds. Our point estimates are not sensitive to omission of year-1998 observations.

[22]In some specifications we use turnover to measure offshore activities. We then transform affiliate turnover over the full sample period to Euros at the exchange rate on December-31 1998.

[23]BA, MIDI-USTAN and MARKUS do not share common firm identifiers. We use a string-matching procedure to identify clearly identical firms and their plants (see Appendix A for a detailed description).

offshore employment greater than 100 times their onshore employment.[24] Of the plant observations, we keep balanced panels to conduct plant-fixed effects estimation for firms that are continuously active offshore. The resulting estimation sample contains 5,064 observations of 1,266 plants at 490 MNES for the sample period 1998-2001. While information on FDI is available from 1996, worker-level information is only available from 1998. Beyond 2001 we have worker-level information, but because of a decline in the coverage of firms in USTAN, this information cannot be matched to corresponding firm-level data. The total number of employees in 1999 in the sample is 667,760, out of which 389,201 are employees in plants belonging to manufacturing MNEs. Aggregate German employment in manufacturing MNEs in 1999 was estimated to 1,597,738 by Becker, Ekholm, Jäckle and Muendler (2005). Based on the proportion of observed employees at manufacturing MNEs to total employees at manufacturing MNEs, we are thus capturing around a quarter of the domestic employment at German MNEs.

Our fourth data source is the BIBB-IAB work survey, which we use to codify the tasks involved in an occupation as non-routine or interactive. For this purpose, we reclassify workers' answers to questions in the Qualification and Career Survey for 1998/99 regarding the use of 81 workplace-tools in their occupations. The German Federal Institute for Vocational Training (Bundesinstitut für Berufsbildung BIBB) and the research institute of the German Federal Labor Agency (Institut für Arbeitsmarkt- und Berufsforschung IAB) conduct the survey.

4.2 Variable construction

Nature of tasks. To classify tasks, we start by coding the answers to 81 yes/no questions whether a worker uses a specific workplace tool or not. The 81 workplace tools range from repair tools to machinery and diagnostic devices to computers and means of transport. We assign two different indicators to the use of any given workplace tool: (i) an indicator whether use of the workplace tool implies a non-routine task (characterized by non-repetitive methods of work), and (ii) an indicator whether use of the same workplace tool implies an interactive task (characterized by frequent personal interaction with coworkers or the firm's customers). To be able to assess the robustness of our estimation results to these classifications, we create two

[24]Head and Ries (2002) also report large ratios of offshore to onshore employment for Japanese MNEs. A considerable number of German MNEs bundles the management of offshore activities in separate German firms. Some onshore activities of corporate MNE groups may go unlinked in our string-match procedure. We therefore exclude outliers as a matter of caution (but we find results to be little sensitive to their inclusion).

different ones. One set of indicators is based on a restrictive interpretation of what might constitute non-interactive and interactive tasks, while another set is based on a more liberal interpretation (see Appendix C).

For our main measure of tasks we map tasks to occupations in three steps. First, we use information on workplace tools in 84 *ISCO88* 2-digit occupations from the BIBB-IAB work survey and calculate the average number of non-routine (interactive) tasks involved in performing a given 2-digit occupation (based on our codification of responses to the 81 survey questions on workplace tools). Second, we find the maximum number of non-routine (interactive) tasks required to perform any 2-digit occupation.[25] Third, we measure a given 2-digit occupation's degree of non-routine (interactive) tasks as the ratio between the average number of non-routine (interactive) tasks in the occupation and the maximum number in any occupation. We standardize by the maximum and minimum number of tasks in any occupation so that task shares vary between zero and one across occupations.

With this standardization each occupation is assigned a number between 0 and 1 which can be thought of as an index of its intensity of non-routine and interactive tasks. In the analysis, we are going to treat this index as a cardinal number that measure labor input of different tasks. That is, we assume that workers with an occupation with the index value x on the intensity of non-routine tasks use a fraction x of their time carrying out non-routine tasks. This is obviously a strong assumption. Ideally, one would like to have information from time studies to create such a measure. However, our empirical strategy in Section 3 is unaffected by the choice of scale and we use several alternative ways of creating the ranking across occupations to check robustness. Apart from rankings created by ourselves, we also use one based on a mapping created by Spitz-Oener (2006) in order to study information technology and labor demand. Whereas our codification of tasks draws on 81 questions regarding workplace-tool use, the Spitz-Oener task classification draws on a complementary set of 15 job descriptions in the same BIBB-IAB survey (for details on the Spitz-Oener mapping see Appendix C).

Offshore activities. We follow Head and Ries (2002) in measuring a plant's exposure to its parent firm's offshore activities with the share of offshore activities in

[25] Under our restrictive codification, the observed maximum of non-routine (interactive) tasks per *ISCO88* 2-digit occupation is 6.7 (3.3)—after averaging over responses by occupation. Under the more liberal codification, the maximum number of non-routine (interactive) tasks per occupation is 15.4 (7.3).

total activities:[26]

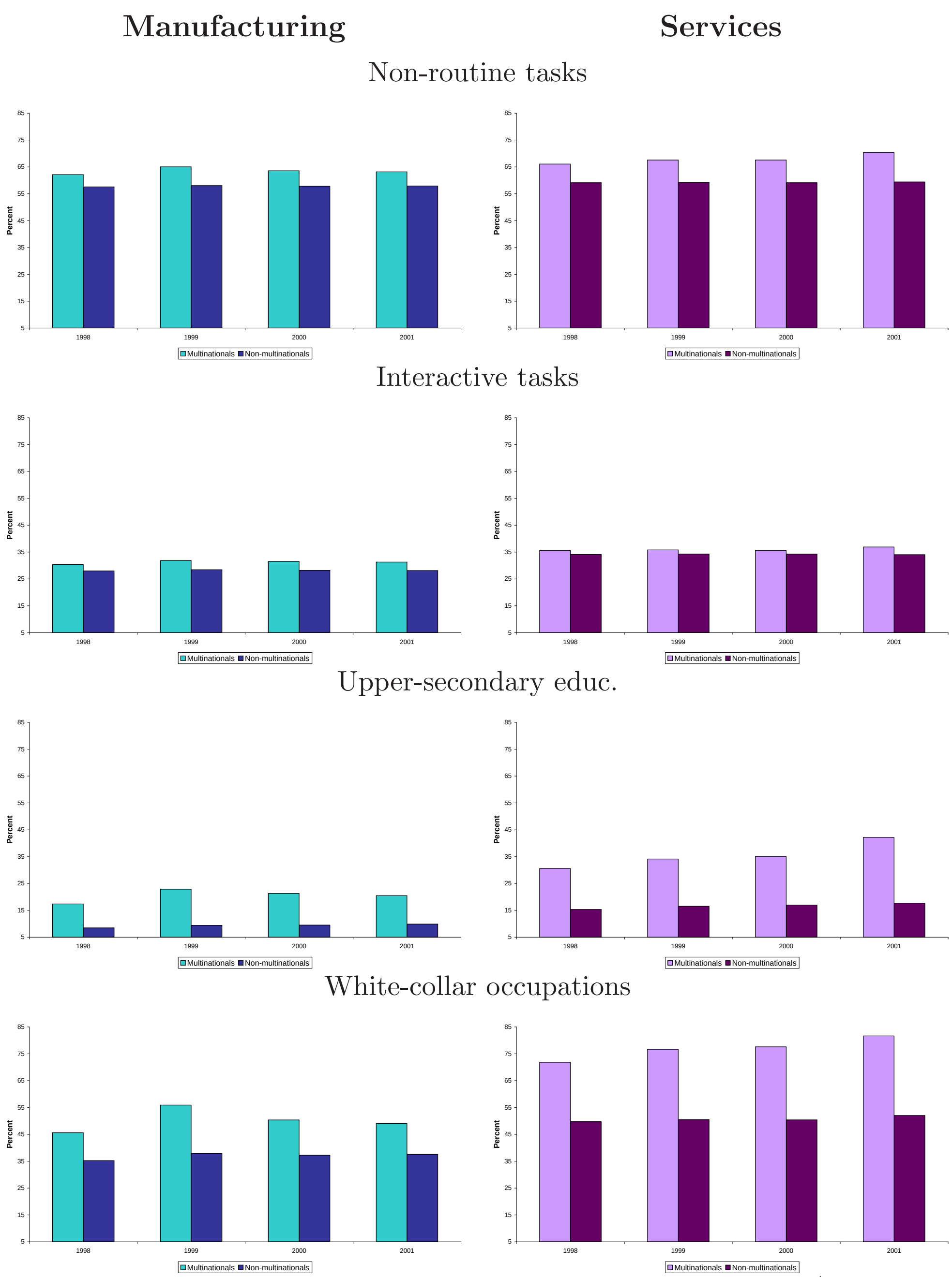
$$OE_{k\ell t} = \frac{\sum_{n\in\ell(k)} x_{nt}}{\sum_{n\in\ell(k)} x_{nt} + \sum_{j\in k} x_{jt}}, \tag{9}$$

where x_{nt} is the activity of MNE k's offshore affiliate n in location $\ell(k)$, and x_{jt} is the activity at MNE k's onshore plant j. For the calculation of (9), x_{nt} is weighted by the parent firm's ownership share in the foreign affiliate. $OE_{k\ell t}$ is a measure of the parent firm's offshore activities and does not vary across an MNE's plants. We report results on two groups of locations ℓ: high-income and low-income countries.[27]

We measure activity with employment since offshore employment is a natural counterpart to relative labor demand at home. Marked productivity differences between offshore and onshore labor, however, may lead to a small measured sensitivity of home labor demand with respect to offshore employment. Sales are an alternative measure of offshore activity but may suffer from the converse problem. Sales can be affected by tax differentials and transfer pricing and to the extent that it understates offshore activity it can potentially lead to an exaggerated sensitivity of onshore labor demand to offshore activity. We find estimation results with offshore sales to be similar to those with employment, and therefore only report results based on employment.

[26] The Head and Ries measure naturally varies between zero and one. An alternative measure is the ratio between offshore and onshore activities (Slaughter 2000). For any location ℓ, that ratio is independent of the size of the parent's operations at another location (the ratio between employment in low-income countries and onshore employment is independent of employment in high-income countries). Being an unbounded ratio, however, it can be more sensitive to outliers.

[27] We have also run regressions using finer regional groupings. Results are available upon request.



Sources: Linked BA-MIDI data 1998-2001 and BIBB-IAB worker survey 1998/99.
Task measures under strict interpretation. Services exclude commerce.

Figure 1: **Wage-bill shares by occupation, task, and skill, 1998-2001**

Table 1: CORRELATIONS BETWEEN PLANT-LEVEL WAGE-BILL SHARES OF DIFFERENT WORK TYPES IN 2004

	Non-rout. tasks	Interact. tasks	Upp.-sec. educ.
Interact. tasks	.519		
	(.000)		
Upp.-sec. educ.	.615	.302	
	(.000)	(.000)	
White-collar	.198	.109	.229
	(.000)	(.000)	(.000)

Sources: Linked BA-MIDI data 2004 and BIBB-IAB worker survey 1998/99. MNE plants only. Task measures based on restrictive interpretation. Figures in parenthesis are p-values.

4.3 Descriptive statistics

Figure 1 shows average wage-bill shares in manufacturing and services (excluding commerce) for four "advanced" work types: non-routine tasks, interactive tasks, upper-secondary education and white-collar occupations. Each graph contrasts the evolution of wage-bill shares at MNEs (left bars) with those at non-MNEs (right bars). At MNEs, wage-bill shares of all four work types exceed those at non-MNEs. The difference is quite striking except in the case of interactive tasks in services. The graphs for the wage-bill share of workers with upper secondary education reveal an upward trend for MNEs as well as non-MNEs over the 1998-2006 period, confirming a general trend towards educational upgrading. However, the trend for the MNEs is more pronounced. A relatively similar pattern emerge for the wage-bill share of white-collar workers. The evolution of the task-based measures is less stark, but there seems to be a general increase in the wage-bill share of non-routine tasks. The graph for the services sector also reveal that the increase is much larger for MNEs compared with non-MNEs.

Table 1 presents the plant-level correlation between the wage-bill shares of different work types in a cross-section of MNE-plants.[28] As is evident from the table, all measures are positively correlated. The correlations between the two task measures and between each of them and the wage-bill share of workers with upper secondary education are particularly high. The highest correlation is between the wage-bill share of our measure of non-routine tasks and the wage-bill share of workers with

[28] The reason for not studying the correlation at the worker level is that the worker survey used to construct the task measures does not contain straightforward information about educational attainment.

upper secondary education (.615).

Wage-bill shares change with relative wage changes and in response to employment shifts. To assess the relative contribution of these two factors, we decompose the observed wage-bill changes. Let θ_i be the wage-bill share of work type i. A change in θ_i between an initial period 0 and t can be split into the components

$$\begin{aligned} \frac{\theta_{it}-\theta_{i0}}{\theta_{i0}} &= \left(\frac{L_{it}}{L_{i0}}\frac{w_{it}-w_{i0}}{w_{i0}} - \frac{L_{-it}}{L_{-i0}}\frac{w_{-it}-w_{-i0}}{w_{-i0}}\right)\Theta_i \\ &\qquad + \left(\frac{L_{it}-L_{i0}}{L_{i0}} - \frac{L_{-it}-L_{-i0}}{L_{-i0}}\right)\Theta_i, \end{aligned} \tag{10}$$

where

$$\Theta_i := (1-\theta_{i0})\,\frac{w_{i0}L_{i0}+w_{-i0}L_{-i0}}{w_{it}L_{it}+w_{-it}L_{-it}}$$

and w_{it} is the wage and L_{it} the employment of work type i (see Appendix D for a derivation). The subscript $-i$ denotes the complementary work type not in i. We use the first term in (10) to approximate the contribution of relative wage changes and the second term to approximate the contribution of employment shifts. The first term includes weights that reflect gross employment growth and may exaggerate the relative wage contribution since most firms in our sample increase their employment over time.

Table 2 reports the overall change and the decomposition of the change for the wage-bill shares of different work types in manufacturing and services. We use the more restrictive task classification (results change little under the more liberal classification) and utilize the full time series available for worker-level data, i.e. 1998-2006.[29] The first column, which reports the overall changes, shows that consistently there have been larger increases in the wage-bill shares of advanced work types in the MNEs compared with non-MNEs. It is also evident that the increases have been larger for highly educated and white-collar workers than for the measures of non-routine and interactive tasks. Comparing changes in wage-bill shares at manufacturing and services MNEs, we see that the increases have been larger in the latter for all "advanced" work types except interactive tasks. Especially for highly educated and white-collar workers, the increases in the wage-bill share are considerably larger in services MNEs than in manufacturing MNEs.

[29]Information on whether workers hold white-collar or blue-collar jobs was discontinued after 2004 so the decomposition for the wage-bill share of white-collar workers is based on the 1996-2004 period.

Table 2: Decomposition of Wage-bill Changes, 1998-2006

	Total change	Wage component contrib.	Wage component percent	Employment comp. contrib.	Employment comp. percent
Manufacturing MNEs					
Non-routine tasks	.044	.016	37.7	.027	62.3
Interactive tasks	.024	.007	28.6	.017	71.4
Upper-secondary educ.	.089	.030	34.2	.058	65.8
White-collar occup.	.075	.030	40.0	.045	60.0
Manufacturing non-MNEs					
Non-routine tasks	.030	.015	50.0	.015	50.0
Interactive tasks	.012	.005	44.4	.007	55.6
Upper-secondary educ.	.042	.017	39.7	.025	60.3
White-collar occup.	.032	.013	41.5	.019	58.5
Services MNEs					
Non-routine tasks	.095	.043	45.6	.051	54.4
Interactive tasks	.003	.007	261	-.004	-161
Upper-secondary educ.	.267	.095	35.4	.172	64.6
White-collar occup.	.183	.056	30.9	.127	69.1
Services non-MNEs					
Non-routine tasks	.018	.016	91.7	.001	8.3
Interactive tasks	-.003	.002	-79.7	-.005	180
Upper-secondary educ.	.068	.032	47.0	.036	53.0
White-collar occup.	.038	.022	58.6	.016	41.4

Sources: Linked BA-MIDI data 1998-2006 and BIBB-IAB worker survey 1998/99. Task measures based on restrictive interpretation. Services exclude commerce. The decomposition of wage-bill shares for white-collar workers is based on the 1998-2004 period.

The decomposition reveals that employment shifts are for the most part the dominant contributing factor. However, for our measure of interactive tasks employment shifts contribute negatively to a small increase in the wage-bill share at services MNEs. Furthermore, at services non-MNEs, a change in the relative wage paid for non-routine tasks contribute more than 90 percent to the overall change in the wage-bill share.

For workers with upper-secondary education, an increase in the relative wage explains between a third and a half of the increase in the wage-bill share across different types of firms. The fact that both the relative wage and the input proportion of workers with upper-secondary education increased is indicative of an increased rel-

Table 3: CORRELATIONS BETWEEN THE CHANGE IN THE SHARE OF OFFSHORE EMPLOYMENT 1998-2001 AND THE WAGE-BILL SHARE IN 1998

	Change in offshore employment 1998-2001		
Initial wage-bill share	Word-wide	High-income	Low-income
Non-rout. tasks	.099	.105	.037
	(.000)	(.000)	(.202)
Interact. tasks	.005	.027	-.019
	(.852)	(.341)	(.501)
Upp.-sec. educ.	.065	.027	.065
	(.026)	(.361)	(.026)
White-collar	-.018	.055	-.079
	(.539)	(.056)	(.006)

Sources: Linked BA-MIDI data 1998-2001 and BIBB-IAB worker survey 1998/99. MNE plants only. Task measures based on restrictive interpretation. Figures in parenthesis are p-values. Correlations are based on 1246 observations.

ative demand for highly educated workers in Germany during the 1996-2004 period (c.f. Berman, Bound and Griliches 1994).

A possible factor contributing to an increased relative demand for skilled workers is offshoring. There is a clear upward trend in the share of offshore employment for services MNEs, in particular regarding offshoring to low-income countries. In manufacturing, however, there is no clear trend. The share of offshore employment in high-income countries has been relatively stable, while there has been an increase of a few percentage points in the share of offshore employment in low-wage countries between 1996 and 2001.

An issue of potential interest in assessing the likely general equilibrium effects of offshoring on wages is whether increases in offshoring tend to occur in firms using a large proportion of skilled or unskilled workers. As discussed in Section 2, the effect of offshoring on relative wages depends on the sector-bias of the cost-reductions generated by offshoring. If offshoring were found to primarily occur in relatively skill-intensive firms, it would be more likely to contribute to a widening than a narrowing of the wage gap. As shown above, German firms carrying out in-house offshoring tend to be considerably more skill-intensive than firms that confine their activities to Germany. Of course, there may be many less skill-intensive firms that offshore activities through sub-contracting, so this is far from any conclusive evidence of any bias towards skill-intensive firms.

Table 3 shows correlations between the change in the share of offshore employment between 1998 and 2001 and the firms' initial wage-bill share of different work types. That is, for our sample of MNE-plants, the table shows whether there is any correlation between the extent to which firms increase the share of foreign employment and their initial composition of the onshore workforce. There is a significant positive correlation between the change in the share of offshore employment in high-income countries and the initial wage-bill share of non-routine tasks. Furthermore, there are significant correlations between the change in the share of offshore employment in low-income countries and the initial wage-bill share of highly educated and white-collar workers, respectively; a positive correlation in the former case and a negative in the latter. This suggests that offshoring to low-wage countries has been biased towards firms with relatively highly educated blue-collar workers. The correlation coefficients are fairly close to zero, however, indicating that the bias is relatively weak and offshoring relatively balanced across firms with different workforce structures.

5 Estimation Results

We now turn to the results from estimating (8) for each of the four "advanced" work types: non-routine and interactive tasks, upper-secondary education and white-collar occupations.

Non-routine and interactive tasks. We start with regressions of the wage-bill shares of non-routine and interactive tasks and fit the model to all MNE-plants as well as separately to MNE-plants in manufacturing, services excluding commerce, and commerce. FDI in commerce primarily involves setting up sales affiliates abroad, which makes it mostly of the horizontal type. FDI in other services, on the other hand, involves activities that differ from those carried out at home. For FDI in other services, cost reduction is likely to be an important motive, implying that it may be also of the vertical type. One might thus expect FDI in services excluding commerce and FDI in commerce to affect the onshore workforce composition differently.

In the main text, we only present results based on the stricter codification of tasks as non-routine and interactive based on the workplace-tool use (Section 4, Appendix C). In appendix, we also present results for the more liberal codification and the Spitz-Oener (2006) definition of non-routine and interactive tasks.

We estimate equation (8) both by fixed and random effects. Results are generally very similar and for the most part we focus on the results from random effects estimatation. Hausman tests support random effects and are preferable for efficiency reasons. Furthermore, the random effects model turns out to be more stable in those specifications where we use instrumental variables.

Table 4 presents results for world-wide offshoring. The first five columns show the results for non-routine tasks while the last five columns show the results for interactive tasks. The two first columns for each of the task types show the results for the whole sample; the first column based on fixed-effects estimations and the second based on random effects estimation. The last three columns show the results from random effects estimations for each of the sectors manufacturing, services and commerce. The point estimates for the offshoring variable show the associated percentage change in the wage-bill share of a change in the offshoring measure from 0 to 1.

Table 4: Offshoring and non-routine and interactive tasks

	Non-routine tasks					Interactive tasks				
	All	All	Manu.	Serv.	Comm.	All	All	Manu.	Serv.	Comm.
	Fixed Effects	Random Effects	Random Effects	Random Effects	Random Effects	Fixed Effects	Random Effects	Random Effects	Random Effects	Random Effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log (assets / value-added)	.033 (.165)	.524 (.144)***	.139 (.223)	-.423 (.355)	.503 (.218)**	.025 (.085)	.042 (.072)	-.053 (.110)	-.477 (.179)***	.029 (.105)
Log value-added	-.331 (.126)***	.322 (.102)***	-.221 (.165)	-.411 (.248)*	.782 (.157)***	.044 (.065)	-.072 (.051)	-.125 (.084)	-.212 (.128)*	.204 (.073)***
Offshore empl.	2.693 (.686)***	2.505 (.585)***	3.671 (.932)***	4.317 (1.490)***	.735 (.798)	1.319 (.352)***	1.653 (.293)***	2.265 (.465)***	2.594 (.762)***	.683 (.374)*
Year 1999	.270 (.124)**	.206 (.125)*	.527 (.194)***	.653 (.371)*	-.217 (.155)	.088 (.064)	.087 (.063)	.292 (.093)***	.272 (.203)	-.167 (.078)**
Year 2000	.305 (.125)**	.243 (.126)*	.592 (.197)***	.781 (.377)**	-.170 (.156)	.103 (.064)	.092 (.064)	.254 (.094)***	.363 (.206)*	-.126 (.079)
Year 2001	.275 (.127)**	.197 (.127)	.613 (.198)***	.654 (.381)*	-.177 (.159)	-.001 (.065)	-.016 (.065)	.198 (.095)**	.209 (.208)	-.228 (.080)***
Hausman test										
$\gamma_\ell^{FE} - \gamma_\ell^{RE}$	.187					-.334				
s.e. $(\gamma_\ell^{FE} - \gamma_\ell^{RE})$	.359					.195				
Obs.	5008	5008	1876	1020	2112	5008	5008	1876	1020	2112
R^2 (within)	.01	.004	.026	.023	.002	.006	.005	.025	.007	.015
R^2 (between)	.003	.069	.012	.001	.098	.013	.024	.022	.067	.00002
R^2 (overall)	.002	.064	.013	.002	.093	.013	.023	.022	.061	.0001

Source: Linked BA-MIDI data 1998-2001, MNE plants only. Hausman test indicates whether random effects specification is adequate. Standard errors in parentheses: * significance at ten, ** five, *** one percent.

As is evident from the table, the estimated coefficient of offshoring is positive and significant at the one percent level in all regressions except the ones for commerce. For non-routine tasks, the estimated coefficient is somewhat higher in services than in manufacturing, but for interactive tasks they are very similar. For commerce the estimated coefficient of offshoring is much closer to zero, which is also reflected in the fact that the estimated coefficients for the full sample are smaller than the ones for manufacturing and services alone.

Table 5 presents corresponding results when offshoring is divided into offshoring to high-income and low-income countries. In this table, all results are based on random effects estimations. Again, the results for manufacturing and services are quite similar, while the results for commerce are different. For both types of tasks, the estimated coefficients of offshoring to high-income as well as low-income countries are positive. They are also significant at the five percent level except in the case of offshoring to low-income countries and non-routing tasks. Thus, we do not find any evidence of a differential relationship between offshoring and the wage-bill share of "advanced" tasks depending on whether offshoring takes place in high-income or low-income countries. For non-routine tasks, the estimated coefficient is larger for offshoring to high-income countries than for low-income countries, while no such difference is found for interactive tasks. On the margin, an increase in offshoring to high-income countries is estimated to be associated with a larger increase in the wage-bill share of non-routine tasks than offshoring to low-income countries.

Table 5: Offshoring and non-routine and interactive tasks: high-wage and low-wage countries

	Non-routine tasks				Interactive tasks			
	All	Manu.	Serv.	Comm.	All	Manu.	Serv.	Comm.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (assets / value-added)	.499	.113	-.478	.496	.036	-.037	-.480	.025
	(.145)***	(.228)	(.359)	(.218)**	(.073)	(.112)	(.180)***	(.104)
Log value-added	.322	-.219	-.417	.771	-.074	-.124	-.212	.195
	(.102)***	(.165)	(.248)*	(.157)***	(.051)	(.084)	(.128)*	(.073)***
Offshore empl. in HW countries	3.307	4.369	5.518	1.825	1.840	1.942	2.674	1.434
	(.816)***	(1.311)***	(1.855)***	(1.249)	(.408)***	(.657)***	(.947)***	(.592)**
Offshore empl. in LW countries	1.786	3.163	2.752	-.161	1.486	2.482	2.484	.039
	(.776)**	(1.144)***	(2.075)	(1.123)	(.391)***	(.561)***	(1.096)**	(.545)
Year 1999	.209	.536	.665	-.226	.088	.288	.273	-.173
	(.125)*	(.196)***	(.371)*	(.156)	(.064)	(.093)***	(.204)	(.078)**
Year 2000	.238	.595	.771	-.185	.091	.253	.362	-.136
	(.126)*	(.198)***	(.377)**	(.157)	(.064)	(.095)***	(.207)*	(.079)*
Year 2001	.202	.625	.669	-.186	-.015	.192	.210	-.234
	(.128)	(.200)***	(.381)*	(.160)	(.065)	(.095)**	(.208)	(.080)***
Obs.	5008	1876	1020	2112	5008	1876	1020	2112
R^2 (within)	.004	.025	.025	.002	.005	.026	.007	.014
R^2 (between)	.073	.019	.001	.102	.026	.019	.066	.002
R^2 (overall)	.068	.019	.002	.097	.025	.019	.06	.002

Source: Linked BA-MIDI data 1998-2001, MNE plants only. Standard errors in parentheses: * significance at ten, ** five, *** one percent.

Highly educated and white-collar workers. In Table 6 results for the other two "advanced" work types – highly educated workers and white-collar workers – are presented. We only report the results for manufacturing and services and put the results for world-wide offshoring and offshoring to high-income and low-income countries together in the same table.[30] The first four columns show the results for the wage-bill share of workers with upper secondary education, while the last four columns show the results for the wage-bill share of white-collar workers.

[30]The results for commerce and the whole sample are available upon request.

Table 6: Offshoring, education and occupations

	Upper-secondary education				White-collar occupations			
	Manu.	Manu.	Serv.	Serv.	Manu.	Manu.	Serv.	Serv.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (assets / value-added)	.123	.145	1.100	.902	-.877	-.834	-.705	-.642
	(.367)	(.375)	(.740)	(.750)	(.516)*	(.527)	(.722)	(.730)
Log value-added	.383	.392	1.120	1.102	-3.371	-3.344	.786	.791
	(.263)	(.263)	(.524)**	(.523)**	(.384)***	(.384)***	(.503)	(.503)
Offshore empl.	7.486		12.328		9.726		2.233	
	(1.507)***		(3.237)***		(2.164)***		(3.021)	
Offshore empl. in HW countries		7.124		16.698		8.974		.855
		(2.115)***		(4.160)***		(3.045)***		(3.765)
Offshore empl. in LW countries		7.724		7.327		10.216		4.025
		(1.877)***		(4.417)*		(2.648)***		(4.194)
Year 1999	.730	.724	.224	.283	1.845	1.833	2.527	2.513
	(.330)**	(.331)**	(.810)	(.809)	(.449)***	(.452)***	(.746)***	(.746)***
Year 2000	1.168	1.165	.782	.764	2.890	2.885	2.146	2.158
	(.334)***	(.334)***	(.822)	(.820)	(.455)***	(.457)***	(.758)***	(.759)***
Year 2001	1.254	1.247	1.346	1.399	2.380	2.365	1.974	1.957
	(.335)***	(.337)***	(.831)	(.830)*	(.457)***	(.461)***	(.767)**	(.767)**
Obs.	1871	1871	1007	1007	1876	1876	1020	1020
R^2 (within)	.038	.038	.036	.043	.096	.097	.022	.023
R^2 (between)	.015	.015	.034	.026	.018	.017	.006	.006
R^2 (overall)	.017	.016	.034	.027	.021	.02	.007	.007

Source: Linked BA-MIDI data 1998-2001, MNE plants only. Standard errors in parentheses: * significance at ten, ** five, *** one percent.

The results for manufacturing are relatively similar for the two work types. The estimated coefficients of world-wide offshoring as well as offshoring to high-income and low-income countries are positive and significant. The estimates are somewhat higher for white-collar workers than for the highly educated workers (around 9-10 compared to around 7-8). For white-collar workers the estimate for offshoring to low-income countries is also somewhat higher than for offshoring to high-income countries (around 10 compared to around 9). The results for services, however, differ depending on whether we measure skills by education or by the white-collar/blue-collar distinction. Not surprisingly, none of the estimated coefficients of offshoring are significant in the regressions for white-collar workers. Since most of the workers in the services sector are white-collar workers to begin with, we would not expect offshoring to be associated with a strong shift in this share. In the regressions for workers with upper-secondary education, however, the estimated coefficients are positive and significant at the 10 percent level or higher. The estimated coefficient of offshoring to high-income countries is more than twice the size of the estimated coefficient of offshoring to low-income countries (16.7 compared to 7.3), indicating that on the margin offshoring to high-wage countries is associated with a substantially larger increase in the wage-bill share of highly educated workers than offshoring to low-wage countries.

Instrumented variable regressions. Table 7 shows results for all four "advanced" work types from instrumental variable regressions using the full sample. The estimated coefficients of world-wide offshoring are all positive and significant except for white-collar workers. The estimated coefficients of offshoring to high-income countries are also all positive and significant at the 10 percent level or higher except for workers with upper secondary education. Regarding offshoring to low-income countries, however, only the estimated coefficient in the regression of the wage-bill share of workers with upper-secondary education is positive (significant at the 10 percent level). The others are negative and in the case of non-routine tasks significant at the 10 percent level.

Table 7: Offshoring, Tasks and Skills: IV estimates

	Non-routine tasks	Inter-active tasks	Upper-sec. educ.	White-collar occu.	Non-routine tasks	Inter-active tasks	Upper-sec. educ.	White-collar occu.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Offshore empl.	4.760	3.136	6.607	4.153				
	(1.463)***	(.680)***	(2.439)***	(3.604)				
Offshore empl. in HW countries					8.063	6.286	1.819	7.510
					(1.521)***	(1.381)***	(5.448)	(3.960)*
Offshore empl. in LW countries					-3.513	-1.538	12.524	-4.767
					(1.951)*	(1.724)	(6.914)*	(5.055)
Log (assets / value-added)	.653	.024	.786	-1.440	1.184	-.010	.992	-1.934
	(.165)***	(.081)	(.320)**	(.371)***	(.154)***	(.083)	(.328)***	(.340)***
Log value-added	.461	-.110	.920	-2.704	1.051	-.161	1.072	-3.393
	(.102)***	(.050)**	(.200)***	(.223)***	(.093)***	(.049)***	(.196)***	(.206)***
Year 1999	.154	.079	.516	1.442	.193	.109	.464	1.588
	(.133)	(.068)	(.280)*	(.281)***	(.199)	(.076)	(.294)	(.385)***
Year 2000	.171	.053	.581	2.050	.259	.069	.564	2.233
	(.137)	(.070)	(.285)**	(.292)***	(.198)	(.076)	(.295)*	(.385)***
Year 2001	.096	-.071	.495	1.840	.256	-.002	.406	2.139
	(.142)	(.072)	(.293)*	(.305)***	(.201)	(.081)	(.317)	(.395)***
First stage estimates for offsh. empl.								
Offshore empl. (t-2)	.872	.872	.875	.872				
	(.007)***	(.007)***	(.007)***	(.007)***				
First stage estimates for offsh. empl. in HW								
Offshore empl. in HW (t-2)					.721	.721	.734	.721
					(.009)***	(.009)***	(.008)***	(.009)***
Offshore empl. in LW (t-2)					.118	.118	.109	.118
					(.011)***	(.011)***	(.011)***	(.011)***
First stage estimates for offsh. empl. in LW								
Offshore empl. in HW (t-2)					.116	.116	.113	.116
					(.008)***	(.008)***	(.008)***	(.008)***
Offshore empl. in LW (t-2)					.785	.785	.788	.785
					(.010)***	(.010)***	(.010)***	(.010)***
Obs.	4900	4900	4815	4900	4900	4900	4815	4900
R^2 (within)	.005	.005	.008	.032	.0004	.0001	.006	.020
R^2 (between)	.067	.023	.060	.092	.104	.034	.057	.101
R^2 (overall)	.061	.020	.052	.091	.095	.03	.051	.097

Source: Linked BA-MIDI data 1998-2001, MNE plants only. Two-period lags of offshore employment serve as instrument for current offshore employment. Standard errors in parentheses: * significance at ten, ** five, *** one percent.

Table 6

Robustness checks for workers with upper secondary education. Ultimately, the skill-demand implications of offshoring may matter most to workers—regardless of whether they are channelled through occupational or task recomposition, or affect demand for workers' skills directly. Therefore, we focus on results for the wage-bill share of workers with upper secondary education and carry out a number of robustness checks, including controlling for the task and occupational composition. Table 8 presents these results.

Table 8: Offshoring and education: robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
Log (assets / value-added)	.890	.870	.892	.761	.370	1.376
	(.297)***	(.297)***	(.297)***	(.298)**	(.269)	(.283)***
Log value-added	.969	.934	.974	.993	.789	1.898
	(.203)***	(.205)***	(.207)***	(.209)***	(.183)***	(.196)***
Offshore empl.	8.443	8.408	8.442	8.189	5.819	6.722
	(1.195)***	(1.195)***	(1.195)***	(1.192)***	(1.078)***	(1.136)***
Year 1999	.380	.323	.381	.064	.456	.173
	(.280)	(.284)	(.282)	(.293)	(.266)*	(.273)
Year 2000	.495	.460	.498	.216	.513	.106
	(.282)*	(.284)	(.290)*	(.296)	(.268)*	(.275)
Year 2001	.388	.411	.390	.204	.432	.052
	(.285)	(.286)	(.288)	(.306)	(.271)	(.278)
Sector-level controls						
Offshoring (narrow)^a		9.853		11.475		
		(8.501)		(10.609)		
Offshoring (broad)^a			-.309			
			(5.321)			
R%D share in production				11.026		
				(34.893)		
Import penetration share in absorption				-3.195		
				(3.938)		
% Workers with upper-sec education				12.156		
				(3.296)***		
Plant-level controls						
% Workers doing non-routine tasks					79.370	
					(3.179)***	
% Workers doing interactive tasks					8.827	
					(6.276)	
% White-collar workers						25.609
						(1.225)***
Obs.	4921	4921	4921	4915	4921	4921
R^2 (within)	.013	.013	.012	.011	.107	.068
R^2 (between)	.052	.051	.052	.075	.336	.198
R^2 (overall)	.049	.048	.049	.070	.317	.189

Source: Linked BA-MIDI data 1998-2001, MNE plants only.
[a]: Following the terminology used by Feenstra and Hanson (1999), narrow offshoring only includes imported intermediate inputs from the importing industry, i.e. an industrys purchases of imported intermediate inputs produced in the same industry. Broad offshoring also includes imported non-energy intermediate inputs from all other industries. Standard errors in parentheses: * significance at ten, ** five, *** one percent.

To facilitate comparison, the first column reports the results for a basic specification with world-wide offshoring but without any additional controls. The next three columns present results from regressions that include different sector-level controls. These controls are only available for manufacturing industries, so the results pertain to the manufacturing sector only.

Our offshoring measure captures situations where the activities located abroad remain within the firm. But it is possible that the work composition is affected by decisions to outsource activities to independent foreign firms. In order to check whether this affects our results, we include a measure of offshoring of intermediate input production based on information on imports from the input-output tables. The measures are similar to what have been used by (Feenstra and Hanson 1996, 1999) in their studies of the impact of offshoring on the relative wage of non-production workers in the United States. Column 2 includes narrow offshoring, which is a measure of the share of imported inputs of goods produced within the industry itself, while column 3 includes broad offshoring, which is a measure of the share of imported inputs produced within the manufacturing sector. Neither of these measures are significantly related to the wage-bill share of highly educated workers, while the estimated coefficient of world-wide offshoring remains positive and significant.

Column 4 includes narrow offshoring together with the industry's research intensity (R&D per output), its import penetration (imports divided by absorption) and its overall share of workers with upper secondary education. R&D intensity is included to control for skilled-biased technological change while import penetration is included to control for possible effects related to increased foreign competition in the home market. The overall share of workers with upper secondary workers is included to control for supply effects. As is evident from the table, only the latter variable is significantly related to the wage-bill share of workers with upper secondary education. The estimated coefficient of world-wide offshoring however remains significant and is only marginally smaller than in the first three columns.

In the last two columns we check weather offshoring is still associated with educational upgrading when we control for changes in the task and occupational composition. In column 4 we include the employment share of non-interactive and interactive tasks and in column 5 we include the employment share of white-collar workers. In these columns, the estimated coefficient of offshoring captures the relationship between offshoring and the wage-bill share of workers with upper-secondary education for a given composition of tasks or occupations. The estimated coefficient is still positive and significant at the one percent level. However, the magnitude is reduced from around 8 to around 6-7. We thus conclude that the wage-bill share of upper-secondary-schooled workers increases with offshoring in excess of what is

Table 9: Offshoring Predictions of Wage Bill Shares

	Coefficient estimate	Pred. change in wage-bill sh.	Contrib. to obs. change
All sectors			
White-collar occup.	6.45	.124	8.3
Upper-secondary educ.	8.44	.126	11.7
Non-routine tasks	2.51	.148	10.2
Interactive tasks	1.65	.097	9.4
Manufacturing			
White-collar occup.	9.73	.384	11.2
Upper-secondary educ.	7.49	.295	9.6
Non-routine tasks	3.67	.145	14.1
Interactive tasks	2.27	.089	9.5
Services			
White-collar occup.	2.23	.202	2.1
Upper-secondary educ.	12.3	1.115	9.6
Non-routine tasks	4.32	.390	9.0
Interactive tasks	2.59	.235	17.1

Sources: Linked BA-MIDI data 1998-2001 and BIBB-IAB worker survey 1998/99. MNE plants only. Services exclude commerce. Task measures under strict interpretation. Predictions based on coefficient estimates in Tables 4, 5, and 6, controlling for plant-fixed and year effects.

implied by changes in the task or occupational composition.

Throughout our regressions, time indicators are highly significant and large predictors of workforce composition. Their magnitudes suggest that common shocks across firms are important elements of wage-bill changes for white-collar occupations and highly educated workers, and important factors for the shift towards more non-routine and interactive tasks. The importance of time effects for wage-bill change warrants caution in the interpretation of results. It remains for future research to discern whether the presence of these common shocks is related to offshore employment, technical change, or to a combination of these and other factors.

Economic significance. To quantify the explanatory power of offshore employment for relative labor demand, we use the offshoring coefficient estimates and the observed changes in offshoring employment between 1998 and 2001 to perform in-sample predictions of the implied changes in wage-bill shares.[31] Between 1998 and

[31] We use the estimates from Tables 4 and 6.

2001, offshore employment at German MNEs changed by .059 across all sectors, .039 in manufacturing, and .090 in services (weighted by onshore plant employment as in the estimation sample). Table 9 presents offshoring coefficient estimates for wage-bill shares by labor type (in column 1) and the implied wage-bill change given offshore employment at German MNE (in column 2). We then relate the contribution of the offshoring-predicted change to the observed change in wage-bill shares (column 3).

The offshoring measure explains around 10-15 percent of the observed shifts in onshore wage-bill shares, with some exception. In manufacturing, the largest contribution is found for the wage-bill share of non-routine tasks (14 percent), while the smallest is found for the wage-bill share of interactive tasks (9.5 percent). The predicted contribution to the observed change in the wage-bill share of white-collar workers of 11 percent is close to the contribution of around 9 percent at Japanese MNEs reported by Head and Ries (2002).

In services, the predicted contribution to the observed changes varies more than in manufacturing. The smallest contribution – 2 percent – is found for the wage-bill share of white-collar workers. As noted above, the estimated coefficient of offshoring in regressions of the wage-bill share of white-collar workers is not even significant. The largest contribution – 17 percent – is found for the wage-bill share of interactive tasks. Offshoring is thus predicted to contribute more to the shift towards interactive tasks in services than in manufacturing.

6 Concluding Remarks

Using novel plant-level data for German multinational enterprises (MNEs), this paper investigates the relationship between offshore employment and the onshore workforce composition. Drawing on detailed work-survey information regarding task types, the paper examines for the first time directly the relationship between offshoring and the composition of onshore tasks, in addition to widely used skill measures.

We find a similar relationship between German MNEs' offshore employment and the wage-bill share of white-collar workers in manufacturing as has been reported for Japanese and U.S. MNEs in previous studies. Furthermore, we find statistically significant positive relationships between offshore employment and the wage-bill shares of non-routine and interactive tasks for manufacturing as well as services. Non-routine tasks involve non-repetitive work methods, and interactive tasks require personal interaction with co-workers or third parties. We find non-routine and interactive tasks to be significantly more prevalent in onshore workforces of MNEs with larger offshore employment, irrespective of the occupation or worker skill. The important association between tasks and offshoring not withstanding, offshoring has a significant direct relationship with the educational upgrading of the onshore workforce. This relationship between offshoring and skilled labor goes beyond the educational recomposition that changing tasks or occupations imply.

Descriptive evidence in Section 4 documents that there is a salient difference in workforce compositions between MNEs and non-MNEs. This suggests that switches from non-MNE to MNE status may explain shifts in workforce composition. It remains for future research to investigate how these switches affect the relationship between offshoring and the onshore workforce composition.

Appendix

A Linked plant-MNE data

We link German plants to their corporate groups and measure the plants' exposure to MNE-wide offshore employment. This requires a two-step procedure. First, we identify all MIDI firms that are in the commercial company structure database MARKUS. Departing from the MIDI firms in MARKUS, we move both down and up in the corporate hierarchy of MARKUS to select the affiliates and ultimate parents of the MIDI firms. Second, we string-match all plants in the BA worker database to the so-selected MARKUS firms for identification of all plants related to German MNEs. A German MNE is an MNE, headquartered in Germany, with reported outward foreign-direct investment (FDI), or a firm in Germany, with reported outward FDI, whose ultimate parents are headquartered elsewhere. We also string-match the plants to MIDI itself for identification of all those firms that report FDI but are not part of a corporate group (German stand-alone MNEs).

We link the data based on names and addresses. By law, German plant names must include the firm name (but may by augmented with qualifiers). Before we start the string-matching routine, we remove clearly unrelated qualifiers (such as manager names or municipalities) from plant names, and non-significance bearing components from plant and firm names (such as the legal form) in order to compute a link-quality index on the basis of highly identifying name components. Our string-matching is implemented as a Perl script and computes link-quality indices as the percentage of words that coincide between any pair of names. We take a conservative approach to avoid erroneous links. We keep two clearly separate subsets of the original data: First, plants that are perfect links to MARKUS or MIDI, i.e. plant names that agree with firm names in every single letter. Second, plants that are perfect non-links, i.e. plant names that have no single word in common with any FDI-related MARKUS or MIDI firm. We drop all plants with a link-quality index between zero and one from our sample, i.e. plants whose name partially corresponds to an FDI firm name but not perfectly so. Those plants cannot be told to be either offshore-expansion or control plants without risk of misclassification.[32] The procedure leaves us with a distinct offshore-expansion group of FDI plants and a control group of non-FDI plants.

[32]The string-matching routine runs for several weeks, checking 3.8 million plants against 65,000 German MNEs. It is infeasible to manually treat possible links with imperfect link-quality rates.

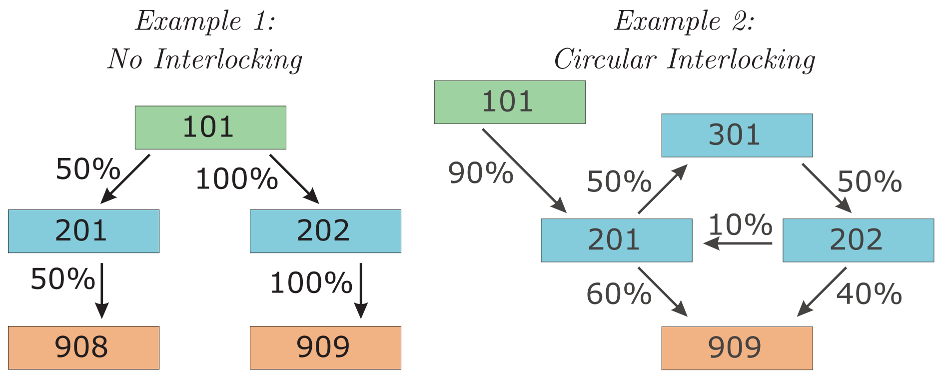


Figure 2: **Examples of Corporate Groups**

The BA plant name file is from November 2002 and contains names of plants that are no longer active so that we include exiting and entering plants. Firm names in the MARKUS database are from three vintages of data, November 2000, November 2001 and November 2002. This is to make sure that in case of name changes in one of the years 2000 through 2002, we do not miss string-matches.

Our procedure is designed to remove laterally related firms (sisters, aunts, or nieces) from the sample so that they neither enter the offshore-expansion nor the control group. Take Example 1 of Figure 2 and consider firm 201 to be the FDI-conducting (and FDI-reporting) firm in the depicted corporate group. The first step of our procedure identifies firm 201 in MARKUS and its affiliate and parent 908 and 101 but does not identify firms 202 (a sister to 201) and 909 (a niece to 201). If any name component of plants in firms 202 or 909 coincides with those of 101, 201 or 908 (but the plant name is not an identical match to 101, 201 or 908), the plants in firms 202 and 909 are discarded and neither enter the offshore-expansion nor the control group. If no single name component of plants in firms 202 or 909 is the same as that of 101, 201 or 908, the plant may enter our control group. If one considers sisters, aunts, and nieces with no single identical name component to be equally affected by FDI of firm 201 as those with common names or direct relations, their inclusion in the control group would make the control group more similar to the offshore-expansion group than it should be. If anything, however, the reduced difference would work against our worker separation estimates. Moreover, interlocking (of which Example 2 of Figure 2 is a special case) limits the number of only laterally related firms.

Table B.1: Ownership Inference

Affiliate-parent pair	Iteration (Length of Walk) 1	2	3	5	9	100
201-101	.9	.90	.900	.92250	.92306	.92308
201-202	.1					
201-301		.05		.00125		
202-101			.225	.22500	.23077	.23077
202-201		.25		.00625		
202-301	.5					
301-101		.45	.450	.46125	.46153	.46154
301-201	.5					
301-202		.05		.00125		
909-101		.54	.540	.64350	.64609	.64615
909-201	.6		.100		.00006	
909-202	.4	.06		.00150		
909-301		.20	.030	.00500	.00001	

B Corporate ownership and FDI exposure

We infer the economically relevant ownership share of a German firm in any other German firm. The relevant ownership share can differ from the recorded share in a firm's equity for two reasons. First, a firm may hold indirect shares in an affiliate via investments in third firms who in turn control a share of the affiliate. We call ownership shares that sum all direct and indirect shares *cumulated* ownership shares. Second, corporate structures may exhibit cross ownership of a firm in itself via affiliates who in turn are parents of the firm itself. We call ownership shares that remove such circular ownership relations *consolidated* ownership shares. This appendix describes the procedure in intuitive terms; graph-theoretic proofs are available from the authors upon request.

Consolidation removes the degree of self-ownership (α) from affiliates, or intermediate firms between parents and affiliates, and rescales the ultimate ownership share of the parent to account for the increased control in partly self-owning affiliates or intermediate firms (with a factor of $1/(1-\alpha)$). Investors know that their share in a firm, which partly owns itself through cross ownership, in fact controls a larger part of the firm's assets and its affiliates' assets than the recorded share would indicate. In this regard, cross ownership is like self-ownership. Just as stock buy-backs increase the value of the stocks because investors' *de facto* equity share rises, so do cross-ownership relations raise the *de facto* level of control of the parents outside the cross-ownership circle.

We are interested in *ultimate* parents that are not owned by other German firms, and want to infer their *cumulated and consolidated* ownership in all affiliates. Consider the following example of interlocking (Example 2 in Figure 2). The ultimate parent with firm ID 101 holds 90 percent in firm 201, which is also owned by firm 202 for the remaining 10 percent. However, firm 201 itself holds a 25 percent stake in firm 202—via its holdings of 50 percent of 301, which has a 50 percent stake in 201. Firms 201 and 202 hold 60 percent and 40 percent of firm 909. Our cumulation and consolidation procedure infers the ultimate ownership of 101 in all other firms.

We assemble the corporate ownership data in a three-column matrix:[33] the first column takes the affiliate ID, the second column the parent ID, and the third column the effective ownership share. Table B.1 shows this matrix for Example 2 in Figure 2 (the third column with the direct ownership share is labelled 1, representing the single iteration 1).

On the basis of this ownership matrix, our inference procedure walks through the corporate labyrinth for a prescribed number of steps (or iterations). The procedure multiplies the ownership shares along the edges of the walk, and cumulates multiple walks from a given affiliate to a given ultimate parent. Say, we prescribe that the algorithm take all walks of length two between every possible affiliate-parent pair (in business terms: two firm levels up in the group's corporate hierarchy; in mathematical terms: walks from any vertex to another vertex that is two edges away in the directed graph).

We choose the following trick to infer the *cumulated and consolidated* ownership for ultimate parents: We assign every ultimate parent a 100 percent ownership of itself. This causes the procedure to *cumulate and consolidate* the effective ownership share for all affiliates of ultimate parents, at any length of walks. There are seven distinct possibilities in the example to move in two steps through the corporate labyrinth. Table B.1 lists these possibilities as iteration 2 (all entries in or below the second row). With our trick, there is now an eighth possibility to move from affiliate 201 to parent 101 in two steps because we have added the 101-101 loop with 100-percent ownership. As a result, our procedure cumulates ownerships of ultimate parents for all walks that are of length two or shorter. The procedure starts to consolidate shares as the length of the walk increases. Iteration 3 in Table B.1

[33] We assemble cleared ownership data by first removing one-to-one reverse ownerships and self-ownerships in nested legal forms (such as *Gmbh & Co. KG*).

shows the cumulated and partially consolidated ownership of ultimate parent 101 in affiliate 201, for all three-step walks, including the first cycle from 201 through 202 and 301 back to 201 and then to 101.

In 2000, the maximum length of direct (non-circular) walks from any firm to another firm is 21. So, for all ultimate parents, the *cumulated and consolidated* ownership shares are reported correctly from a sufficiently large number of iterations on. Table B.1 shows iteration 100. The ownership share of 101 in 201 has converged to the exact measure ($.9/(1-.1\cdot.5\cdot.5) = .\overline{923076}$) at five-digit precision. Firm 101 controls 92.3 percent of firm 201's assets, among them firm 201's offshore affiliates.

To calculate the FDI exposure at any hierarchy level in the corporate group, we use a single-weighting scheme with ownership shares. The economic rationale behind single-weighting is that ultimate parents are more likely to be the corporate decision units (whereas FDI conducting and reporting firms in the group may be created for tax and liability purposes). We first assign FDI exposure measures (offshore affiliate employment by world region) from onshore affiliates to their ultimate German parents. Suppose firm 201 in Example 2 of Figure 2 conducts FDI in the corporate group. We assign 92.3 percent of 201's FDI exposure to firm 101, the ultimate German parent. We then assign the same 92.3 percent of 201's FDI exposure to all affiliates of 101 (201 itself, 202, 301, 909). So, jobs throughout the group (including those at 201 itself) are only affected to the degree that the ultimate parents can control offshore-affiliate employment (or turnover). We assign only 92.3 percent of 201's FDI exposure to 201 itself because the ultimate parent only has 92.3 percent of the control over employment at 201.[34]

Because we choose single-weighting in the onshore branches of the MNE, we also single-weight offshore-affiliate employment by the ownership share of the German parent in its offshore affiliates. Mirroring the minimal ownership threshold of 10

[34] An alternative assignment scheme would be double-weighting, first weighting FDI exposure by ownership and then assigning the FDI exposure to jobs throughout the corporate group using ownership weights again. We decide against double-weighting. Any weighting scheme results in exposure measures that are weakly monotonically decreasing as one moves upwards in the corporate hierarchy because ownership shares are weakly less than one. Double-weighting aggravates this property. Revisit Example 1 in Figure 2 and suppose firm 201 conducts FDI. Single-weighting assigns 50 percent of 201's exposure to affiliate 908, double-weighting only 12.5 percent. If 908 itself conducts the FDI, single-weighting assigns 25 percent of its own FDI exposure to 908, double-weighting only 6.25 percent. In economic terms, double-weighting downplays the decision power of intermediate hierarchies in the corporate group further than single-weighting so that we favor single-weighting. Recall that purely laterally related firms (sisters, aunts and nieces) are excluded from our offshore-expansion group so that firms 202 and 909 in Example 1 of Figure 2 are not relevant for the choice of weighting scheme.

percent in the MIDI data on offshore affiliates, we also discard the FDI exposure of onshore affiliates with ownership shares of less than 10 percent in our single-weighting assignment of FDI exposure to onshore jobs throughout the corporate group.

C Construction of tasks measures

Our main tasks measures build on a set of 81 questions in the BIBB-IAB work survey (Qualification and Career Survey 1998/99) regarding workplace-tool use. Table C.1 lists the 81 workplace tools that are surveyed. Workers report both their occupation and whether or not they use the listed tool. We codify whether or not the use of a tool indicates that the task is non-routine (involving non-repetitive work methods) or interactive (requiring interaction with co-workers or third parties). We choose to classify the use of the workplace tools under two different interpretations: our strict interpretation judges possibly few task elements to indicate non-routine work or interactive work, and our lenient interpretation judges possibly many task elements to indicate non-routine or interactive work. Table C.1 reports our codification. Based on these classifications, we compute the task intensity of occupations as described in Subsection 4.2.

As a robustness check to our classification of tasks, we reuse a classification by Spitz-Oener (2006) for information technology and labor demand. The Spitz-Oener (2006) mapping is based on a set of 15 job descriptions, also in the BIBB-IAB work survey. Table C.2 lists the job descriptions. Spitz-Oener (2006) classifies job descriptions with codes v192 and v200 as (manual) routine tasks, we take the complementary 13 job descriptions to imply non-routine tasks. Following Spitz-Oener (2006), we take job descriptions v189, v190, v194, v195, and v198 to imply interactive tasks. For the mapping from tasks to occupations, we proceed similar to our own task classifications and compute the task intensity of occupations as described in Subsection 4.2.

Table C.1: Workplace Tools and Non-routine or Interactive Tasks

	Non-routine tasks		Interactive tasks	
	Strict def.	Lenient def.	Strict def.	Lenient def.
Work involving	(1)	(2)	(3)	(4)
Tools or devices				
Simple tools				
Precision-mechanical, special tools	x	x		
Power tools				
Other devices		x		
Soldering, welding devices				
Stove, oven, furnace				
Microwave oven				
Machinery or plants				
Hand-controlled machinery				
Automatic machinery		x		
Computer-controlled machinery				
Process plants				
Automatic filling plants				
Production plants				
Plants for power generation				
Automatic warehouse systems				
Other machinery, plants		x		
Instruments and diagnostic devices				
Simple measuring instruments		x		
Electronic measuring instruments		x		
Computer-controlled diagnosis		x		
Other measuring instruments, diagnosis		x		
Computers				
Personal or office computers		x		
Connection to internal network		x		
Internet, e-mail		x		
Portable computers (laptops)		x		x
Scanner, plotter		x		
CNC machinery		x		
Other computers, EDP devices		x		
Office and communication equipment				
Simple writing material		x		x
Typewriter		x		x
Desktop calculator, pocket calculator				
Fixed telephone	x	x		
Telephone with ISDN connection	x	x		
Answering machine	x	x		
Mobile telephone, walkie-talkie, pager	x	x		
Fax device, telecopier				
Speech dictation device, microphone		x	x	x
Overhead projector, beamer, TV	x	x	x	x
Camera, video camera	x	x	x	x
Means of transport				
Bicycle, motorcycle			x	x
Automobile, taxi			x	x
Bus			x	x
Truck, conventional truck			x	x
Trucks for hazardous good, special vehicles		x	x	x
Railway		x	x	x
Ship		x	x	x
Aeroplane		x	x	x
Simple means of transport			x	x
Tractor, agricultural machine				
Excavating, road-building machine			x	x
Lifting-aids on vehicles			x	x
Forklift, lifting truck				x
Lifting platform, goods lift				x
Excavator				
Crane in workshops				x
Erection crane				x
Crane vehicle				x
Handling system				
Other vehicles, lifting means		x		x
Other tools and aids				
Therapeutic aids	x	x	x	x
Musical instruments	x	x	x	x
Weapons	x	x	x	x
Surveillance camera, radar device		x		x
Fire extinguisher	x	x	x	x
Cash register			x	x
Scanner cash register, bar-code reader			x	x
Other devices, implements		x		x
Software use by workers with computers				
Word processing program		x		
Spreadsheet program		x		
Graphics program	x	x		
Database program		x		
Special, scientific program	x	x		
Use of other software		x		
Computer handling by workers with computers				
Program development, systems analysis	x	x		x
Device, plant, system support	x	x		x
User support, training	x	x	x	x
Computer use by any worker				
Professional use: personal computer	x	x		x
Machinery handling by workers with machinery				
Operation of program-controlled machinery				
Installation of program-controlled machinery	x	x		
Programming of program-controlled machinery	x	x		
Monitoring of program-controlled machinery	x	x		
Maintenance, repairs	x	x	x	x

Source: BIBB-IAB worker survey 1998/99. Authors' classification of workplace-tool use associated with non-routine or interactive tasks. The strict (lenient) interpretation considers few (many) task elements to indicate non-routine or interactive work.

Table C.2: Non-routine and Interactive Tasks by Spitz-Oener

Code	Task	non-routine	interactive
v189	Training, teaching, instructing	x	x
v190	Consulting, informing others	x	x
v191	Measuring, testing, quality controlling	x	
v192	Surveillance, operating machinery, plants, or processes		
v193	Repairing, renovating	x	
v194	Purchasing, procuring, selling	x	x
v195	Organizing, planning	x	x
v196	Advertising, public relations, marketing, promoting business	x	
v197	Information acquisition and analysis, investigations	x	
v198	Conducting negotiations	x	x
v199	Development, research	x	
v200	Manufacture or production of merchandize		
v201	Providing for, waiting on, caring for people	x	
v223	Practicing labor law	x	
v224	Practicing other forms of law	x	

Source: BIBB-IAB Qualification and Career Survey 1998/1999. Classification of non-routine or interactive tasks by Spitz-Oener (2006). v189-v224 codes are variable abbreviations in the BIBB-IAB data.

D Wage-bill decomposition

Consider the change in the wage-bill share of work type i between 0 and t,

$$\theta_{it} - \theta_{i0} \equiv \frac{w_{it}L_{it}}{W_t} - \frac{w_{i0}L_{i0}}{W_0}, \tag{D.1}$$

where

$$W_t \equiv w_{it}L_{it} + w_{-it}L_{-it} \quad \text{and} \quad W_0 \equiv w_{i0}L_{i0} + w_{-i0}L_{-i0}.$$

Multiplying numerator and denominator of the first term in (D.1) with W_0 and multiplying numerator and denominator of the second term with W_t yields

$$\theta_{it} - \theta_{i0} = \frac{w_{it}L_{it} \cdot w_{-i0}L_{-i0} - w_{-it}L_{-it} \cdot w_{i0}L_{i0}}{W_t W_0} \tag{D.2}$$

after simplifications. Multiplying and dividing the first term in (D.2) by $w_{i0}L_{i0}$ and the second term by $w_{-i0}L_{-i0}$, we find

$$\begin{aligned}
\theta_{it} - \theta_{i0} &= \theta_{i0}\Theta_i \cdot \left(\frac{w_{it}L_{it}}{w_{i0}L_{i0}} - \frac{w_{-it}L_{-it}}{w_{-i0}L_{-i0}} \right) \\
&= \theta_{i0}\Theta_i \cdot \left(\frac{w_{it} - w_{i0}}{w_{i0}} \frac{L_{it}}{L_{i0}} + \frac{L_{it}}{L_{i0}} - \frac{w_{-it} - w_{-i0}}{w_{-i0}} \frac{L_{-it}}{L_{-i0}} - \frac{L_{-it}}{L_{-i0}} \right),
\end{aligned} \tag{D.3}$$

where

$$\theta_{i0}\Theta_i \equiv \frac{w_{i0}L_{i0} \cdot w_{-i0}L_{-i0}}{W_t W_0} = (1-\theta_{i0})\,\theta_{it}\,\frac{w_{i0}L_{i0}}{w_{it}L_{it}}.$$

Adding $L_{-i0}/L_{-i0} - L_{i0}/L_{i0} = 0$ to the terms in parentheses in (D.3) yields (10) in the text.

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