# Offshoring and the Onshore Composition of Occupations, Tasks and Skills*

Sascha O. Becker¶
*LMU Munich, CESifo and IZA*

Karolina Ekholm
*Stockholm U, CEPR and CESifo*

Marc-Andreas Muendler
*UC San Diego and CESifo*

March 24, 2007

*First and preliminary draft.*

**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. There is no statistically significant association between offshoring and the share of white- and blue-collar jobs in the onshore wage bill. The proportion of non-routine and interactive tasks, however, increases with offshoring, especially at services MNEs. 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 workers with upper-secondary education. While this excess educational upgrading beyond occupational and task recomposition is statistically significant, the economic effect of offshoring on the wage-bill composition is small.

*We thank Heinz Herrmann, Alexander Lipponer, Beatrix Stejskal-Passler, and Elisabetta Fiorentino for support with BuBa firm data, and Stefan Bender, Iris Koch and Stephan Heuke at BA for assistance with the plant records. Karin Herbst and Thomas Wenger kindly shared string-matching expertise, and Alexandra Spitz-Oener generously contributed task classifications for robustness checks. Ming Zeng provided excellent research assistance. We gratefully acknowledge financial support from the VolkswagenStiftung, the Fritz-Thyssen-Stiftung, the Wallander Foundation, the Swedish Council for Working Life and Social Research, and the Ifo Institute.

¶sbecker@lmu.de (*www.sobecker.de*), corresponding. Ph: +49 (89) 2180-6252.

# 1 Introduction

There is considerable agreement among economists that offshoring of different production stages likely affects the relative demand for skilled labor across countries. Whereas empirical studies based on trade flows find that imports lead to marked relative demand increases for white-collar workers (Feenstra and Hanson 1999), studies based on the offshore activities of multinational enterprises (MNEs) report only a weak or no effect on the relative demand for white-collar workers at parent firms (Slaughter 2000, Head and Ries 2002). The small effect of offshoring on the occupational composition is particularly surprising since MNEs transact a large part of international trade.

Empirical researchers posit that education-based measures may be more adequate than the occupational distinction between white- and blue-collar jobs to measure the effect of offshoring on the relative demand for labor (Head and Ries 2002, Hansson 2005). Recent theoretical arguments suggest, moreover, that the nature of tasks performed on the job may be more relevant for a job's propensity to be offshored than either the skill-intensity of the occupation or the education level of the worker (Grossman and Rossi-Hansberg 2006). Several important characterizations of the nature of tasks 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.[1] 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 MNEs to revisit the effect of offshoring on skill demand. The data cover activities in manufacturing as well as services between 1998-2001 and link information on MNEs' offshore activities to their onshore plant workforces. The data allow us to infer information on all three kinds of relevant workforce characteristics: occupation categories, the nature of performed tasks, and workers' educational attainment. To classify tasks, we codify information from a

[1]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.

German work survey on workplace-tool use along two dimensions:[2] we discern non-routine tasks that involve non-repetitive work methods versus routine tasks, and we discern interactive tasks that require personal interaction with co-workers or third parties versus non-interactive tasks. 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.

We investigate the relationship between an MNE's offshore activities and the composition of occupations, tasks and worker skills at the parent firm's German plants. The binary definitions of occupations, tasks and skills allow us to collapse the relative demand for onshore labor into a single reduced-form equation, similar to cost function estimation. We estimate the equation for all three kinds of workforce characteristics and compare the relevance of offshoring across occupations, tasks and skills. Similar to much of the prior literature, offshoring by German MNEs has no clear effect on the relative demand for white-collar workers at the German plants. Task-based measures, however, 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. Offshoring exerts a stronger effect on task recomposition in services than in manufacturing. But the predicted economic effect of offshoring on the task composition is minor.

The educational composition of the parent-firm workforce is related to offshoring in a statistically significant and expected way: onshore workers are more highly educated at MNEs with more offshore employment. What is more important, our data show that offshoring predicts educational upgrading above and beyond both the occupational recomposition and the task recomposition of the onshore workforce. To identify this excess educational upgrading, we measure the educational profile implied by a plant's occupational composition and its task composition and show that offshoring predicts educational upgrading beyond the implied educational composition. This finding is consistent with the hypothesis that the educational composition is more responsive to offshoring than the occupational and task composition. So the distinction between white- and blue-collar workers does not offer a complete measure of the component of skills affected by offshoring. Neither do dichotomous task

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

measures, although significantly related to offshoring, suffice for a characterization of workforce recompositions. The predicted economic effect of offshoring on the educational composition of onshore workforces is nevertheless small. Our estimates translate into a contribution of offshoring to changes in the wage-bill share of workers with upper-secondary education in the order of a few percent—a small effect compared to the 15-40 percent contribution of overall imports to the change in the wage-bill share of white-collar 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. We offer a more detailed discussion below. 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 is typically expected to increase the demand for skilled labor both because of a specialization in skill-intensive final goods and because of a shift to 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.

MNEs are driving forces behind offshoring. Offshore affiliates of MNEs ship a third of world exports, and the share of value added at MNE affiliates in world output is 10.1 percent in 2005, up from 6.7 percent in 1990 (UNCTAD 2006). Several studies of in-house offshoring by MNEs, 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 offshore production has no clear effect on the relative demand for non-production workers.[3] 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 offshoring 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.[4] Using data on Swedish manufacturing MNEs and measuring skills by educational attainment, Hansson (2005) repeats the analysis and distinguishes between offshoring to OECD and non-OECD host countries in addition. The generally small economic effects of offshoring on workforce composition, excepting non-OECD-country offshoring by Swedish MNEs, suggest the interpretation that offshoring across firms may exert a stronger effect on relative labor demand than offshoring within MNEs.

Recent theoretical considerations, however, shift attention from the offshoring effect on occupations to the effect on tasks. Grossman and Rossi-Hansberg (2006) develop a model where offshoring involves the cross-border transfer of tasks rather than the production of final goods. Skilled and unskilled workers carry out tasks that vary by offshoring cost. A reduction in offshoring costs leads to an increase in the range of offshored tasks, but also reduces production costs for offshoring firms and thus increases their productivity. Depending on demand parameters, productivity growth can benefit the factor intensely used in the sector with decreasing offshoring costs, which may or may not be less skilled labor. Most important for empirical research, unless the offshoring cost of a task is perfectly correlated with its skill intensity, the effect of offshoring on occupations, tasks and skills is predicted to differ.

Several recent studies investigate the effect of technological change on the relative demand for skills, paying particular attention to tasks and their substitutability with information technology. Autor, Levy and Murnane (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 non-

[3]Slaughter (2000) estimates the relationship between MNE production transfers and within-industry shifts in occupational composition, assuming capital to be a quasi-fixed factor. The regression predicts the non-production wage-bill share with other factor uses and the level of offshoring.

[4]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.

routine activities can be considered complementary to information technology. We follow Autor et al. (2003), and related research by Spitz-Oener (2006), in that we also link occupations to the involved share of routine versus non-routine tasks. In addition, we link occupations to the prevalence of personal interaction for the involved tasks. The latter aspect is more closely related to the relative importance of physical contact and geographic proximity.

# 3 Estimation Strategy

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

**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 foreign direct investment (FDI) at location $\ell(k)$ in year $t$:

$$\theta_{ijt} = \alpha_j + \beta_K \ln \tfrac{K_{kt}}{Y_{kt}} + \beta_Y \ln Y_{jt} + \beta_w \ln \tfrac{w_{it}}{w_{-it}} + \textstyle\sum_\ell \gamma_\ell \, FDI_{k\ell t} + \delta_t + \varepsilon_{ijt}, \qquad (1)$$

where $\theta_{ijt}$ is the share of factor input $i$ in the total wage bill at plant $j$, $\alpha_j$ 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 $j$, $w_{it}$ is the wage of work type $i$, $w_{-it}$ is the composite wage of the complementary work type not in $i$, $\delta_t$ is a year effect, and $\varepsilon_{ijt}$ an additive error term.

Equation (1) is the common model in related prior research (Slaughter 2000, Head and Ries 2002, Hansson 2005). It specifies a reduced-form relationship for relative onshore labor demand, given MNE employment at offshore locations. Several adjustments to a conventional factor-demand system are required to arrive at (1). The specification collapses offshore employments (from otherwise multiple offshore equations) into a scalar sum of FDI measures by location: $\sum_\ell \gamma_\ell \, FDI_{k\ell t}$.[5] An implicit identifying assumption is that MNEs determine their offshore activities $FDI_{k\ell t}$ prior to onshore labor demand. 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 $\theta_{ijt}$ that is explained by relative factor prices and restricts the own- and composite cross-wage coefficients to be

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

equal in absolute value. 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 $\theta_{ijt}$ due to capital deepening. Time dummies control for changes to the workforce composition that are common to all plants. The plant-fixed effect conditions on unobserved time-invariant plant heterogeneity.

The coefficients of foremost interest are $\gamma_\ell$. We wish to test whether a $\gamma_\ell$ coefficient is statistically significantly different from zero. We are also interested in the economic importance of the predicted magnitudes of $FDI_{k\ell t}$ variation for the wage-bill variation across three kinds of workforce characteristics: occupation categories (white-collar $i$ and blue-collar $-i$), 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 $-i$).

Simultaneity problems may affect equation (1). If offshore employment at $\ell$ and onshore demand for work type $i$ are simultaneously determined and substitutes, a downward bias in $\gamma_\ell$ could be expected. This kind of bias, however, does not necessarily impair our intended tests. If offshore and onshore labor are substitutes indeed, as structural estimation in prior work leads us to expect (Muendler and Becker 2006), simultaneity bias reduces the test statistic for our hypothesis that $\gamma_\ell$ differs from zero and thus works against us.

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 cluster standard errors at the parent-firm level and weight observations by plant size. We estimate several variants of specification (1) to assess robustness. We drop plant size weights, and we include additional controls such as R&D intensity and import penetration at the industry level. We also try alternative measures of non-routine and interactive tasks.

**Excess education effects.** Occupations and tasks are filled and performed by workers with different education. So, shifts in a workforce's occupational or task composition alone account for shifts in the workforce's educational profile. In the absence of evidence that the onshore white-collar wage bill is related to MNE offshoring, we hypothesize that offshoring predicts shifts in the educational profile beyond the accounted shifts in occupational or task composition.

Let $\eta_{ih}$ be the economy-wide share of workers with upper-secondary schooling $i$ in the wage bill of white-collar workers $h$ in the base year (1998). This constant serves as our reference value for the educational composition of white-collar occupations in an average German plant at the beginning of our sample period. Let $\lambda_{hjt}$ be the share of white-collar workers $h$ in total wage bill at plant $j$ in year $t$.

To test the hypothesis that offshoring predicts excess educational upgrading beyond occupational change, consider workers with upper-secondary schooling $i$ and augment equation (1) to

$$\theta_{ijt} = \alpha_j + \beta_K \ln \tfrac{K_{kt}}{Y_{kt}} + \beta_Y \ln Y_{jt} + \beta_w \ln \tfrac{w_{it}}{w_{-it}} + \textstyle\sum_{\ell} \gamma_\ell \, FDI_{k\ell t} + \beta_\theta \, \bar{\theta}_{ijt} + \delta_t + \varepsilon_{ijt}, \quad (2)$$

where $\bar{\theta}_{ijt} \equiv \eta_{ih}\lambda_{hjt}$ is the part of labor $i$'s wage-bill share that white-collar occupations $h$ in the plant workforce $jt$ accounted for. If occupational change completely accounted for variations in the wage-bill share of upper-secondary-schooled workers, $\gamma_\ell$ would lose significance in the presence of a statistically significant $\beta_\theta$. If, on the other hand, $\gamma_\ell$ remains significant in the presence of a significant $\beta_\theta$ coefficient, we reject the alternative to our hypothesis that offshoring predicts excess educational upgrading.

Similar exercises for non-routine and interactive tasks allow us to test whether offshoring predicts excess educational upgrading beyond task change. Let $\eta_{ih}$ be the economy-wide average share of upper-secondary-schooled workers $i$ in the wage bill of workers performing non-routine (interactive) tasks $h$ in the base year (1998), and let $\lambda_{hjt}$ be the share of workers performing non-routine (interactive) tasks $h$ in the total wage bill at plant $j$ in year $t$. Then a test whether $\gamma_\ell$ remains significant in the presence of a significant $\beta_\theta$ coefficient in equation (2) is a test for excess educational upgrading beyond task recomposition.

# 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.[6]

[6] 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.

## 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 1998-2001, representing around 80 percent of the formally employed German workforce.[7] 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.[8] 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 Deutsche Bundesbank (1998) for a documentation of USTAN (which reports parent-level operations of German MNEs). The outward FDI data cover all offshore affiliates of German MNEs according to minimal reporting thresholds.[9] 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

[7] 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.

[8] 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.

[9] 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.

according to the plant's employment share in parent employment. We transform nominal offshore variables over the full sample period to Euros at the exchange rate on December-31 1998 and deflate onshore and offshore variables to the December-31 1998 value.

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.[10]

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. In estimation Section 5, we report results from an MNE sample that excludes parent firms with offshore employment greater than 100 times their onshore employment.[11] 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.

Fourth, we use the BIBB-IAB work survey 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

[10]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).

[11]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).

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 distinct 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 third parties). To be able to assess the robustness of our estimation results to these classifications, we create one set of indicators under a strict interpretation of tool use and another set under a lenient interpretation.

We then map tasks to occupations in three steps. Fist, 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.[12] 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 number of tasks in any occupation so that task shares vary between zero and one across occupations, just as the expected occupation and education level of a given worker varies between zero and one. Our empirical strategy in Section 3 is unaffected by the choice of scale. To motivate our standardization, consider a fictitious average radiology assistant in the BIBB-IAB work survey and a fictitious maintenance worker. Suppose the maximum (tool-related) number of non-routine tasks in any *ISCO88* 2-digit occupation is 9 (out of 81). It is the fictitious average maintenance worker who reports many different tool uses and they imply the maximum of 9 non-routine tasks; maintenance orders exhibit a high degree of idiosyncracy, say. The fictitious

[12]Under our strict 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 lenient codification, the maximum number of non-routine (interactive) tasks per occupation is 15.4 (7.3).

average radiology assistant reports tool-use that implies only 3 non-routine tasks; there are just a few cases when image interpretation requires other tools beyond the main diagnostic device, say. Our standardization makes the fictitious maintenance job the only fully non-routine occupation in the sample, with a non-routine task share of one. The fictitious radiology assistant's job is a third non-routine, compared to the benchmark.

To gauge how sensitive our results are to the choice of task-to-occupation mapping, we also use the Spitz-Oener (2006) mapping for 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).

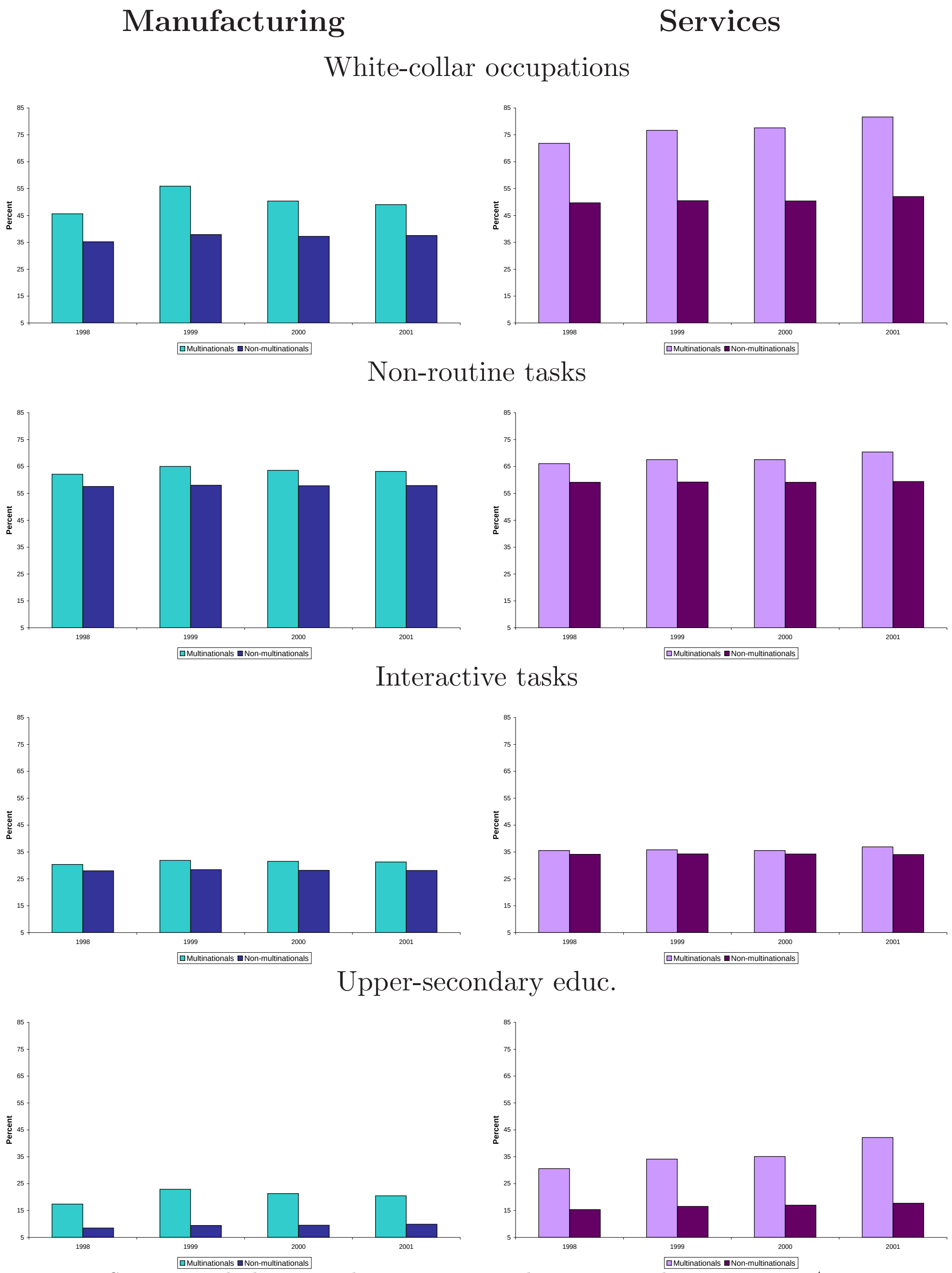
**Offshore activities.** We follow Head and Ries (2002) in measuring a plant's exposure to its parent firm's offshore activities with the share of offshore activities in total activities:[13]

$$FDI_{k\ell t} = \frac{\sum_{n\in\ell(k)} x_{nt}}{\sum_{n\in\ell(k)} x_{nt} + \sum_{j\in k} x_{jt}}, \tag{3}$$

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 (3), $x_{nt}$ is weighted by the parent firm's ownership share in the foreign affiliate. $FDI_{k\ell t}$ 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 $\ell$: high-income and low-income countries.

We measure activity with employment. 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, thus understating offshore activity and potentially leading to an exaggerated sensitivity of onshore labor demand to offshore activity. Surprisingly, we find estimation results with offshore sales to be similar to those with employment, and report results based on employment.

[13]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 $\ell$, 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.




*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**

## 4.3 Descriptive statistics

Figure 1 shows average wage-bill shares in manufacturing and services (excluding commerce) for four advanced work types: white-collar occupations, non-routine tasks, interactive tasks, and upper-secondary education. Each figure 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 advanced work types exceed those at non-MNEs. The services sector exhibits a noticeable upward trend in the wage-bill shares for all four advanced work types among MNEs but not among non-MNEs, where only workers with upper-secondary education experience an increase in their wage-bill share. In manufacturing, wage-bill shares of the four advanced work types rise somewhat at MNEs over the full period 1998-2001, but the augment is mainly due to a marked increase between 1998 and 1999, followed by modest decreases after 1999. As in the services sector, with the exception of the wage-bill share of workers with upper-secondary education, there is no clear increase in these wage-bill shares at non-MNEs. Overall, there is educational upgrading. The increase in wage-bill shares is strongest for education-based measures, while changes in the composition of tasks are relatively small. There is an especially large increase in the wage-bill share of workers with upper-secondary education between 2000 and 2001 in services, mainly in the business services sector.

Wage bills change with wage changes and in response to employment shifts. To assess the relative contribution, we decompose the observed wage bill changes into wage changes and employment shifts. Let $\theta_i$ be the wage-bill share of work type $i$. A change in $\theta_{it}$ over an initial period 0 can be split into the components

$$\begin{aligned}\frac{\theta_{it}-\theta_{i0}}{\theta_{i0}} = & \left(\frac{L_{it}}{L_{i0}}\frac{w_{it}-w_{i0}}{w_{i0}} - \frac{L_{-it}}{L_{-i0}}\frac{w_{-it}-w_{-i0}}{w_{-i0}}\right)\Theta_i \\ & + \left(\frac{L_{it}-L_{i0}}{L_{i0}} - \frac{L_{-it}-L_{-i0}}{L_{-i0}}\right)\Theta_i, \qquad (4)\end{aligned}$$

where

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

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 (4) to approximate the contribution of wage changes to the wage-bill share, and the second term to approximate the contribution of employment shifts. The first term includes weights that reflect gross employment growth and thus tends to exaggerate the wage contribution.

Table 1: Decomposition of Wage-bill Changes at MNEs, 1998-2001

| | Total change | Wage component contrib. | Wage component percent | Employment comp. contrib. | Employment comp. percent |
|---|---|---|---|---|---|
| **Manufacturing** | | | | | |
| White-collar occup. | .034 | .013 | 36.8 | .022 | 63.2 |
| Non-routine tasks | .010 | .004 | 42.2 | .006 | 57.8 |
| Interactive tasks | .009 | .002 | 27.5 | .007 | 72.3 |
| Upper-secondary educ. | .031 | .012 | 38.9 | .019 | 61.1 |
| **Services** | | | | | |
| White-collar occup. | .099 | .035 | 35.4 | .064 | 65.6 |
| Non-routine tasks | .044 | .017 | 38.6 | .027 | 61.4 |
| Interactive tasks | .014 | .006 | 41.1 | .007 | 58.9 |
| Upper-secondary educ. | .118 | .031 | 26.5 | .087 | 73.5 |

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

Table 1 reports the decomposition for white-collar occupations, non-routine and interactive tasks, and upper-secondary schooled workers at manufacturing and services MNEs. We use the strict task classification (results change little under the lenient classification). The overall growth in wage-bill shares at services MNEs exceeds that at manufacturing MNEs. Employment shifts are the dominant contributor to the wage-bill share growth for all four advanced work types in both sectors—even under our exaggerated wage-contribution proxy. Between one half and three quarters of the overall wage-bill share increase between 1998 and 2001 can be attributed to an increase in the proportion of jobs, tasks and skills in the workforce, while the wage contribution ranges between a quarter and a half depending on work type and sector. The wage contribution to wage-bill share growth for workers with upper-secondary education, for instance, is around 39 percent in manufacturing and 27 percent in services. Most important for our analysis, the signs of both wage and employment changes point in the same direction during the sample period. This suggests that it is increasing demand at MNEs that drives the observed increase in the wage-bill share for all four advanced work types.

A candidate predictor for onshore labor demand changes is the surge in offshore employment during the sample period. As Table 2 documents for German MNEs' majority-owned affiliates, total offshore employment rises from 3.1 to 3.7 million workers. The fastest relative increases occur in low-income countries: by 37 percent

Table 2: Offshore Employment of German MNEs by Foreign Region

| | 1998 | 1999 | 2000 | 2001 |
|---|---|---|---|---|
| Central and Eastern European countries | 487.9 | 541.2 | 631.0 | 668.8 |
| Developing countries | 572.4 | 610.4 | 681.1 | 693.5 |
| Overseas industrialized countries | 751.3 | 821.3 | 819.1 | 839.1 |
| Western European countries | 1,271.3 | 1,332.4 | 1,454.0 | 1,488.3 |
| *Total* | 3,083.0 | 3,305.2 | 3,585.2 | 3,689.7 |

*Source*: MIDI 1998-2001. Employment (in thousands) at majority-owned foreign affiliates.

in Central and Eastern Europe over the four-year period from 1998 to 2001 and by 21 percent in developing countries, compared to 20 percent overall. We turn to the relation between this surge in offshore employment and the onshore workforce composition.

# 5 Estimation Results

We investigate the predictive power of German MNEs' offshore activities for four types of onshore work characteristics: white-collar occupations, non-routine tasks, interactive tasks, and workers' upper-secondary education.

**White-collar occupations.** Labor demand model (1) guides our analysis. We start with a regression of the white-collar wage-bill share on predictors mirroring a main specification by Head and Ries (2002). Beyond manufacturing, we also fit the model to MNEs in services and commerce. We separate commerce from services because outward FDI in commerce arguably duplicates onshore sales operations (horizontal FDI), whereas services FDI can be driven by either cost-reducing motives (vertical FDI) or by horizontal FDI, or both. One might thus expect FDI in services and FDI in commerce to affect the onshore workforce composition differently.

Table 3 shows the results separately for manufacturing, services, and commerce (columns 1 to 3), and for the pooled MNE sample (columns 4 and 5). The overall fit in our employment-weighted regressions, including the fixed-effects prediction, exceeds 90 percent in all specifications (this remains the case, and we do not report the fit in subsequent Tables). Manufacturing estimates are similar to those reported in Head and Ries (2002) for Japanese manufacturing MNEs, and carry over to services, commerce, and the sample as a whole. Coefficients of the capital-output ratio

Table 3: OFFSHORING AND WHITE-COLLAR OCCUPATIONS

| | Manuf. (1) | Services (2) | Commerce (3) | All sectors (4) | All sectors (5) |
|---|---|---|---|---|---|
| Log (Capital / Value added) | -5.707 | -.359 | -.191 | -4.273 | -4.908 |
| | (2.855)** | (1.366) | (.802) | (2.380)* | (2.502)** |
| Log Value added | -20.872 | -1.691 | -2.645 | -17.389 | -20.879 |
| | (9.721)** | (2.652) | (1.670) | (8.794)** | (8.993)** |
| Offshore employment | 4.353 | 5.920 | .023 | 4.571 | 4.060 |
| | (2.913) | (4.707) | (1.339) | (2.404)* | (2.737) |
| Log Wage ratio | | | | | 16.940 |
| | | | | | (5.278)*** |
| Year 1999 | 5.928 | 3.355 | .514 | 5.214 | 4.420 |
| | (2.435)** | (1.293)*** | (.221)** | (2.245)** | (1.832)** |
| Year 2000 | 4.901 | 3.855 | 1.175 | 4.248 | 3.979 |
| | (1.076)*** | (1.108)*** | (.550)** | (.889)*** | (.872)*** |
| Year 2001 | 5.364 | 4.072 | 1.295 | 4.771 | 4.550 |
| | (1.223)*** | (1.207)*** | (.343)*** | (1.084)*** | (1.066)*** |
| Obs. | 1,871 | 2,114 | 1,026 | 5,064 | 5,064 |
| $R^2$ (overall) | .945 | .977 | .967 | .956 | .956 |

*Source*: Linked BA-MIDI data 1998-2001, MNE plants only. Controlling for plant-fixed effects. Observations weighted by plant employment. Robust standard errors in parentheses: * significance at ten, ** five, *** one percent.

and output (measured as value added) are negative and the estimated coefficient of offshore employment is positive. In Head and Ries's (2002) Japanese manufacturing MNE sample, however, the coefficient estimate for offshore employment is statistically significant. For the shorter time span in our German MNE sample, the offshore coefficient turns statistically significant at the ten-percent level only in the pooled sample across all sectors. In commerce, the offshore coefficient is minute and remains so in subsequent regressions for other work types. We choose to report no further results for commerce. Including the wage ratio between white-collar and blue-collar jobs as a regressor (column 5) has no statistically detectable effect on other covariates in this and subsequent regressions, and the remaining reported regressions omit the wage ratio. Year effects are highly significant across specifications in this and subsequent regressions, but do not indicate a statistically significant time trend. In these and subsequent regressions, omission of plant-fixed effects typically results in larger and more frequently statistically significant point estimates.

Table 4: Offshoring and Tasks

| Task: | Strict def. Non-rout. | Strict def. Interact. | Lenient def. Non-rout. | Lenient def. Interact. | Spitz-Oener def. Non-rout. | Spitz-Oener def. Interact. |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Log (Cap./Val. add.) | -.997 | -.523 | -1.222 | -.221 | -1.218 | -1.328 |
| | (.676) | (.330) | (.814) | (.173) | (.646)* | (.736)* |
| Log Value added | -4.303 | -2.024 | -5.345 | -.981 | -5.034 | -5.396 |
| | (2.538)* | (1.235) | (3.049)* | (.659) | (2.402)** | (2.727)** |
| Offshore emplmt. | 1.738 | 1.171 | 2.062 | .436 | 1.250 | 1.321 |
| | (.689)** | (.431)*** | (.837)** | (.244)* | (.674)* | (.725)* |
| Obs. | 5,064 | 5,064 | 5,064 | 5,064 | 5,064 | 5,064 |

*Sources*: Linked BA-MIDI data 1998-2001 and BIBB-IAB worker survey 1998/99. MNE plants only. Pooled data for manufacturing, services, and commerce. Controlling for plant-fixed and year effects. Observations weighted by plant employment. Robust standard errors in parentheses: * significance at ten, ** five, *** one percent.

**Non-routine and interactive tasks.** Our codifications of tasks as non-routine and interactive are based on two interpretations of workplace-tool use (Section 4, Appendix C): our strict interpretation considers possibly few task elements to imply non-routine work or interactive work, and our lenient interpretation takes possibly many task elements to indicate non-routine or interactive work. For comparisons, we also use the Spitz-Oener (2006) definition for non-routine and interactive tasks.

Table 4 shows regression results by task measure for the pooled sample (all sectors) and the three task definitions of wage-bill shares: under the strict interpretation (columns 1 and 2), the lenient interpretation (columns 3 and 4), and the Spitz-Oener (2006) interpretation (columns 5 and 6). None of our workplace-tool based task measures is statistically significantly related to the capital-output ratio or output at the five-percent significance level. This stark contrast to the highly significant capital-output-ratio and output coefficients in the white-collar-occupation regressions before (Table 3) suggests that our task measures do indeed capture aspects of work that are not related to the occupation. In contrast, the job-description based task measures by Spitz-Oener (2006) are significantly related to output. The converse is the case for the coefficient estimates on offshoring. While the Spitz-Oener (2006) measures show only a weak statistical association with offshoring, offshoring is a statistically significant predictor of wage-bill share increases for non-routine and interactive tasks, especially under our preferred strict interpretation (columns 1 and 2). The proportion of non-routine tasks increases particularly strongly with

Table 5: Offshoring and Tasks by Sector

| | Strict def. | | Lenient def. | | Spitz-Oener def. | |
|---|---|---|---|---|---|---|
| Task: | Non-rout. | Interact. | Non-rout. | Interact. | Non-rout. | Interact. |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | | | **Manufacturing Sector** | | | |
| Log (Cap./Val. add.) | -1.381 | -.724 | -1.713 | -.331 | -1.638 | -1.762 |
| | (.822)* | (.398)* | (.989)* | (.213) | (.782)** | (.885)** |
| Log Value added | -5.229 | -2.530 | -6.477 | -1.221 | -6.085 | -6.529 |
| | (2.828)* | (1.364)* | (3.391)* | (.734)* | (2.638)** | (2.997)** |
| Offshore emplmt. | 1.633 | 1.076 | 2.036 | .468 | 1.584 | 1.502 |
| | (.796)** | (.451)** | (.992)** | (.301) | (.891)* | (.893)* |
| Obs. | 1,871 | 1,871 | 1,871 | 1,871 | 1,871 | 1,871 |
| | | | **Services Sector** | | | |
| Log (Cap./Val. add.) | -.011 | .001 | .009 | .070 | -.247 | -.199 |
| | (.481) | (.333) | (.532) | (.136) | (.262) | (.319) |
| Log Value added | -.467 | .041 | -.648 | -.004 | -.376 | -.223 |
| | (.768) | (.233) | (.953) | (.105) | (.600) | (.709) |
| Offshore emplmt. | 3.033 | 3.046 | 3.281 | 1.123 | .624 | .680 |
| | (1.437)** | (1.198)** | (1.595)** | (.449)** | (.783) | (.994) |
| Obs. | 2,114 | 2,114 | 2,114 | 2,114 | 2,114 | 2,114 |

*Sources*: Linked BA-MIDI data 1998-2001 and BIBB-IAB worker survey 1998/99. MNE plants only. Services exclude commerce. Controlling for plant-fixed and year effects. Observations weighted by plant employment. Robust standard errors in parentheses: * significance at ten, ** five, *** one percent.

offshoring, more so than the proportion of interactive tasks under both the strict and lenient task definition.

The statistical relationship between offshore employment and the onshore composition of tasks may vary across sectors. Table 4 repeats the exercise for manufacturing and services MNEs separately. In manufacturing, our workplace-tool based task measures are now weakly related to the capital-output ratio and output at the ten-percent significance level, whereas the job-description based measures by Spitz-Oener (2006) are highly significantly related to capital-output ratio and output. In services, however, neither our workplace-tool based measures nor the job-description based measures by Spitz-Oener (2006) are statistically related to either the capital-output ratio or output. Using our workplace-tool based task measures, offshoring predicts a statistically significant increase in non-routine and interactive tasks both in manufacturing and services. Offshoring is not statistically significantly related

Table 6: Offshoring and Upper-secondary Education

| | Specification | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Log (Cap./Val. add.) | -1.457 | -1.492 | -1.460 | .484 | .485 |
| | (1.140) | (1.141) | (1.120) | (.323) | (.327) |
| Log Value added | -6.050 | -6.051 | -6.125 | 1.770 | 1.771 |
| | (4.193) | (4.192) | (4.178) | (.726)** | (.729)** |
| Offshore emplmt. | 4.642 | | 4.815 | 2.864 | 2.943 |
| | (1.573)*** | | (1.588)*** | (1.327)** | (1.628)* |
| in High-inc. countries | | 5.682 | | | |
| | | (2.080)*** | | | |
| in Low-inc. countries | | 3.635 | | | |
| | | (2.372) | | | |
| R&D per output | | | -38.027 | | |
| | | | (22.749)* | | |
| Import penetration | | | 2.059 | | |
| | | | (2.179) | | |
| White-coll. occ. Predictor | | | | 118.360 | 118.436 |
| | | | | (4.805)*** | (5.393)*** |
| × Offsh. emplmt. | | | | | -.392 |
| | | | | | (9.512) |
| Obs. | 5,064 | 5,064 | 1,871 | 5,064 | 5,064 |

*Sources*: Linked BA-MIDI data 1998-2001. MNE plants only. Pooled data for manufacturing, services, and commerce; excepting column 3 with manufacturing data only. Controlling for plant-fixed and year effects. Observations weighted by plant employment. Robust standard errors in parentheses: * significance at ten, ** five, *** one percent.

to the job-description based Spitz-Oener (2006) measures, however, similar to our prior finding (in Table 3) that the occupational profile and offshoring are not clearly related. Both in manufacturing and services, the proportion of non-routine tasks increases particularly strongly with offshoring, more so than interactive tasks. We find offshoring to exert a stronger effect on task recomposition in services than in manufacturing, especially under our preferred strict interpretation of tasks (columns 1 and 2).

**Upper-secondary education and occupational recomposition.** Ultimately, the skill-demand implications of offshoring matter most to workers—regardless of whether offshoring is channelled through occupational or task recomposition, or affects demand for workers' skills directly. It is nevertheless a matter of economic relevance to understand the extent to which occupational or task recomposition can explain the skill-demand effects of offshoring. We turn to these issues by regressing the wage-bill share of workers with upper-secondary schooling on predictors under labor demand model (2).

Table 6 reports results for the pooled MNE sample across all sectors. The estimated coefficient of offshore employment is positive and significant at the one-percent level (column 1). Splitting the offshoring regressor into an offshoring measure for high-income and low-income countries shows that the relationship between high-income country offshoring drives the positive relationship between the wage-bill share for workers with upper-secondary schooling and offshoring (column 2). This finding is consistent with the hypothesis that offshore activities in high-income countries are complementary to the wage-bill share of skilled labor. Hansson (2005), in contrast, finds a statistically significant and positive relationship between low-income country offshoring and the wage-bill share of skilled labor at Swedish MNEs. Sector-level controls for a plant's competitive environment—the industry's research intensity (R&D per output) and the industry's penetration with imports (per absorption)—do not significantly change the coefficient estimate for offshoring. These findings suggest that educational upgrading may be a foremost channel through which in-house offshoring correlates with onshore labor demand.

To investigate the relationship between offshoring and educational upgrading more closely, we include as a regressor the proportion of the upper-secondary-schooled workers' wage-bill share that is directly accounted for by white-collar occupations in the plant workforce. For this purpose, we compute the fraction of the white-collar wage bill that is earned by workers with upper-secondary schooling. Starting from 35.6 percent in 1998, this fraction increases steadily to 40.6 percent in 1999, to 42.5 percent in 2000, and to 43.4 percent in 2001. We multiply the initial value of 35.6 percent with the share of white-collar workers in the total wage bill at the plant in a given year. By design, the so-constructed proportion of upper-secondary-schooled workers in the white-collar wage-bill share at a plant is a highly significant predictor of the workers' wage-bill share (column 4). But offshore employment remains a statistically significant covariate of educational upgrading even in the presence of the constructed skill-intensity predictor. The interaction of the constructed skill-intensity predictor with offshoring is not statistically significant (though it taints statistical significance of offshoring). We conclude that the wage-bill share of upper-secondary-schooled workers increases with offshoring in excess of what is implied by changes in occupational composition.

Table 7: Offshoring, Upper-secondary Education and Tasks

| | uncond. | Non-routine tasks | | Interactive tasks | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Log (Cap./Val. add.) | -1.457 | .128 | .086 | -.194 | -.163 |
| | (1.140) | (.272) | (.274) | (.400) | (.399) |
| Log Value added | -6.050 | 1.011 | .973 | -1.142 | -1.111 |
| | (4.193) | (.596)* | (.610) | (1.238) | (1.215) |
| Offshore emplmt. | 4.642 | 2.475 | -8.857 | 2.672 | 13.686 |
| | (1.573)*** | (1.180)** | (7.184) | (1.547)* | (7.791)* |
| Task predictor | | 640.986 | 626.390 | 883.901 | 915.158 |
| | | (15.761)*** | (19.642)*** | (90.514)*** | (91.865)*** |
| × Offsh. emplmt. | | | 74.074 | | -143.837 |
| | | | (49.527) | | (103.685) |
| Obs. | 5,064 | 5,064 | 5,064 | 5,064 | 5,064 |

*Sources*: Linked BA-MIDI data 1998-2001 and BIBB-IAB worker survey 1998/99. MNE plants only. Pooled data for manufacturing, services, and commerce. Task measures under strict interpretation. Controlling for plant-fixed and year effects. Observations weighted by plant employment. Robust standard errors in parentheses: * significance at ten, ** five, *** one percent. Column 1 repeats column 1 of Table 6 for comparison.

**Educational upgrading beyond task recomposition.** Table 7 revisits educational upgrading, now including a task predictor for the wage-bill share of upper-secondary workers by plant. For this purpose, we compute the fraction of the wage-bill share that workers with upper-secondary schooling earn in non-routine tasks. Similarly, we compute the fraction of the wage-bill share that workers with upper-secondary schooling earn in interactive tasks. Compared to the unconditional regression (column 1), the predicted effect of offshoring on the wage-bill share of skilled workers drops in magnitude when task predictors are included. But the offshoring coefficient continues to be statistically significant for non-routine tasks and weakly significant for interactive tasks, although the task predictors themselves are highly significant predictors. The interaction term between tasks and offshoring, however, is not a significant predictor.

The non-routine and interactive fraction of the wage-bill share for skilled workers are calculated as the task recomposition due to occupational change over the years 1998-2001. We cannot exclude that, over this four-year time span, there is additional within-occupation upgrading towards more non-routine or interactive tasks (Spitz-Oener 2006). Given the short time dimension of our sample, however, our finding of excess educational upgrading is mainly driven by cross-sectional differ-

Table 8: Offshoring Predictions of Wage Bill Shares

| | MNE Offshoring | | | Sector imports |
|---|---|---|---|---|
| | Coefficient estimate | Pred. change in wage-bill sh. | Contrib. to obs. change | Contrib. to obs. change |
| **All sectors** | | | | |
| White-collar occup. | 4.57 | .124 | 4.6 | |
| Non-routine tasks | 1.74 | .047 | 1.2 | |
| Interactive tasks | 1.17 | .032 | 1.0 | |
| Upper-secondary educ. | 4.64 | .126 | 4.2 | |
| **Manufacturing** | | | | |
| White-collar occup. | 4.35 | .198 | 3.4 | 10.1 |
| Non-routine tasks | 1.63 | .074 | 1.0 | 7.5 |
| Interactive tasks | 1.08 | .049 | 0.9 | 0.8 |
| Upper-secondary educ. | 5.29 | .241 | 3.1 | 11.3 |
| **Services** | | | | |
| White-collar occup. | 5.92 | .119 | 1.2 | |
| Non-routine tasks | 3.03 | .061 | 1.4 | |
| Interactive tasks | 3.05 | .061 | 4.5 | |
| Upper-secondary educ. | 6.12 | .123 | 1.1 | |

*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 3, 4, 5 and 6, controlling for plant-fixed and year effects.

ences across plants, mitigating the effect of within-occupation upgrading towards more non-routine or interactive tasks. We conclude that offshoring predicts an increase in the wage-bill share of workers with upper-secondary education in excess of the task recomposition of the workforce. While the excess educational upgrading, beyond occupational and task recomposition, is statistically significant, it remains to investigate the economic importance of the prediction.

**Economic significance.** To quantify the explanatory power of offshore employment for relative labor demand, we use 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.[14] Between 1998 and 2001, offshore employment at German MNEs changes by .027 across all sectors, .046 in manufacturing, and .020 in services (weighted by onshore plant employment

[14]We use offshoring coefficient estimates from Tables 3, 4, 5 and 6 (and sector-specific coefficient estimates for task upgrading) under labor-demand model (1), omitting the wage ratio.

as in the estimation sample). Table 8 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 only a small fraction of the observed shifts in onshore wage bill shares. For upper-secondary schooled workers and white-collar occupations, growth in offshore employment predicts 4 to 5 percent of the observed change in wage-bill shares. This is lower than the offshoring contribution of around 9 percent at Japanese MNEs, reported by Head and Ries (2002). For non-routine and interactive tasks, growth in offshore employment explains around 1 percent of changes in the wage-bill across all sectors, but contributes more than 4 percent in services.

A reason for the generally small explanatory power of offshoring for MNE wage-bill variations is perhaps that in-house offshoring within MNEs captures only one part of overall offshoring and neglects outsourced offshoring to independent suppliers of intermediate inputs. For the manufacturing sector, we can use industry-wide import penetration as a proxy for outsourced offshoring and import competition. Similar to our calculations for offshoring, we take the import-penetration coefficient estimate, and observed changes in import penetration between 1998 and 2001, to perform an in-sample prediction of the implied changes in wage-bill shares.[15] Table 8 reports the contribution of import-penetration prediction to observed wage-bill share changes. We find the largest total contribution, adding offshoring and import penetration, for workers with upper-secondary schooling and white-collar jobs: 14.4 and 13.5 percent, respectively. These estimates come close to the lower bound of 15 percent, reported by Feenstra and Hanson (1999) for white-collar wage-bill shares in U.S. industries under a somewhat different estimation strategy. For non-routine and interactive tasks, however, the joint contribution of offshoring and import penetration to changes in the wage-bill shares is considerably lower: 8.5 percent and 1.7 percent, respectively.

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-

[15] We use the import-penetration coefficient estimate from Tables 4 (and similar estimates for other work types) under labor-demand model (1), including sector R&D but omitting the wage ratio.

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.

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. In fact, structural estimation in Muendler and Becker (2006) shows that roughly half of the onshore employment effect of German MNEs' offshore expansions is explained by entry into a foreign location, and the other half by expansions at existing locations. While estimation of offshore effects using a balanced panel is in the spirit of static trade theory, a comprehensive future assessment of the economy-wide relationship between offshoring and the onshore workforce composition ought to account for switches from non-MNE to MNE status.

# 6 Concluding Remarks

Using novel plant-level data for German multinational enterprises (MNEs), this paper investigates the relationship between offshore employment and 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. Similar to findings for Japanese and U.S. MNEs in previous studies, there is only a weak relationship between German MNEs' offshore employment and the occupational workforce composition that separates white-collar from blue-collar jobs. There is a statistically significant positive relationship, however, between offshore employment and the proportion of non-routine and interactive tasks. 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 advanced 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. Though statistically significant, offshoring-related educational upgrading is a quantitatively small part of the observed wage-bill changes at German MNEs.

# 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.[16] The procedure leaves us with a distinct offshore-expansion group of FDI plants and a control group of non-FDI plants.

[16]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.

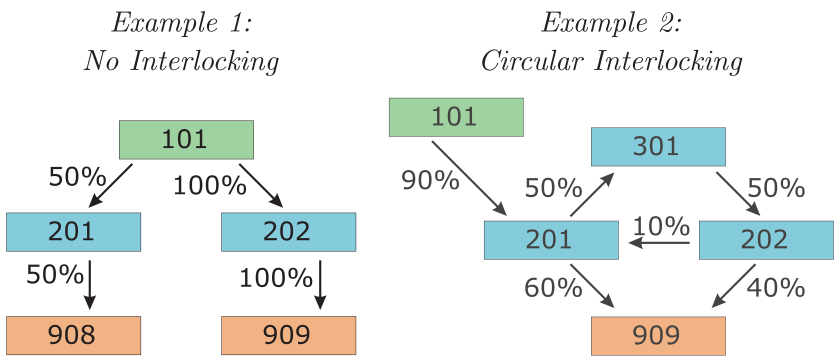



Figure 2: **Examples of Corporate Groups**

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 | 1 | 2 | 3 | 5 | 9 | 100 |
|---|---|---|---|---|---|---|
| | Iteration (Length of Walk) | | | | | |
| `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 ($\alpha$) 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:[17] 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

[17]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.[18]

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

[18]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

$$\theta_{it} - \theta_{i0} = \frac{w_{it}L_{it} \cdot w_{-i0}L_{-i0} - w_{-it}L_{-it} \cdot w_{i0}L_{i0}}{W_tW_0} \tag{D.2}$$

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

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

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 (4) in the text.

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